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COLLECTIVE RESPONSE TO SCARCITY:

HOW THE RESOURCE ENVIRONMENT SHAPES SOCIAL NETWORKS

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All that is good in my life, and all that is good in me, I owe to my advisor, Reid Hastie.

TABLE OF CONTENTS

LIST OF FIGURES

Figures in Main Text

Figures in Supplement

LIST OF TABLES

Tables in Main Text

Tables in Supplement

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ABSTRACT

The present research program investigates the underlying mechanisms that drive changes in the structure of communication networks among strategic decision-makers confronted with changes in their resource environment. This investigation is carried out through five experiments that engage human participants in a novel *n*-armed bandit task either as individuals (Studies 1, 2A, and 2B) or as members of interactive groups (Studies 3A and 3B). This research program makes several novel contributions. Primary among these is an important refinement to the “scarcity” construct employed by a number of disciplines across the social sciences. Despite a lack of consensus around the definition of scarcity, there is apparent agreement that a downward shift in resource levels is a key component. The present experiments cleanly separate the effect of downward shifts in resource levels from other components of the scarcity construct. I find that a downward shift in resource levels *alone* is not sufficient to produce the "scarcity effects" identified by prior research that did not control for comorbid components of scarcity that often present as confounds. However, I find that competition (Study 3B) *does* produce behaviors consistent with scarcity effects (e.g. reduced information-seeking and information hoarding). I situate these results in the context of the scarcity and social learning strategies literatures and discuss the implications for constructing a coherent definition of scarcity.

1 INTRODUCTION AND OVERVIEW

The present research program investigates the underlying mechanisms that drive changes in the structure of communication networks among strategic decision-makers. I have three overarching goals for this investigation: 1) to advance our understanding of the way exogenous environmental factors shape the structure of communication networks, 2) to disambiguate the effects of distinct elements of scarcity on behavior, and 3) to refine extant theories of communication network emergence and social learning strategies by exploiting the complementarity of these two traditions.

This investigation is carried out through five experiments with human participants engaged in a novel task that balances control for confounding variables with concern for "mundane realism" (Carlsmith, Ellsworth, and Aronson, 1976). The task is structured as an *n*-armed bandit with continuous rewards (Gittins & Jones, 1974; Weber, 1992). Participants repeatedly sample from a set of resources that each have an unknown reward distribution. Each time a resource is sampled, the participant receives a reward drawn from that resource's distribution. When selecting which resource to sample next, the participant faces a trade-off between exploiting the resource that has produced the highest (average) reward so far, or exploring alternatives to see if she can find resources that produce higher rewards. This flavor of decision problem is often referred to as the exploration-exploitation dilemma.

This research program makes several novel contributions. First, I offer an important refinement to the "scarcity" construct employed by a number of disciplines, including social psychology, organizational behavior, behavioral ecology, and communication network studies. There is currently no consensus around the definition of scarcity. The only point of agreement across definitions is a persistent reference to resource *levels* (Cannon, Roux, & Goldsmith, 2018;

Roux, Goldsmith, & Bonezzi, 2015). To be clear, I am using the term resource *levels* to refer to the *range* of values that can be extracted from an environment (e.g. fish in Pond A weigh between 5 and 10 pounds, fish in Pond B weigh between 10 and 20 pounds). I am *not* referring to the *frequency* at which different resource magnitudes occur (e.g. the ratio of big to small fish in Pond A is 10:1, the ratio of big to small fish in Pond B is 5:1). Nor am I referring to the *probability* that *any* value will be extracted from the environment at a specific point in time (e.g. on a given day, there is a 50% chance you'll catch a fish from Pond A, and a 20% chance you'll catch a fish from Pond B).

Despite apparent agreement that resource levels are a key component of resource scarcity (perhaps *the* key component), the effect of shifts in resource levels is never evaluated in isolation (for a review of scarcity manipulations in experimental research see Cannon, Roux, & Goldsmith, 2018).[1] Instead, it is almost always presented in combination with additional, confounding components of the scarcity construct. Prior research often uses umbrella terms like "munificence" to refer interchangeably to distinct qualities of the resource environment. This suggests a widespread misconception that these qualities are equivalent, but they are not. For example, changes in environmental resource levels, uncertainty, and ambiguity each engage distinct neural processes and have different effects on human behavior (Berns & Bell, 2012; Huettel et al. 2006; Smith et al., 2009; Tobler et al., 2007). A lack of clarity in the language used

[1] The effect of shifts in resource levels has been isolated using the Successive Negative Contrast (SNC) paradigm in the animal learning literature. But, SNC experiments with human participants are quite rare. The most well-known study with animal participants is Crespi (1942). Briefly, rats were trained using either a large reward or a small reward. Rats were then offered rewards from the opposite level than the one used during training (large to small, small to large). Large-reward rats ran slower toward a reward that was smaller than what they saw during training, and small-reward rats ran faster toward a reward that was larger than what was used in training. For a review of reward-shift experiments with animal participants, see Flaherty (1982).

to describe scarcity, and a lack of precision in the way scarcity is operationalized experimentally, have resulted in conflicting interpretations of past observational and experimental results.

The present experiments are designed to cleanly separate the effect of shifts in resource levels from other components of the scarcity construct that often present as confounds in prior research, including: 1) *expected* uncertainty (variance in the amount of energy extracted from a given resource across samples), 2) *unexpected* uncertainty or *ambiguity* (ignorance of the average amount of energy that can be extracted from a given resource), 3) resource *competition* (negative interactions between individuals, particularly those that impede access to resources), 4) emotional stress, 5) social comparison, and 6) negative affect.

Second, I disambiguate the effect of shifts in resource levels from other features of organizational crises that are often conflated in the communication networks and organizational behavior literatures. The present experiments are the first to cleanly separate the effect of shifts in resource levels from frequently comorbid conditions of organizational crisis such as negative affect, stress, identity threat, and interpersonal or intergroup conflict. Observational studies of communication networks under crisis are unable to perfectly isolate the effects of these conditions from one another, which limits our ability to draw strong causal inferences about the relationships between distinct characteristics of crises and changes in communication network structure.

Controlled experiments provide an opportunity to make causal inferences that are necessary for theory building. But, very few experimental studies of the way human communication networks function under different environmental conditions have allowed those networks to emerge endogenously. Instead, different network structures are imposed on participants, and the consequences of those structures (e.g. on achievement, satisfaction, etc.) are compared across environments (e.g. Mason & Watts, 2012; Wisdom, Song, and Goldstone, 2013). The present experiments contribute important methodological and empirical insights to the small but growing body of experimental studies in communication network emergence.

Finally, the present research program is the first to compare the behavior of participants sampled from the *same* population within the *same* experimental paradigm across contexts that vary only in the nature of opportunities to sample the resource distribution. I contrast participant behavior across five versions of the same explore-exploit task: 1) solo participants with no access to side observations of the resource values (Study 1), 2) solo participants with full access to side observations selected by a random sampling algorithm (Study 2A), 3) solo participants with full access to side observations selected by past participants (Study 2B), 4) groups of *non*-competing participants with contingent access to side observations selected by peers playing contemporaneously (Study 3A), and 5) groups of *competing* participants with contingent access to side observations selected by peers playing contemporaneously (Study 3B).

Past experimental research has compared the behavior of participants across the following combinations of the contexts described above: (1) and (3); (1) and (4); (1) and (5); or (1), (4), and (5). To my knowledge, no prior experimental research has compared the behavior of participants sampled from the *same population* across *all five* of the above contexts. Such a global comparison within a unified experimental framework provides new and important insights into human strategies for managing explore-exploit dilemmas, and how the source of side observations affects tendencies (not) to use that information. In particular, the absence of context (2) – access to samples of the resource distribution drawn by a random sampling algorithm – from experimental designs in the social learning strategies literature makes it difficult to interpret past results, and to extrapolate from experimental participant behavior to real world contexts.

The rest of the discussion proceeds as follows. I describe the relevant empirical and theoretical context for the present research in Section 2. Section 3 describes elements of the experimental design common to all five studies, and my statistical methods. Section 4 presents Study 1, which establishes a baseline for behavior in the explore-exploit task when participants are playing solo and have no access to side observations of the reward distributions. Section 5 presents Studies 2A and 2B. These studies are designed to investigate solo participants' appetite for side observations of the reward distributions when these observations are selected by a random sampling algorithm (Study 2A), or by a past participant (Study 2B).

Section 6 presents Studies 3A and 3B. These studies are designed to investigate the emergence of communication networks among groups of experimental participants when access to side observations of the reward distributions is contingent on participants' willingness to share information with each other. In Study 3A, there is no competition among members of each experimental group. In Study 3B, experimental groups are incentivized using a rank order competition.

Section 7 concludes with a general discussion of the experimental results, limitations of the present studies, and directions for future research.

2 THEORETICAL AND EMPIRICAL MOTIVATION

A small and somewhat disconnected cluster of observational and experimental studies have revealed structural changes in communication networks during adverse events. These adverse events are generally described as “negative shocks” or “crises.” The definition of a crisis varies across studies, but usually includes some combination of the following individual- and group-level phenomena: surprise, uncertainty (expected or unexpected), resource constraint, emotional stress, threat (to personal identity, physical safety, social order), tension, interpersonal or intergroup competition, and time pressure. I will briefly highlight a few examples of structural changes observed in studies of communication networks in crisis. Then, I’ll explain how gaps in theories of communication network emergence limit our ability to reason about the underlying mechanisms that give rise to these changes. Finally, I will recommend an experimental strategy for addressing these gaps that leverages theoretical and methodological tools from the social learning strategies literature.

2.1 Communication Network Response to Crisis

A constellation of structural changes in communication networks is often observed during and following crisis events. The most common observation across studies is that individuals decrease communication with “weak ties” – people with whom they communicated infrequently before the crisis, and to whom they do not feel an especially close emotional connection. This has come as a surprise to many researchers from the social networks tradition, because it contradicts behavior predicted by Granovetter’s (1973) theory of weak ties. Paraphrasing Granovetter: People who you talk to less frequently, and with whom you have fewer friends in common, are more likely to know stuff you don’t already know. Talking to your close friends isn't going to help you navigate situations that are shocking or confusing, because they have the same information you do. They are probably just as shocked and confused as you are. Instead, you should talk to people who have *different* information than you do. The assumption being that access to new and different information can help you form more accurate beliefs about the world, so you won't be so disoriented by the situation you found so surprising.

The second most common observation across studies is that networks become more "centralized" – a few people are responsible for sending (and receiving) most of the messages exchanged within the network. The third observation is an increase in the number of messages people send to "strong ties" (close friends, people with whom they communicated frequently in the past).

Romero, Uzzi, and Kleinberg (2016, 2019) refer to this cluster of structural changes as "turtling up." The authors studied the response of hedge fund employees' communication networks to "price shocks" (changes in stock prices that are "extreme" compared with a rolling three-day average). Using electronic records of instant messages sent between employees the authors found that communication networks "turtled up" immediately following a price shock. Employees reduced their number of communication partners, and increased communication with coworkers in their own functional unit with whom they spoke most frequently in the past.

A similar pattern has been observed in the Enron email corpus, which includes all email communications sent by over 150 Enron executives as the company disintegrated over the course of 2000-2001 (Diesner, Frantz, & Carley, 2005; Hossain, Murshed, & Uddin, 2013; Uddin, Murshed, & Hossain, 2011). At the height of the crisis, researchers observed increased centralization, decreased transitivity (pairs of communication partners are less likely to share a third-party contact in common), increased reciprocity (people tend to respond to messages they receive), and emergence of cliques (sub-groups of people who all communicate frequently with everyone else in the group). Similar structural changes (increased centralization, increased density, decreased transitivity, and the emergence of cliques) were found by Danowski and Edison-Swift (1985) in their study of emails exchanged between employees of a Midwestern state extension agency following a budget and hiring freeze.

Other observational studies have used mixed methods including diaries and retrospective self-reports to understand the response of communication networks to crisis. Ramirez-Sanchez and Pinkerton (2009) found that fisherfolk's self-reported communication networks contracted (fewer contacts, more communication with "strong ties") whenever fish became scarce. Loosemore and Hughes (2001) observed the emergence of cliques and increased centralization in their diary study of communication among stakeholders in a construction project over the course of a contract dispute that occurred during a slump in the construction industry.

Quasi-experimental studies with military recruits and professionals have found similar patterns during training exercises. Kalish et al. (2015) surveyed military recruits during a multi-day training exercise, collecting self-reports of emotional stress and communication partners. The authors found that trainees who reported higher levels of emotional stress formed fewer communication ties with their peers. Fitzhugh and DeCostanza (2018) collected digital communication records during a large-scale multi-week simulation exercise with military professionals. Following a crisis that occurred within the simulation, participants reduced their number of communication partners, and increased communication with structurally advantageous contacts (people who pass information between sub-groups that are otherwise isolated from each other) and with those in formal coordinator roles.

2.2 Theories of Communication Network Emergence

Current theories of communication network emergence emphasize the effect of *pre-existing* network structure on individual outcomes, or *stable* individual preferences for types of relationship partners (Borgatti & Cross, 2003; Contractor et al., 2012; Monge & Contractor, 2001, 2003; Nebus, 2006; Rivera, Soderstrom, & Uzzi, 2010). Aside from physical proximity, the effect of *exogenous* environmental variables on communication network emergence has been largely ignored (Entwisle et al., 2007; McFarland et al., 2014).

One of the reasons for this gap in theory building arises from a tendency originating in organization analysis to define the network environment in terms of itself (the "environment" *is* the set of relations on actors that comprise the network) or in terms of socially constructed reality (e.g. culture, exchange relationships, institutional processes). To the extent that energetic resources are considered, they are usually cast in terms of a competition or exchange relation induced on actors pursuing control of the same limited resource (Monge & Contractor, 2003; also see Sutcliffe, 2001, for a historical overview of different theoretical perspectives on organizational environments).

In their exposition of a multitheoretical multilevel approach to communication network analysis, Monge and Contractor (2003) provide a framework for classifying types of independent variables that affect the emergence of communication network structure. Variables are classified across two dimensions. The first dimension is endogenous versus exogenous. Endogenous variables are "inside the network" or characteristics of the relation on the set of nodes that comprise the network. Exogenous variables are "outside the network" or objects that are *separate and distinct* from the set of nodes and their relation. The second dimension is local versus global. Local variables are characteristics of (usually small) sets of nodes in the network (e.g. individual actors, pairs of actors). Global variables are characteristics of the full network structure.

	Endogenous	Exogenous
Local	structural autonomy status transitivity RELATIONAL / ASSORTATIVE	gender age education ASSORTATIVE
Global	centralization density hierarchy RELATIONAL	other relations past time periods residence PROXIMITY

Figure 2.1. **Framework for Classifying Independent Variables.** Adaptation of Monge and Contractor's (2003) framework for classifying independent variables that affect the emergence of communication network structure. Examples of candidate variables cited by the authors are provided in each quadrant in black text. Rivera and colleagues' (2010) typology of mechanisms that drive change in dyadic tie formation overlaid in red, capital letters. Note that "residence" (lower-right quadrant in red) is cited as a candidate variable by Rivera and colleagues, but not by Monge and Contractor.

Figure 2.1 illustrates Monge & Contractor's framework as four quadrants representing each combination of levels across the two dimensions, with examples of independent variables provided by the authors in each quadrant. It's somewhat surprising that the only two examples of exogenous, network-level variables (lower-right quadrant of Figure 2.1, black text) provided by Monge and Contractor are 1) other relations on the actors in the communication network (e.g. a "friendship" or "co-authorship" relation on the same set of actors), and 2) the communication network's *own structure* in previous time periods. This seems like it would be a good place to put characteristics of the *physical* environment (like resource levels) or even the *social* environment (culture, industry, etc.).

Rivera, Soderstrom, and Uzzi (2010) provide a complementary typology for mechanisms that drive dynamic tie formation among pairs of actors in a network. The authors classify mechanisms into three types: Assortative, Relational, and Proximity. Relational mechanisms include endogenous attributes at the local level (e.g. the two actors both have high "status" in the network) or global level (e.g. the network is highly centralized). Assortative mechanisms include local level attributes that can be endogenous (e.g. the two actors both communicate with the same third party) or exogenous (e.g. the two actors both have the same gender identity). Proximity mechanisms include *stable* attributes of the social or cultural environment, such as actors' place of residence (physical location). Rivera and colleagues make no mention of aspects of the physical environment other than the relative location of two actors.

There are two problems with these schemata. First, we don't get much traction for reasoning about the emergence of ad hoc communication networks among agents with no prior knowledge of each other's personal characteristics. This might seem like an edge case that would only arise infrequently, but it isn't. Many US firms have announced permanent remote-work schemes after realizing they could cut fixed costs without losing much productivity during the Covid-19 pandemic. It has also become increasingly common for employers to hire temporary remote workers for short term projects. And, many large-scale, open-source software platforms are developed collaboratively by mostly anonymous self-organizing collectives. Understanding how patterns of communication emerge in these contexts, where social cues are limited and there is often no formal role hierarchy, is a matter of both practical and theoretical importance.

Second, we don't get much traction for reasoning about the effects of crisis on communication network structure. Neither Monge and Contractor (2003) nor Rivera and colleagues' (2010) locate crisis variables like stress, threat (to identity, physical safety, social order), or changes in the resource environment (magnitude, uncertainty, ambiguity) within their respective schema. But, most of the crisis variables would fit neatly into the relatively underexplored Global-Exogenous or Proximity dimensions of the theoretical frameworks suggested by each group of authors. Identifying the causal relationships between crisis variables and communication network structure will close important gaps in extant theories of communication network emergence.

I propose that controlled experiments are especially useful to investigate these causal relationships. Of the many crisis variables implicated as potential drivers of communication network structure, I have chosen to focus on a specific component of scarcity (shifts in resource levels). There are a few reasons. The first is that scarcity is one of the most salient features of "crisis." The second is that scarcity is a compound construct, but its elements are often conflated in the literature. This is a problem because each element of scarcity has potentially distinct effects on behavior. The third is that scarcity, as a feature of the resource environment, offers a bridge between theories of communication network emergence and social learning strategies. This allows me to exploit theoretical and methodological tools offered by the social learning strategies literature that make experimental study of communication network emergence more tractable.

2.3 Social Learning Strategies

Social learning strategies (SLS) describe an agent's rules for deciding *when* to learn from others, *whom* to learn from, and *what* to learn. The answer to each of these questions often depends on the structure of the resource environment. As a result, SLS provide a framework for reasoning about how changes in the environment affect a person's decision to communicate with peers, and which peers are chosen as communication partners. From the SLS perspective, *asocial* learning occurs when an agent acquires information about the true state of the environment by sampling it directly. In contrast, *social* learning occurs when the agent acquires information about the true state of the environment vicariously by observing the behavior of other agents (Hoppitt and Laland, 2013).

I will provide a brief overview of the most relevant results from the SLS literature, and illustrate how these results help us form hypotheses about the way people (and groups) respond to shifts in resource levels (the specific component of scarcity that we will explore in this research program). Let's start with the SLS predictions for *when* people choose to learn socially, versus asocially (independently).

People are *more* likely to rely on social learning *when*: 1) asocial learning is costly, unreliable, or difficult (Kameda & Nakanishi, 2002; McElreath, Bell, Efferson, Lubell, Richerson, Waring, 2008; Mesoudi & O'Brien, 2008; Morgan, Rendell, Ehn, Hoppitt, & Laland, 2012; Toelch, Bruce, Newson, Richerson, & Reader, 2014), 2) there is a high level of *expected* uncertainty (Morgan, Rendell, Ehn, Hoppitt, & Laland, 2012), or 3) they are dissatisfied (Atkisson, O'Brien, & Mesoudi, 2012; Mesoudi & O'Brien, 2008). People are *less* likely to rely on social information when there is a high level of *unexpected* uncertainty (ambiguity) (Toelch, van Delft, Bruce, Donders, Meeus, & Reader, 2009).

These results suggest two potential (conflicting) hypotheses for what behavior we might observe following a downward shift in resource values. If a person *does not* recognize a decline rewards as a signal that resource levels have shifted, and instead becomes dissatisfied with her own performance or bad luck, she will choose to *increase* her reliance on social learning. Her communication rate will increase, and her network will expand as she searches for more sources of social information.

On the other hand, if a person *does* recognize a decline in rewards as a shift in resource levels, this will induce a sense of *unexpected* uncertainty (ambiguity), and she will choose to *decrease* her reliance on social learning. Believing the reward distributions of the resources in her environment have changed, she will assume her peers' information is outdated, and will choose to explore independently to obtain updated information about the true (current) state of the environment.

To understand how individual behavior might influence communication at the group level, we can turn to the SLS predictions for *whom* people choose to learn from, and *what* they choose to learn. People are most likely to learn socially from actors *who*: 1) are successful (Mesoudi, 2011; Mesoudi & O'Brien, 2008), 2) are friends or kin (Laland, 2004), 3) have high social status or prestige (Atkisson, O'Brien, & Mesoudi, 2012), 4) constitute a majority (Boyd & Richerson, 1985; Morgan et al., 2012). In terms of *what* information people learn from others, there is a tendency to copy traits associated with actors who extract higher rewards from the environment (Kendal et al., 2008; Mesoudi, 2011; Mesoudi & O'Brien, 2008).

Suppose we assume a decline in rewards leads each member of a group to become dissatisfied and choose to rely on social learning more than asocial learning. Collectively, they explore the environment less, and are less likely to discover higher rewards. At the same time, they copy each other's behavior at higher rates. As a result, performance across group members becomes more homogeneous. The distance between the rewards captured by highest and lowest performers shrinks. This leads members of the group to distribute their attention more evenly across peers. The network would not become "centralized" around a single group member.

Conversely, if a decline in rewards leads each member of the group to believe resource levels have shifted, they will all reduce their rates of social learning and instead choose to explore the environment independently. This increases the odds that at least one of the group members discovers a resource that yields higher rewards. His discovery attracts the attention of his peers. To the extent that group members do observe each other, these infrequent observations will be directed toward the peer who discovered higher rewards. In this case, the network becomes centralized around this top performer.

Reasoning from the SLS framework, we now have some more tractable hypotheses for what behavior we might observe following a downward shift in resource levels. Now we can start to flesh out the design of the experiments.

3 COMMON DESIGN ELEMENTS AND STATISTICAL METHODS

This section describes elements of the experimental design common to all five studies in the present research program (Studies 1, 2A, 2B, 3A, and 3B). Dependent variables common to all five studies are also described, as well as statistical methods used to investigate differences in the response values of these dependent variables between experimental Conditions.

3.1 Background

The design of my novel experimental paradigm was inspired by previous work investigating the effect of communication network structure on collaborative learning and social information foraging (Mason, Jones, & Goldstone, 2008; Mason & Watts, 2012; Wisdom, Song, & Goldstone, 2013), and by work investigating how the structure of the resource environment shapes social learning strategies (McElreath, Bell, Efferson, Lubell, Richerson, & Waring, 2008; McElreath, Lubell, Richerson, Waring, Baum, Edsten, Efferson, & Paciotti, 2005; Mesoudi, 2008, 2011; Mesoudi & O'Brien, 2008; Toelch, Bruce, Newson, Richerson, & Reader, 2014).

I selected an explore-exploit task for two reasons. First, the decisions people make in this type of task are influenced by both prior beliefs about resource levels (Acuna & Schrater, 2008; Reverdy, Srivastava, & Leonard, 2014; Steyvers, Lee, & Wagenmakers, 2009), and by access to social information (e.g. about peers' past choices and outcomes; Adrian, Siddharth, Baquar, Jung, & Deák, 2019; Toelch, Bruce, Meeus, & Reader, 2010). Second, individual strategies for managing this trade-off directly impact an organization's ability to achieve an appropriate balance between exploring the environment for new opportunities, and exploiting existing capabilities (Chandrasekaran, Linderman, & Schroeder, 2012; Hong, Yu, & Hyun, 2018; Schnellbächer, Heidenreich, & Wald, 2019; Laureiro-Martínez, Brusoni, & Zollo, 2010; Simsek, 2009). Achieving this balance is crucial to an organization's survival (Levinthal & March, 1993; O'Reilly & Tushman, 2013).

I was also careful to select a cover story that is both familiar to most adults living in the United States, and relevant to a persistent challenge in modern firms that has not received sufficient attention. Participants in the present experiments take on the role of salesperson. The "resources" in the environment are platforms sold by a software company. The "reward" associated with each platform represents the value customers place on that platform. Participants "sample" these resources by pitching the company's platforms to several customers, and receiving feedback on the value each customer assigns to the platforms the participant chooses to pitch.

The reason this particular cover story is interesting is two-fold. First, though the explore-exploit task paradigm has been well-studied, no prior work has presented participants with an explore-exploit dilemma situated in a modern firm context. Superficial changes to the context can lead people to employ different heuristic strategies, even if the underlying task structure is the same (Liberman, Samuels, & Ross, 2004). So, before we can extrapolate from experimental results to make predictions for workplace behavior, it is important that we verify people respond consistently across contexts. In particular, it is important to test whether the sales context evokes heuristic strategies that may arise from cultural traditions around the sales function or lay theories of the secrets to sales success.

Second, salespeople in modern firms are notoriously reluctant to share market information with coworkers within or outside of their functional department (Albaum, 1964; Anaza & Nowlin, 2017; Le Bon & Merunka, 2006; Nowlin, Anaza, & Anaza, 2015; Robertson, 1974; Saegert & Hoover, 1980). Despite ample documentation of this phenomenon and its negative consequences for performance, little is known about what causes salespeople's reluctance to engage in knowledge-sharing (Evans,Hendron, & Oldroyd, 2015; Webster, Brown, Zweig, Connelly, Brodt, & Sitkin, 2008). Because salespeople span the boundary between the firm and its environment, their special position provides them access to information critical to the firm's survival (Bell, Mengüç, & Widing, 2010; Chonko, Dubinsky, Jones, & Roberts, 2003). Identifying mechanisms that promote or suppress salesperson knowledge sharing is, therefore, a matter of great practical importance.

3.1 Design

3.1.1 Recruitment and Compensation

Participants were recruited through the Center for Decision Research (CDR) at the University of Chicago Booth School of Business, and through Amazon Mechanical Turk (MTurk). MTurk participants were required to live in the United States, to have completed at least 1000 Human Intelligence Tasks (HITs), and to have an approval rating of at least 98%.[1] CDR participants were paid a $10.00 base fee upon completion of the focal study, and earned a variable performance-based bonus (bonus calculations are described in *3.1.3 Procedure*). MTurk participants were paid a $6.00 base fee upon completion of the focal study, and earned an Active Participation Bonus of $4.00 if they consistently submitted responses within the time limits.[2] MTurk participants also earned a variable performance-based bonus.

[1] These criteria were selected in consultation with senior program managers at MTurk, and with the founder of the largest and most active MTurk Worker forum.
[2] Following the Comprehension Check, each page of the focal procedure had a time limit for submitting responses (described in *3.1.3 Procedure*). The Active Participation Bonus was added to the MTurk version of the procedure for two reasons: 1) to encourage participants to stay engaged and prevent delays, 2) to protect against bad actors on the MTurk platform. Participants were warned three times before the start of the focal procedure that if they "repeatedly fail to submit responses before the time limits" they will be marked as a "dropout," will not be allowed to complete the game, and will not receive the Active Participation Bonus. A definition of "repeatedly" was not

Prior to participating in the focal studies, participants completed an Enrollment Survey. CDR participants' responses to the Enrollment Survey were not used as a screening mechanism. All CDR participants who completed the Enrollment Survey were automatically eligible to participate in the focal studies. After completing the Enrollment Survey, CDR participants could register for the focal study by selecting their preferred date from a calendar of pre-scheduled sessions. Participants did not receive payment upon completing the Enrollment Survey. Instead, participants' compensation for the Enrollment Survey was built into the participant fee for the focal experiment, and participants received payment upon completion of the focal experiment.[3] Most CDR participants chose to participate in the focal experiment within 1 week of completing the Enrollment Survey.

MTurk participants' responses to the Enrollment Survey *were* used as a screening mechanism. A rapid, severe escalation in the number of fraudulent Mturk Worker accounts took place over the course of 2020. By the end of July, 2020, up to 50% of participants in earlier versions of the present studies (studies run *before* we introduced the Enrollment Survey) were suspected operants of fraudulent Worker accounts. In order to combat this widespread fraud epidemic, we introduced the Enrollment Survey as a screening mechanism. MTurk participants

provided to participants, so they did not know how many failures were allowed before they would be marked as a dropout. The cumulative number of failures were tracked across Trials, and the threshold for dropout status increased as the participant advanced in the experiment. Participants were marked as dropouts if they accrued more than six failures before Trial 16, more than 8 failures before Trial 31, or more than 10 failures before Trial 45. This increasing threshold was constructed to minimize time delays caused by participants who dropped out of the experiment, while still allowing engaged participants some slack in case failures resulted from technical issues outside of the participants' control. Once marked as a "dropout," the experiment automatically advanced the participant through all remaining Trials, and the participant was not allowed to enter any further responses. A similar dropout management process was implemented for the CDR participants.

[3] Withholding compensation until participants complete the focal experiment is consistent with best practices recommended by CDR leadership. Because compensation for the Enrollment Survey was withheld, I could not use responses to the Enrollment Survey to screen out suspicious participants (e.g. participants may have misrepresented their identity, location, demographic information, and other characteristics, or may have maintained multiple participant profiles in the CDR participant registry).

received $1.25 for completing the Enrollment Survey. Participants whose responses were not marked as “highly suspicious” (based on criteria described in the Supplement under *A.1 MTurk Screening Criteria*) were eligible to participate in the focal experiment.

After becoming eligible to participate in the focal experiment, MTurk participants could choose to participate in the focal experiment during any available session. Reminder emails were sent 15 minutes before the start of each session, and again at the start of each session. Most MTurk participants chose to participate in the focal experiment within 1–3 days of completing the Enrollment Survey.

Surveys and experiments used in the present research program were programmed in oTree (Chen, Schonger, and Wickens, 2016), and hosted on a Heroku cloud server. For MTurk participants, surveys and experiments were served directly into the Amazon Mechanical Turk (MTurk) environment through an iFrame. CDR participants encountered surveys and experiments as a standalone website.

3.1.2 Enrollment Survey

In addition to acting as a screening mechanism for MTurk participants, the purpose of the Enrollment Survey was to collect basic demographic information, structural characteristics of participants’ personal social networks, and information related to participants’ perceptions of Covid-19 as well as the impact of Covid-19 on their daily lives.

Feelings Inventory. At the start of the enrollment survey, participants completed the Feelings Inventory. Participants were asked to report their emotional state by rating the extent to which they were currently experiencing each of the following six emotions: happy, frustrated, successful, friendly, hostile, anxious. Participants rated each emotion on a scale of 0 (“you are not experiencing that feeling at all”) to 100 (“you are experiencing that feeling very much right now”).[4]

Demographics and Work History. Next, participants reported their demographic information, which included: age, gender, highest academic degree, location, years of professional work experience, most recent industry, most recent role, and the industry in which they have worked the longest.[5]

Social Networks Questionnaire. After reporting their demographic information, participants responded to a name generator designed to elicit their closest social contacts.[6] Participants were required to report at least one contact, and were encouraged to name at least three (there was no upper limit on the number of contacts a participant could name). After reporting their closest contacts, participants were asked to rate how close they felt to each of these contacts on a scale of 0 (“Very Distant”) to 100 (“Very Close”).[7] Finally, participants were

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[4] “How are you feeling right now? Please rate each feeling below on the scale given. A rating of 0 means that you are not experiencing that feeling at all right now. A rating of 100 means you are experiencing that feeling very much right now.” Participants used continuous sliding scales to enter their responses.

[5] Gender: Participants were asked, “With which gender do you most closely identify,” and could select “Male,” “Female,” or “Other.” The “Other” option was selected by a tiny number of participants. Highest Academic Degree: Participants selected from “No Degree,” “High School Diploma,” “2-Year College Degree or Skilled Trade Program,” “4-Year College Degree,” “Masters Degree or Higher.” Location: Participants selected from a drop-down list of US States and Territories, which included the option “Prefer not to disclose.” Industry and Role: Participants selected from drop-down lists that included the US Census categories for industries and professional roles.

[6] Adapted from Burt (1984) and Burt & Reagans (work-in-progress, retrieved from personal correspondence with the authors): “From time to time, most people discuss important matters with others whom they trust. The range of important matters varies from person to person across work, leisure, family, politics, etc. These trusted people could be colleagues, family members, friends, advisors, or anyone else you turn to when you have something important you want to talk about. If you look back over the last six months, who are the people you turned to most often when you wanted to talk about something that was important to you? Enter each contact’s first name below, one at a time. Try to name at least three contacts. (If you are not comfortable sharing your contacts’ first names, you may use a nickname for each contact. Just make sure you remember what nicknames you used. We will ask about them again on the next page.)”

[7] “Select ‘Very Distant’ if you speak infrequently or not at all with that contact, and know very little or nothing about what's going on in their life. Select ‘Very Close’ if you speak very frequently with that contact, and are very familiar with what's going on in their life.”

asked to rate how close each contact is to each of the other contacts on a scale of 0 ("Very Distant") to 100 ("Very Close").[8]

News Diet. Participants then reported their news diets ("Which of these news providers do you trust and consult most often? Select all that apply."). Participants could select from a list of 20 possible news sources. Included in this list were 13 of the most popular news outlets, representing neutral, left- and right-skewed providers. Participants could also select "My local news station," "Social Media," "Friends and members of my family," "Other" (if their preferred news source was not listed), or "None" (if they did not consult any news sources).[9]

Covid-19 Questionnaire. Finally, participants rated their level of familiarity with Covid-19, the extent to which their daily life has been impacted by Covid-19, whether their local or state government had recently issued a stay-at-home order, and whether they were not currently working because they had been laid off, fired, or furloughed in the past few months.

3.1.3 Procedure

3.1.3.1 Introduction

Participants first complete the Feelings Inventory (described above) to establish a baseline emotional state, then proceed to the instructions. Participants are told that they will play the role of Technical Sales Representative for three different software companies. Participants work for one Company at a time, before moving on to work for the next Company. Each Company sells 20 different software platforms. The only information participants are provided about each

[8] "Select 'Very Distant' if two contacts speak with each other infrequently or not at all, and know very little or nothing about what's going on in each other's lives. Select 'Very Close' if two contacts speak very frequently with each other, and are very familiar with what's going on in each other's lives."
[9] The final two items in the list were "American Post," and "NTWC," neither of which exist. These nonexistent news sources were included as an attention check (and were used as part of the process to detect fraud among the MTurk participant responses).

platform is the platform's code name. Participants make 15 pitches to 15 different customers for each of the 3 Companies. Each pitch constitutes one Trial. On each Trial, participants must select exactly 3 of a Company's 20 platforms to pitch to a new customer. After the pitch is submitted, participants are shown the point values the customer assigned to each platform included in the pitch. Each platform sold by a given company has a different average point value. Customers assign point values close to the average value of each platform. At the end of the game, participants receive a bonus based on the sum of the points earned across all 45 Trials (= 15 Trials x 3 Companies). Essentially, each company is a 20-armed bandit, and participants have 15 Trials to search each Company's 20 arms for the 3 arms with the highest average point values.

The experiment proceeds in three Phases. Each Phase comprises one 15-Trial search task for one of the three Companies.[10] Participants in the Control Condition face the same distribution of platform values in each of the three Phases. In the Abundance Condition, the distribution of platform values shifts upward on each new Phase. In the Scarcity Condition, the distribution of platform values shifts downward on each new Phase. The trajectory of platform values (constant, increasing, decreasing) is the focal manipulation of resource availability in each of the present experiments.

There are three levels of platform values, defined by intervals over which a given Company's 20 platform values are distributed: Low, Medium, and High. At the Low level, mean point values assigned to each of the 20 platforms are uniformly distributed on the interval [100,

[10] In Phase 1, participants work for Company B. Company B's platforms are all named after different songbirds. In Phase 2, participants work for Company S, whose platforms are all named after different spices. Finally, in Phase 3, participants work for Company E, whose platforms are all named after different elements. I chose these naming conventions to reinforce the idea that participants are facing a *new* company with a *different* set of platforms each Phase.

300]; at the Medium level, the 20 platform values are uniformly distributed on the interval [350, 550]; at the High level, the 20 platform values are uniformly distributed on the interval [600, 800]. For participants in the Control Condition, point values are drawn from the Medium level in all three Phases of the experiment. Participants in the Abundance Condition first face point values drawn from the Low level in Phase 1, then from the Medium level in Phase 2, and finally from the High level in Phase 3. Participants in the Scarcity Condition first face point values drawn from the High level in Phase 1, then from the Medium level in Phase 2, and finally from the Low level in Phase 3. A visual representation of this progression can be found in Figure 3.1.

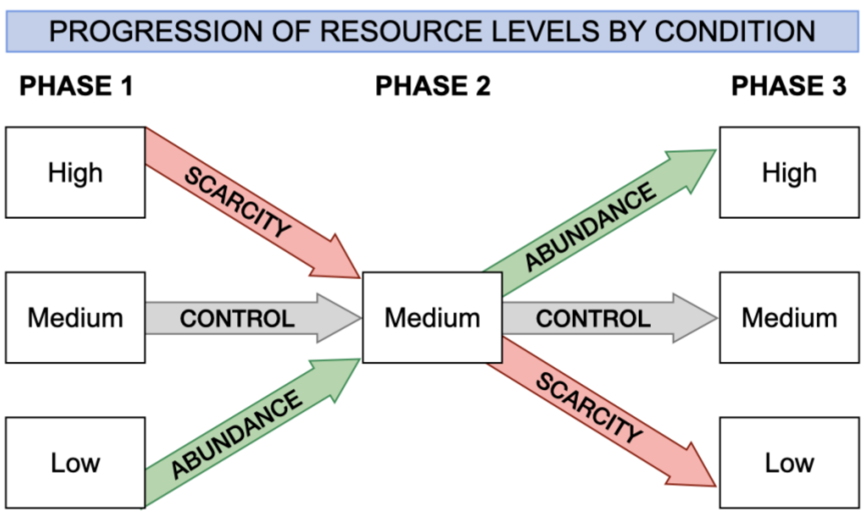
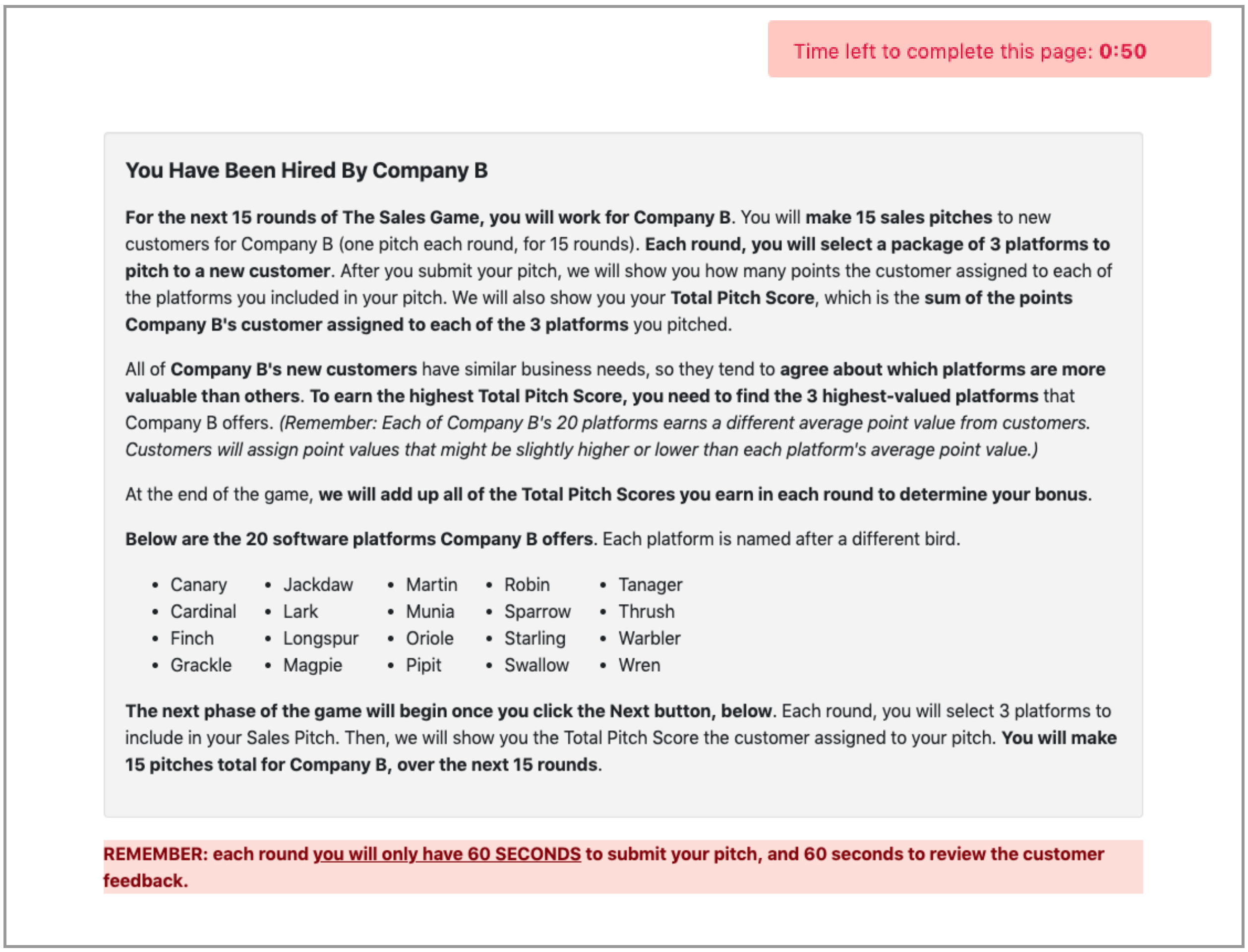


Figure 3.1. Progression of Resource Levels by Condition. Participants in the Control Condition (gray arrows) face values drawn from the Medium level [350, 550] in all three Phases of the experiment. Participants in the Scarcity Condition (red arrows) first face values drawn from the High level [600, 800], followed by the Medium level [350, 550], and finally the Low level [100, 300]. Participants in the Abundance Condition (green arrows) first face values drawn from the Low level [100, 300], followed by the Medium level [350, 550], and finally the High level [600, 800].

After reading the instructions, participants observe a practice Trial that illustrates the functionality of the experimental interface. During the practice Trial, participants are exposed to sample platform values drawn from the same distribution as they face in Phase 1 (Control participants observe sample values drawn from the Medium distribution, Abundance participants observe sample values from the Low distribution, and Scarcity participants observe sample values from the High distribution). Participants must then pass a Comprehension Check before advancing to the focal experimental procedure.



Time left to complete this page: **0:50**

You Have Been Hired By Company B

For the next 15 rounds of The Sales Game, you will work for Company B. You will **make 15 sales pitches** to new customers for Company B (one pitch each round, for 15 rounds). **Each round, you will select a package of 3 platforms to pitch to a new customer**. After you submit your pitch, we will show you how many points the customer assigned to each of the platforms you included in your pitch. We will also show you your **Total Pitch Score**, which is the **sum of the points Company B's customer assigned to each of the 3 platforms** you pitched.

All of **Company B's new customers** have similar business needs, so they tend to **agree about which platforms are more valuable than others. To earn the highest Total Pitch Score, you need to find the 3 highest-valued platforms** that Company B offers. *(Remember: Each of Company B's 20 platforms earns a different average point value from customers. Customers will assign point values that might be slightly higher or lower than each platform's average point value.)*

At the end of the game, **we will add up all of the Total Pitch Scores you earn in each round to determine your bonus**.

Below are the 20 software platforms Company B offers. Each platform is named after a different bird.

- Canary
- Cardinal
- Finch
- Grackle
- Jackdaw
- Lark
- Longspur
- Magpie
- Martin
- Munia
- Oriole
- Pipit
- Robin
- Sparrow
- Starling
- Swallow
- Tanager
- Thrush
- Warbler
- Wren

The next phase of the game will begin once you click the Next button, below. Each round, you will select 3 platforms to include in your Sales Pitch. Then, we will show you the Total Pitch Score the customer assigned to your pitch. **You will make 15 pitches total for Company B, over the next 15 rounds**.

REMEMBER: each round you will only have 60 SECONDS to submit your pitch, and 60 seconds to review the customer feedback.

Figure 3.2. Screenshot of Introduction to Company B at Start of Phase 1. Participants have 60 seconds to read the New Company Introduction before the procedure automatically advances to the next screen.

3.1.3.2 Focal Experimental Task

At the start of each Phase in the focal experiment, participants read an introduction about the Company they will work for, which includes the list of platforms offered by that Company (Figure 3.2). Participants have 60 seconds to read the New Company Introduction before the procedure automatically advances to the next screen.

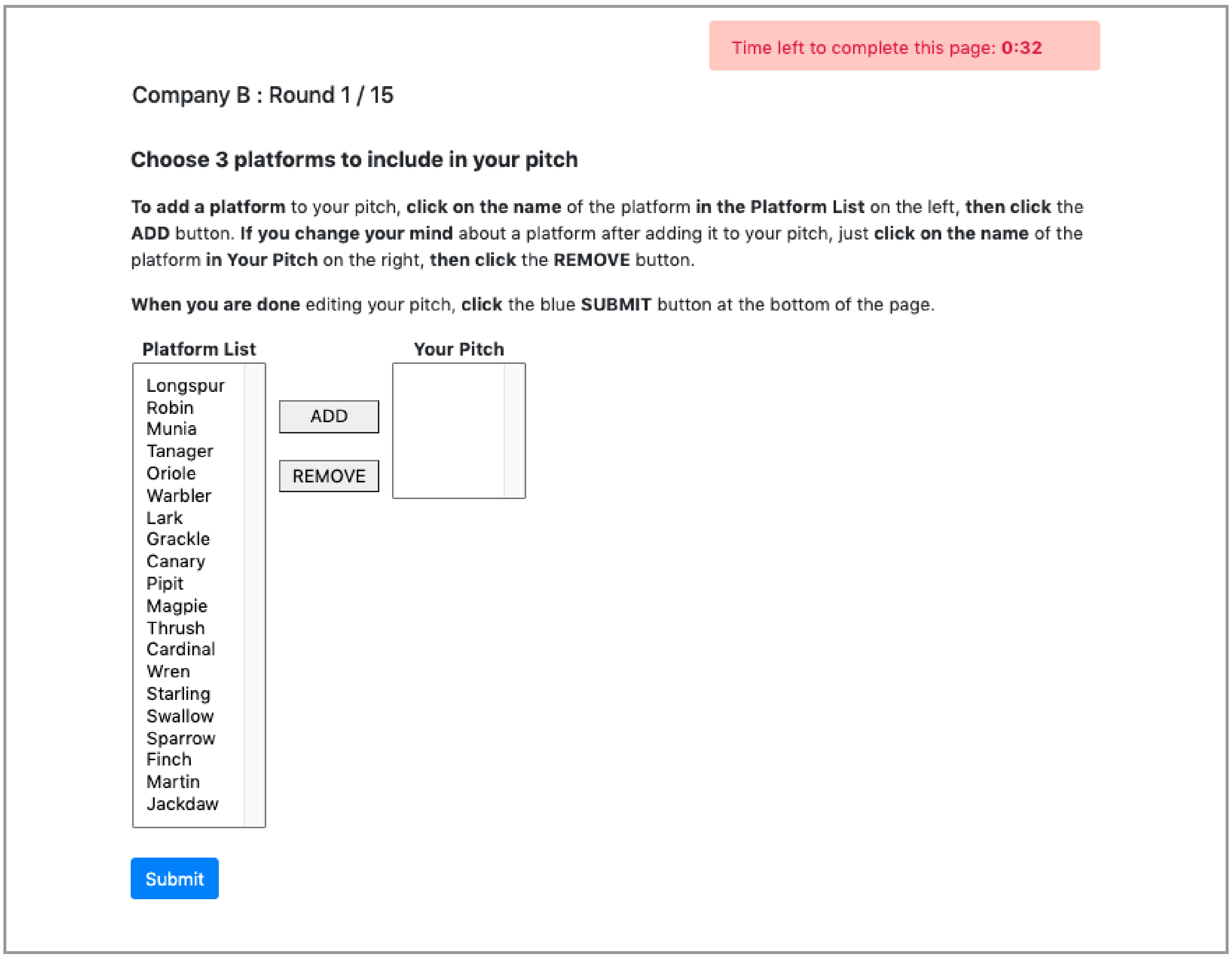


Figure 3.3. Screenshot of Pitch Selection Screen on Trial 1 of Phase 1. Participants have 60 seconds to select their pitch before the procedure automatically advances to the next screen. If participants do not submit a pitch in under 60 seconds, no points are earned for the current Trial.

On each Trial (of the 15 in each Phase), participants have 60 seconds to select 3 platforms and submit their pitch (Figure 3.3). A countdown clock in the upper right-hand corner of the screen keeps track of how much time is left.

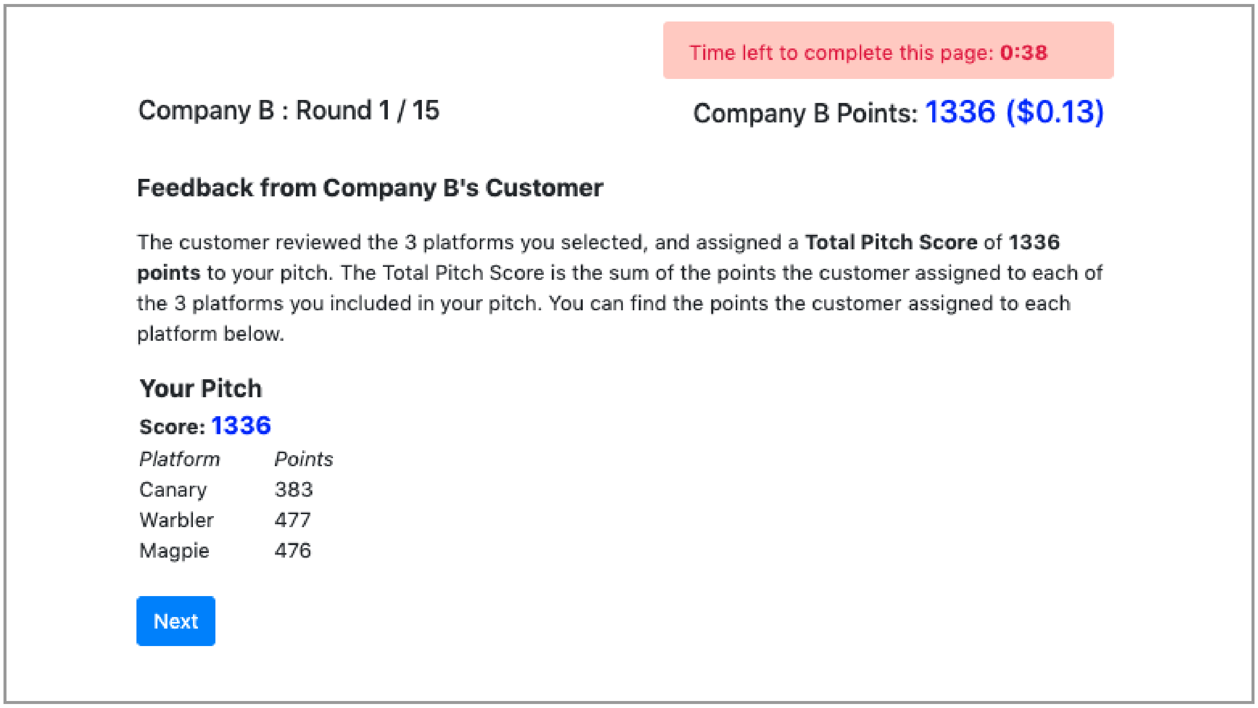


Figure 3.4. Screenshot of Results Screen Following Trial 1 of Phase 1. Taken from the perspective of a participant in the Control Condition. Participants have 60 seconds to review their results before the procedure automatically advances to the next screen.

If participants do not submit their pitch in less than 60 seconds, the page automatically advances to the results screen, and the participant earns zero points for the current Trial. On the results screen (Figure 3.4), participants are shown the results for the current Trial – the points the customer assigned to each platform in the pitch, and the Total Pitch Score (the sum of the three platforms' point values). On each Trial, each platform's point value is drawn from a normal distribution having mean equal to that platform's average point value, and a standard deviation of 20 points. Participants have 60 seconds to review their results before the procedure automatically advances to the next screen.

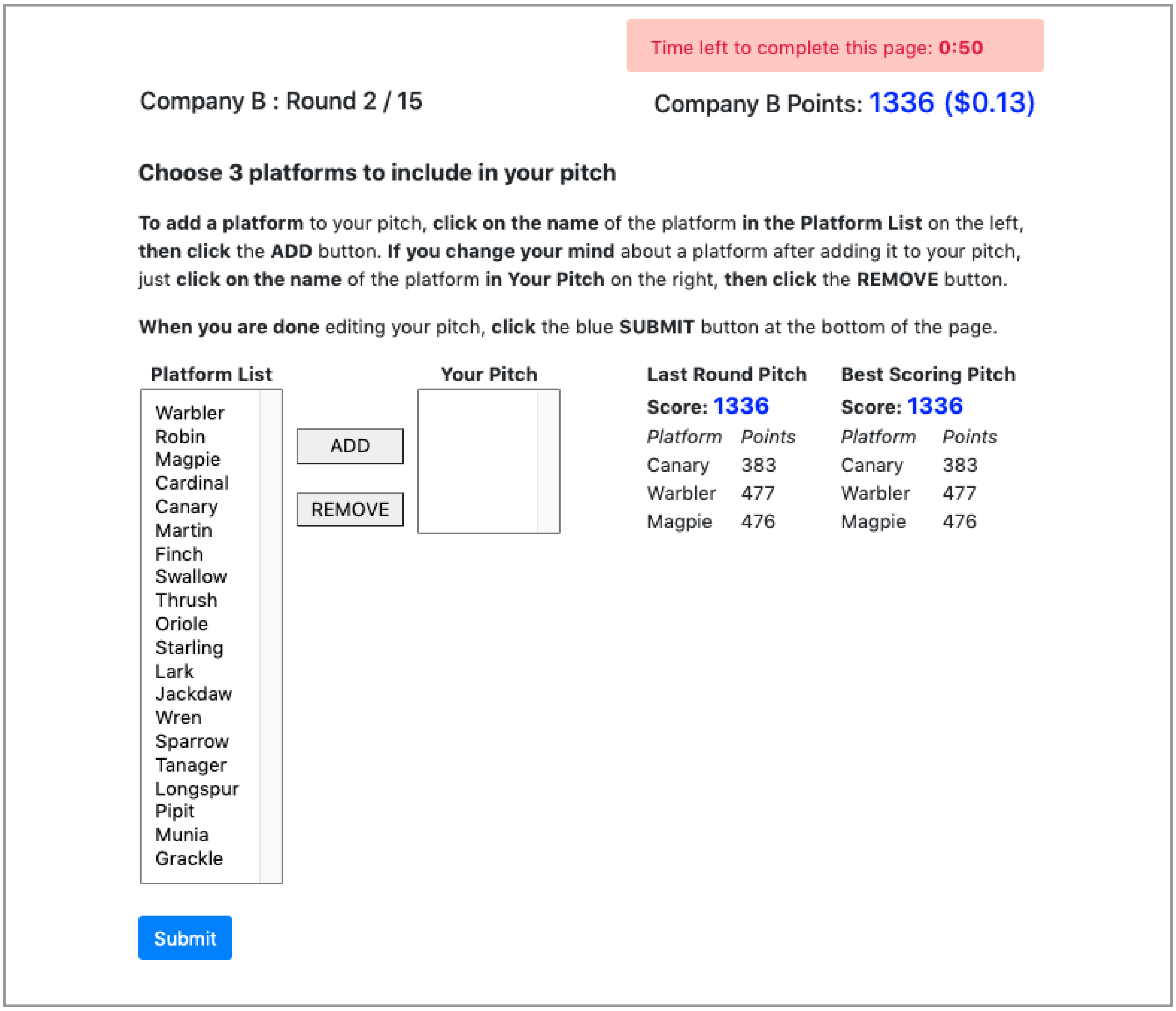


Figure 3.5. Screenshot of Pitch Selection Screen on Trial 2 of Phase 1. Taken from the perspective of a participant in the Control Condition. Note that the cumulative points the participant has earned over preceding trials in the current Phase are displayed in the upper right-hand corner of the screen. Next to the cumulative points is the bonus amount earned in dollars (participants earn 1 cent for every 100 game points). The cumulative points (and dollars) earned are displayed for the current Company only (they zero out at the start of each new Phase).

Starting with the second trial of each Phase, participants can see the results from the pitch they selected on the immediately preceding trial (Last Round Pitch), and from the highest-scoring pitch they've selected over all preceding trials in the current Phase (Best Pitch). The cumulative points (Sum of Total Pitch Scores) earned over all preceding trials in the current Phase is presented in the upper right-hand corner of the screen (Figure 3.5). Next to the cumulative points is the bonus amount earned in dollars (participants earn 1 cent for every 100 game points). The cumulative points (and dollars earned) are reset at the start of each Phase, when a new Company, and a new list of platforms, is introduced. At any point in time, participants can only see their cumulative points (and dollars earned) for the current Phase (Company).

Following the 8th and 15th trials of each Phase, participants complete the Feelings Inventory again (they have 30 seconds to enter their responses before the procedure automatically advances to the next screen). Participants are then asked to estimate the average value of each of the 20 platforms sold by the current Company (Figure 6). Participants have 2 minutes to enter their Platform Value Estimates for all 20 platforms. After submitting their estimates, participants are shown their list of estimates in order from highest to lowest average value, and are asked to rate their level of confidence in the accuracy of their estimates on a scale of 0% ("Totally Wrong") to 100% ("Totally Right").[11] Participants have 30 seconds to enter their Confidence Rating.

[11] "How accurate are your estimates? We have used your estimates on the last page to rank the platforms in order from highest to lowest average value. The resulting rank-ordered list of platforms can be found below. Focus on the platforms for which you entered valid estimates. How accurate is your raking of [Company Name]'s platforms?"

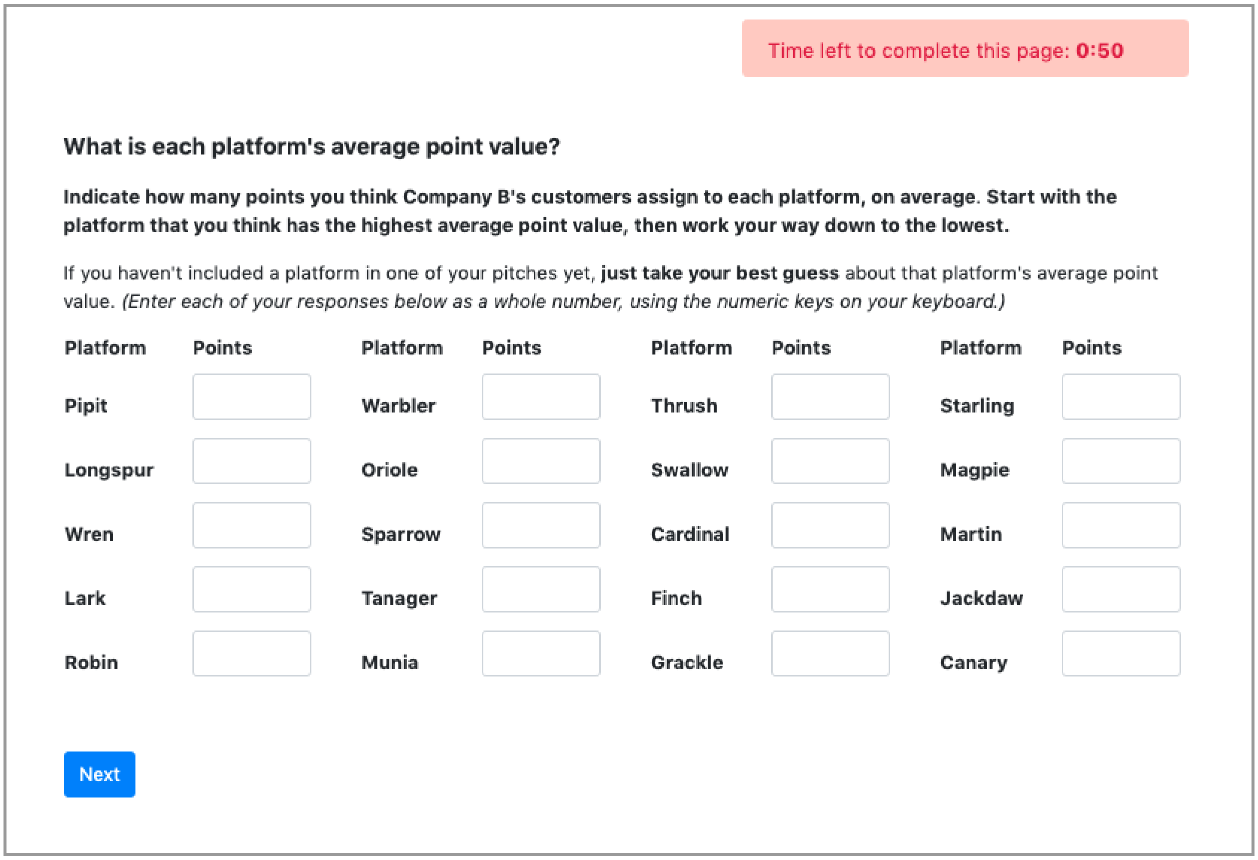


Figure 3.6. Screenshot of Platform Value Estimates Screen on Trial 8 of Phase 1. Participants have 2 minutes to enter their estimates for each of the 20 platforms.

At the end of each Phase, participants are shown the total points (and bonus dollars) earned for the current Company (they have 30 seconds to review this information before the procedure automatically advances to the next screen). Then, they are introduced to the next Company. In Phases 2 and 3, the New Company Introduction includes a warning that the platform values participants are about to encounter may be significantly different than the values they encountered in the previous Phase:

> [Company Name]'s platforms are different from the platforms sold by the last company you worked for, and [Company Name] sells to a different type of customer. The points [Company Name]'s customers assign to [Company Name]'s platforms might be significantly different than what you saw when you worked for the last company.

After completing the focal experimental task, participants are debriefed with a recap of their performance and their final bonus amount (in dollars). Participants are asked to imagine a friend of theirs is about to play the experimental game, and to describe what strategy their friend should use to perform well in the game. Participants are then asked to rate their performance in the game on a scale of 0 ("Worst Performance") to 100 ("Best Performance").[12] They also have the opportunity to provide open feedback on the procedure. Figure 3.7 presents the full workflow of the experimental procedure from start to finish.

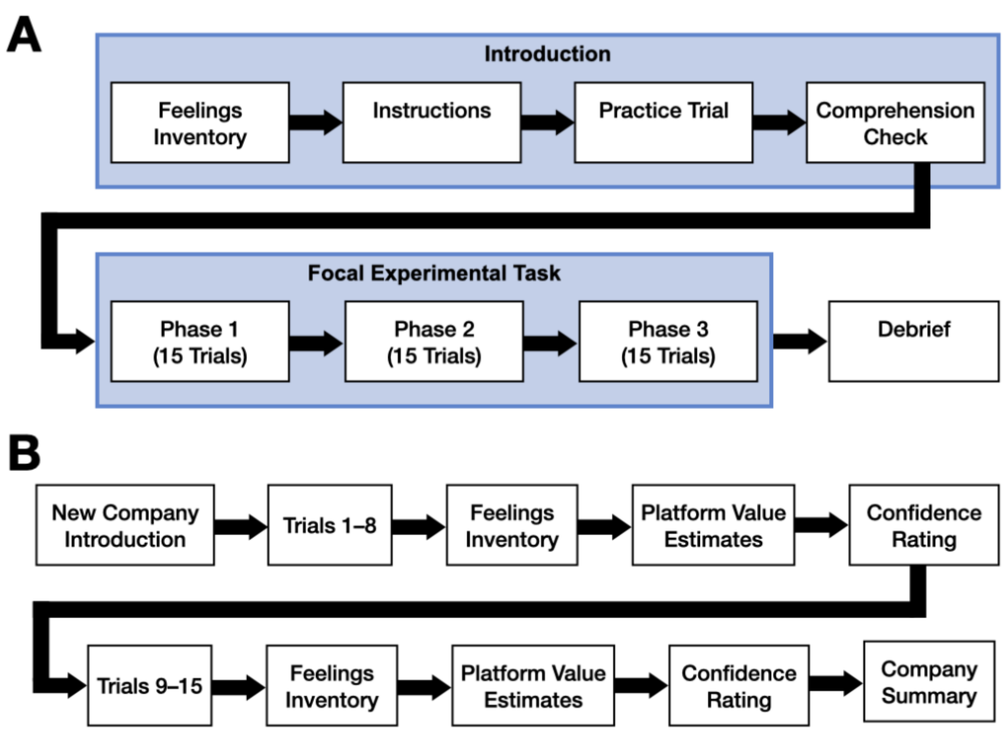


Figure 3.7. Overview of Procedure. Full workflow of the experimental procedure (A), and detailed overview of each Phase (B).

[12] "How do you think your performance in The Sales Game compares with other players? Indicate your response on the scale below. At least 100 people have played The Sales Game so far. Select "Worst Performance" if you think every other person performed better than you did. Select "Best Performance" if you think you performed better than every other person who has played the game."

3.2 Methods

3.2.1 Dependent Variables

Exploration. To understand participants' rates of Exploration, I look at the number of Never-Seen platforms participants select on each Trial. A Never-Seen platform is one that the participant has not selected on any preceding Trial in the current Phase. On a given Trial, the number of Never-Seen platforms ranges from 0 (each of the three platforms selected by the participant has been selected on at least one preceding Trial) to 3 (none of the three platforms selected by the participant have been selected on any preceding Trial). Across Trials 1–15 in a given Phase, the *cumulative* number of times a participant selects Never-Seen (unique) platforms ranges from 3 (the participant selects the same three platforms on every Trial) to 20 (the participant selects each of the 20 platforms on at least one Trial).[13]

Exploitation. To understand participants' rates of Exploitation, I look at the number of Personal-Best platforms participants select on each Trial. A platform is classified as a Personal-Best if it has one of the top three highest empirical averages of the platforms the participant has explored across all of the preceding Trials in a given Phase. (A platform's empirical average is the mean of the realized point values the participant observed each time he selected that platform on any preceding Trials. The empirical average of Never-Seen platforms is zero.) On a given Trial, the number of Personal-Best platforms ranges from 0 (none of the three platforms selected have one of the three highest empirical averages) to 3 (the three platforms selected have the three highest empirical averages). Across Trials 2–15 in a given Phase, the *cumulative* number times a

[13] This is a narrower definition of Exploration than what is usually encountered in the multiarmed bandit and reinforcement learning literature. A decision is usually classified as "explore" if 1) the option selected has the highest uncertainty (e.g. it has been selected less often than other options in the past), or 2) the option *does not* have the highest empirical average of any options sampled over preceding Trials. I have restricted my definition for ease of Exposition and visual representation within the text. A narrow lens is also more informative in the present experimental context, where participants can sample multiple platforms on each Trial.

participant selects Personal-Best platforms ranges from 0 (each time a platform's empirical average rises to the top three the participant has seen so far, it is never selected again) to 42 (the participant selects the same three platforms on every Trial).[14]

Mental Models. To evaluate participants' knowledge of the resource environment, I look at the Mean Absolute Difference between participants' estimates of each platform's average value, and the true average value of each platform (the mean absolute value of the difference between the participant's estimates of each platform's value minus each platform's true average value). I will use the terms "average error" and Mean Absolute Difference interchangeably in the discussion.

Rewards. There are two types of achievement to consider in the current context. The first is the participant's payoffs or rewards – the points they earn on each Trial that are converted into a bonus payment at the end of the experiment. The range of expected point values varies across Phases and Conditions, so I construct a standardized measure of participants' earnings in order to facilitate comparison across Conditions and Phases. To construct this measure, I begin with the true average point value for each platform the participant selected on a given Trial. I subtract the lowest possible average point value in the current range from each platform's average point value. For example, the lowest average point value in the Low range [100, 300] is 100, so I subtract 100 points from each platform's average point value when participants face the Low range (Scarcity in Phase 3, Abundance in Phase 1). The resulting standardized average point values for each platform now range from 0 to 200.

[14] Trial 1 is excluded from the cumulative number of times a participant selects Personal-Best platforms, because on Trial 1 no platform has ever been sampled in the past and I consider all Never-Seen platforms to have an empirical average of zero.

To find the standardized Total Pitch Score for a given Trial, I sum the standardized average point values of the 3 platforms selected by the participant on that Trial. I then divide the standardized Total Pitch Score by the maximum possible Total Pitch Score (561 points). This gives me a value between 0.07 and 1.00, which represents the participant's standardized Total Pitch Score as a proportion of the maximum Total Pitch Score.[15] For ease of exposition, I then multiply this result by 100, to produce the participant's Standardized Achievement Score. Standardized Achievement Scores range from 7 to 100. A Standardized Achievement Score of 7 indicates that the participant selected the 3 lowest-valued platforms on a given Trial. A Standardized Achievement Score of 100 indicates that the participant selected the 3 highest-valued platforms on a given Trial.

A participant's cumulative Standardized Achievement Score across Trials 1–15 in a given Phase ranges from 105 (if the participant selects the 3 lowest-valued platforms on every Trial of the current Phase) to 1500 (if the participant selects the 3 highest-valued platforms on every Trial of the current Phase).

Discovery. The second type of achievement to consider is participants' success in discovering the highest-valued platforms offered by each Company in each Phase. A True Top Three platform is a platform that has one of the three highest true average values. On a given Trial, the number of True Top Three platforms ranges from 0 (each of the three platforms selected by the participant has one of the three highest true average values) to 3 (none of the three platforms selected by the participant have one of the three highest true average values).

[15] The standardized average point values for the three highest-valued platforms in each Phase are 173, 188, and 200. So, the maximum standardized Total Pitch Score is 561. The standardized average point values for the three lowest-valued platforms in each Phase are 1, 14, and 17. So, the minimum standardized Total Pitch Score is 42, and 42 / 561 = 0.07. After multiplying the standardized Total Pitch Scores by 100, the range of possible Standardized Within-Trial Achievement Scores is [7, 100].

Across Trials 1–15 in a given Phase, the *cumulative* number of times a participant selects True Top Three platforms ranges from 0 (the participant never selects any of the platforms with the three highest true average values) to 45 (the participant selects the three platforms with the highest true average values on every Trial, 1–15).

Individual Differences. A full analysis of individual differences is beyond the scope of the present discussion. Exploratory analyses revealed no substantive differences between the models presented here in the main text and expanded models that include individual difference measures. Interested readers may find summary statistics for Study 3A and Study 3B participants' responses to the demographics, social networks, and Covid-19 questionnaires in the Supplement under *A.4 Demographics*. A summary of Study 3A and Study 3B participants' responses to the Feelings Inventory (collected before the experiment and twice during each Phase) can be found in the Supplement under *A.3 Feelings Inventory*.

3.2.2 Statistical Analysis

Multilevel mixed-effects linear regressions (the mixed package in Stata 16) are used to investigate the effect of the changes in resource levels (Abundance = increasing; Control = Constant; Scarcity = decreasing) on the dependent variables of interest. In Studies 1, 2A, and 2B, participants complete the experimental procedure as individuals. The data from these studies are organized at two levels: Time ($i = 0, \ldots, n$) and Participant ($j = 1, \ldots, m$). For cumulative measures, like Number of Unique Platforms Viewed and Cumulative Standardized Achievement, I am interested in identifying the effect of changes in resource levels (platform values) *across* Phases, so Phase serves as the unit of Time in the analysis. Change in participants' responses *across* Phases is nonlinear for most of the cumulative dependent variables. In these cases, participants' trajectories are best fit by using two spline basis functions: one for the slope between Phases 1 and 2, and a second for the slope between Phases 2 and 3. The "empty" (intercept and slope) two-level model in this case is:

$$y_{ij} = \beta_0 + \beta_1 z_{1j} + \beta_2 z_{2j} + \zeta_{1j}^{(2)} + \zeta_{2j}^{(2)} t_{ij} + \epsilon_{ij}$$

where *i* denotes a time point (Phase) and *j* denotes an individual participant. In the fixed part of the model, y_{ij} is the value of the dependent variable for Participant *j* at Time *i*; β_0 is the intercept (the "grand mean," or the average value of the dependent variable at a given time point in the procedure); β_1 is the change in the average response value between Phases 1 and 2 (z_{1j} = Phase 2 indicator); β_2 is the change in the average response value between Phases 2 and 3 (z_{2j} = Phase 3 indicator).

In the random part of the model, $\zeta_{1j}^{(2)}$ is the Participant-level (Level-2) random intercept, and $\zeta_{2j}^{(2)}$ is the Participant-level random coefficient (slope). Note that here I am using a linear slope, t_{ij} , where Time is expressed as the number of Phases that have passed since the start of the experiment ($t_{ij} = 0$ in Phase 1). Using a single linear coefficient in the random part of the model is more computationally efficient than estimating two different random coefficients for each of the spline basis functions for each participant (and produces similar, if not identical, results). The final term in the random part of the model, $\boldsymbol{\epsilon}_{ij}$, is the Level-1 error term. We let all observed covariates for Participant *j* be denoted $\mathbf{X}_j$. It is assumed that the Participant-level random-intercept $\zeta_{1j}^{(2)}$ has zero mean and variance $\psi^{(2)}$, given the covariates $\mathbf{X}_j$; and that the Level-1 error term $\boldsymbol{\epsilon}_{ij}$ has zero mean and variance θ, given $\psi^{(2)}$ and $\mathbf{X}_j$.

The empty two-level model will be presented as the "baseline" for Studies 1, 2A, and 2B, and its estimates will be contrasted with more complex models that account for main effects of and interactions between elements of the experimental design. For example, the model below includes additional fixed effects for Scarcity and Abundance (w_{1j} and w_{2j} , respectively) and two-way interactions between each of the fixed effects and Time (Phase).

$$y_{ij} = \beta_0 + \beta_1 z_{1j} + \beta_2 z_{2j} + \beta_3 w_{1j} + \beta_4 w_{2j} + \beta_5 z_{1j} w_{1j} + \beta_6 z_{1j} w_{2j} + \beta_7 z_{2j} w_{1j}$$
$$+ \beta_8 z_{2j} w_{2j} + \zeta_{1j}^{(2)} + \zeta_{2j}^{(2)} t_{ij} + \epsilon_{ij}$$

In the fixed part of the model, y_{ij} is the value of the dependent variable for Participant j at Time i; β_0 is the average value of the dependent variable for participants in the *Control Condition in Phase 1*. β_1 is the change in the average response value among *Control* participants between Phases 1 and 2 (z_{1j} = Phase 2 indicator); β_2 is the change in the average response value among *Control* participants between Phases 2 and 3 (z_{2j} = Phase 3 indicator). β_3 is the *difference* between the average response value among *Scarcity* participants and *Control* participants in *Phase 1*. β_4 is the *difference* between the average response value among *Abundance* participants and *Control* participants in *Phase 1*.

It is important to note that the coefficients on the interaction terms here are measures of the difference between the effect of Time (Phase) among Scarcity and Abundance participants, and the effect of Time (Phase) among Controls. It is *not* a measure of the change in the average response value among Scarcity participants in Phase 2 versus the average response value among Scarcity participants in Phase 1, for example. Instead it is a measure of the extent to which this change among Scarcity participants is different than the change among Controls over the same time period. In the above formulation, β_6 is the difference between the change in average response value among Control participants in Phase 2 versus Phase 1, and the change in average response value among Scarcity participants in Phase 2 versus Phase 1.

Though this "difference in differences" measure is useful, we are also interested in pairwise comparisons between the average response values for Scarcity (Abundance) participants and Controls within a given Phase (e.g. Did Abundance participants pitch a significantly lower number of unique platforms than Controls in Phase 2?), and comparisons between the average response values in Phase 2 (3) versus Phase 1 (2) within a given Condition (e.g. Did Scarcity participants accumulate significantly higher scores in Phase 3 than they did in Phase 3?). To answer these questions, I will present the results of planned contrasts between the "predictive margins" (the predicted marginal value of a given response variable at each level of a given factor variable, e.g. the predicted number of unique platforms pitched by participants in each Condition).[16,17]

In Study 3, participants complete the experimental procedure in groups of size 6. The data from these studies are organized at three levels: Time (i = 0, ... , n), Participant (j = 1, ... , m), and Group (k = 1, ... , l). The baseline three-level model is as follows:

$$y_{ijk} = \beta_0 + \beta_1 z_{1jk} + \beta_2 z_{2jk} + \beta_3 w_{1k} + \beta_4 w_{2k} + \beta_5 z_{1jk} w_{1k} + \beta_6 z_{1jk} w_{2k} + \beta_7 z_{2jk} w_{1k}$$
$$+ \beta_8 z_{2jk} w_{2k} + \zeta_{1jk}^{(2)} + \zeta_{2j}^{(2)} t_{ijk} + \zeta_{1k}^{(3)} + \zeta_{2k}^{(3)} t_{ijk} + \epsilon_{ijk}$$

[16] Predictive margins are the mean estimated value of the response variable when we evaluate the other covariates at their means.

[17] These contrasts are performed using the postestimation command – `margins a, over(b) contrast(effects)` – in Stata 16; where "a" is the *between* factor (e.g. when "a" = Condition, we are comparing predicted marginal values *between Conditions* within a given Phase), and "b" is the "within" factor (e.g. when "`b`" = Condition, we are comparing predicted marginal values *between Phases* within a given Condition).

where i denotes a time point, j denotes an individual participant, and k denotes the experimental group in which j is a member. In the random part of the model, $\zeta_{1k}^{(3)}$ is the Group-level (Level-3) random intercept, $\zeta_{2k}^{(3)}$ is the Level-3 random slope, and $\boldsymbol{\epsilon}_{ijk}$ is the Level-1 error term. (Here again I am using a linear slope, t_{ijk} , in the random part of the model for the reason stated above.) We let all observed covariates for Group k be denoted $\mathbf{X}_k$. It is assumed that the Group-level random-intercept $\zeta_{1k}^{(3)}$ has zero mean and variance $\psi^{(3)}$ given $\mathbf{X}_k$; that the Participant-level random-intercept $\zeta_{1jk}^{(2)}$ has zero mean and variance $\psi^{(2)}$, given $\zeta_{1k}^{(3)}$ and $\mathbf{X}_k$; and that the Level-1 error term $\boldsymbol{\epsilon}_{ijk}$ has zero mean and variance θ, given $\zeta_{1k}^{(3)}$, $\zeta_{1jk}^{(2)}$, and $\mathbf{X}_k$. (Note: In the subsequent analyses, the error terms in the models are assumed to be uncorrelated across levels and an unstructured covariance matrix is specified for the random effects within each level.)

Likelihood-ratio tests will be used to compare the fit of nested models. The overall model deviance (–2 log likelihood) will also be reported as a measure of (lack of) fit. I will report the Aikake Information Criterion (AIC) and Bayesian Information Criterion (BIC) for each model, following convention, but each criterion should only be viewed as an informal index of lack of fit.[18]

[18] There is no apparent theoretical justification for the use of AIC or BIC for longitudinal or clustered data (e.g. for the BIC, it is not clear how one should define the sample size for clustered data). See Rabe-Hesketh, S., & Skrondal, A. (2012). Multilevel and Longitudinal Modeling Using Stata. StataCorp LP. p. 346.

4 STUDY 1: SOLO PARTICIPANTS, NO SIDE OBSERVATIONS

Study 1 provides a baseline for participant behavior in the novel experimental paradigm used across studies in the present research program. In Study 1, participants' only opportunity to learn about the value of each platform is to sample that platform directly by including it in their pitch. Each participant completes the procedure solo.

4.1 Participants

165 people participated in Study 1 (Female = 82; Average Age: 39, SD = 11). All participants were recruited through Amazon Mechanical Turk (MTurk). Participants were paid a $6.00 base fee upon completion of the focal procedure, and earned a variable performance-based bonus (Average Bonus: $6.50, SD = $0.55). Participants also earned an Active Participation Bonus of $4.00 if they consistently submitted their responses before the time limits (described in *3.1.1 Recruitment and Compensation*).

Participants were randomly assigned to one of three experimental Conditions: Control (N = 54), Abundance (N = 54), Scarcity (N = 57). Control, Scarcity, and Abundance refer to the trends in platform values described in *3.1.3 Procedure* (Control = constant; Abundance = increasing; Scarcity = decreasing).

4.2 Procedure

Participants first complete the Feelings Inventory to establish a baseline, then proceed to the instructions. Participants must then pass a Comprehension Check before advancing to the focal experimental procedure. The focal experimental procedure is identical to that described in *3.1.3*

Procedure. After completing the focal procedure, participants in Study 1 complete the Debrief Questionnaire described in *3.1.3 Procedure.*

4.3 Results

I exclude participants who were marked as dropouts after repeatedly failing to submit their responses before the time limits . One participant in the Abundance Condition met this exclusion criteria. I also exclude Trials on which participants failed to submit their response before the time limit expired (timeouts).

4.3.1 Exploration

Figure 8 presents the average number of Never-Seen platforms participants selected on each Trial, in each Phase of Study 1. Never-Seen platforms are those that the participant has not selected on any preceding Trial in the current Phase. The curves within each Phase start on Trial 2 for ease of visual comparison. (On Trial 1, the number of Never-Seen platforms is always equal to 3, because the participants have never selected any of the platforms before.)

Participants in all three Conditions select a similar number of Never-Seen platforms on each Trial in Phase 1. Scarcity participants select a higher number of Never-Seen platforms than Control and Abundance participants on Trials 2 and 3 of Phase 2, and on Trial 2 of Phase 3.[1]

[1] Between-Condition differences on Trial 2 (two-sample t-tests): Scarcity Trial 2 – Abundance Trial 2 = 0.58, t = 4.14, p = 0.000; Scarcity Trial 2 – Control Trial 2 = 0.30, t = 2.35, p = 0.021. Between-Condition differences on Trial 3 (two-sample t-tests): Scarcity Trial 3 – Abundance Trial 3 = 0.48, t = 3.03, p = 0.003; Scarcity Trial 3 – Control Trial 3 = 0.342, t = 2.88, p = 0.005.

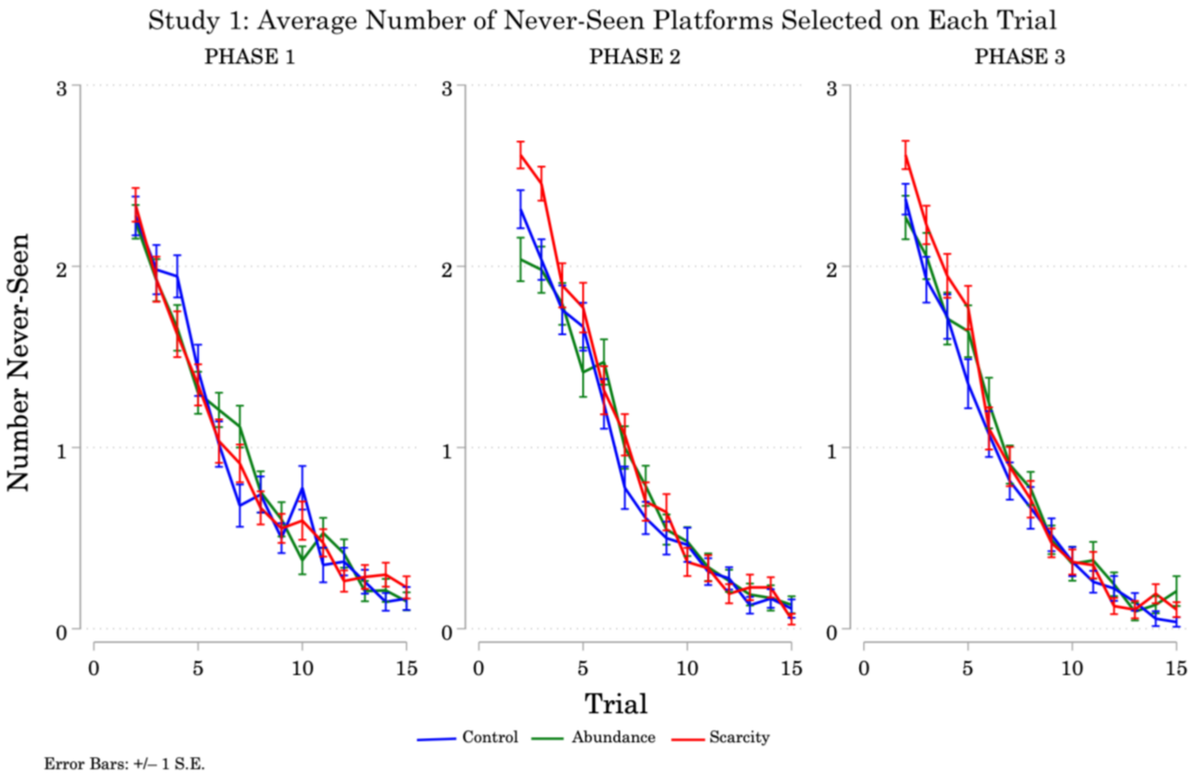


Figure 4.1. Study 1: Exploration. Average number of Never-Seen platforms selected on each Trial, by Phase and Condition. Error bars = +/– 1 S.E. Green = Abundance (N = 53); Blue = Control (N = 54); Red = Scarcity (N = 57). Note that the curves begin on Trial 2, the first opportunity to observe differences (the number of Never-Seen platforms on Trial 1 is always 3 for every participant). In Phase 1, participants in all three Conditions select a similar number of Never-Seen platforms across Trials. Across the first few Trials of Phases 2 and 3, Scarcity participants select a higher number of Never-Seen platforms than Control and Abundance participants.

Table 1 presents the parameter estimates and fit statistics from three different Two-Level Random Coefficient models for the total number of times participants selected Never-Seen (unique) platforms across Trials 1– 15 of each Phase in Study 1. The total number of unique platforms participants explore across Trials 1–15 ranges from 3 (the participant selects the same three platforms on every Trial) to 20 (the participant selects every platform at least once across Trials 1–15). This is a *cumulative* measure, so Phase is the relevant unit of Time.

Table 4.1. Study 1: Exploration. Maximum likelihood estimates of Two-Level Random-Coefficient models for the total number of unique platforms participants explored across Trials 1–15 of each Phase. Model 1: Intercept-Slope; Model 2: Main Effects; Model 3: Design Interactions. N = 164.

	Model 1		Model 2		Model 3	
	Est	(SE)	Est	(SE)	Est	(SE)
Fixed Effects						
Intercept β_0	15.53***	0.23	15.24***	0.37	15.63***	0.41
Phase 2 β_1	0.42	0.25	0.43	0.25	–0.26	0.42
Phase 3 β_2	–0.68**	0.25	–0.68**	0.25	–0.89*	0.42
Abundance β_3			0.23	0.50	0.01	0.58
Scarcity β_4			0.61	0.49	–0.30	0.57
Abundance × Phase 2 β_5					0.20	0.60
Scarcity × Phase 2 β_6					1.79**	0.59
Abundance × Phase 3 β_7					0.68	0.60
Scarcity × Phase 3 β_8					–0.04	0.59
Random Effects						
L2 Random Intercept Variance $\psi_{11}^{(2)}$	4.64	0.99	4.70	1.00	4.78	0.98
L2 Random Slope Variance $\psi_{22}^{(2)}$	1.36	0.45	1.36	0.45	1.31	0.44
L1 (Residual) Error Variance θ	4.28	0.47	4.28	0.47	4.11	0.45
Log likelihood	–1222		–1221		–1215	
AIC | *BIC*	2458 | 2488		2461 | 2499		2456 | 2510	

* $p \leq 0.05$; ** $p \leq 0.01$; *** $p \leq 0.001$; SE = standard error of the mean

Model 1 is the baseline model, and includes an intercept and piecewise linear slopes for Phases 2 and 3 (in the form of two linear spline functions for the change between Phases 1 and 2, and between Phases 2 and 3). The random part of Model 1 includes a random intercept and a random linear slope for Phase at the Participant level (Level 2).[2] Model 2 includes the main effect of Condition, and Model 3 introduces interactions among elements of the experimental design (Condition, Phase). Model 3 provides a significant improvement over Model 2 [*LR* $\chi^2(4)$

[2] Including a single linear slope in the random part of the model is more computationally efficient than estimating two separate slopes for each of the linear spline functions, and produces similar estimates.

= 12.69, p = 0.013], and over Model 1 [$LR\ \chi^2(6)$ = 14.24, p = 0.027], so I will focus on the predictions from Model 3.

The Model 3 estimates are presented in the far-right columns of Table 1. I will start by walking through the substantive interpretation of each term in far-right columns of Table 1 (under "Model 3") to orient the reader to the manner in which results will be presented in this and all subsequent analyses.

In the second row of Table X, under Model 3, in the column labeled "Est" (Estimate), we find the Model 3 estimate of the Intercept, β_0 = 15.63 (*s.e.* = 0.41). The intercept is the average Number of Platforms Pitched among *Control* participants by the end of *Phase 1*. By the end of Phase 1, Control participants explored about 15.63 (z = 38.51, p < 0.000) out of 20 platforms. In all subsequent analyses the intercept will represent the average value of the response variable among *Control* participants at the end of Phase 1.

In the third row, we find the coefficient for Phase 2, β_1 = –0.26 (*s.e.* = 0.42). The coefficient for Phase 2 is the *change* in the average Number of Unique Platforms Pitched between Phase 1 and Phase 2 among *Control* participants. Control participants explored about 15.37 (= $\beta_0 + \beta_1$ = 15.63 – 0.26) platforms by the end of Phase 2, which is slightly less than they explored by the end of Phase 1, but this decrease was not significant (z = –0.62, p = 0.537). In all subsequent analyses, the coefficient for Phase 2 will represent the change in the average value of the response variable between Phases 1 and 2 among Control participants.

In the fourth row, we find the coefficient for Phase 3, β_2 = –0.89 (*s.e.* = 0.42). The coefficient for Phase 3 is the *change* in the average Number of Platforms Pitched between Phase 2 and Phase 3 among *Control* participants. Control participants explored about 14.48 (= $\beta_0 + \beta_1 + \beta_2$ = 15.63 – 0.26 – 0.89) platforms by the end of Phase 3, which is a significant decrease of –

0.89 from the number they explored by the end of Phase 2 (z = –2.12, p = 0.034). In all subsequent analyses, the coefficient for Phase 3 will represent the change in the average value of the response variable between Phases 2 and 3 among Control participants.

In the fifth and sixth rows, we find the coefficients for Abundance, $\beta_3 = 0.01$ (*s.e.* = 0.58), and for Scarcity, $\beta_4 = -0.30$ (*s.e.* = 0.57). The coefficient for Abundance is the *difference* between the average Number of Platforms Pitched by *Abundance* participants and the average Number of Platforms Pitched by *Control* participants at the end of *Phase 1*. Abundance participants explored about 15.64 (= $\beta_0 + \beta_3 = 15.63 + 0.01$) platforms by the end of Phase 1, which is not significantly different from the number explored by Control participants (z = 0.02, p = 0.984). The coefficient for Scarcity is the *difference* between the average Number of Platforms Pitched by *Scarcity* participants and the average Number of Platforms Pitched by *Control* participants at the end of *Phase 1*. Scarcity participants explored about 15.33 (= $\beta_0 + \beta_4 = 15.63 - 0.30$) platforms by the end of Phase 1, which is less than the number explored by Controls, but this difference was not significant (z = –0.52, p = 0.601). In all subsequent analyses, the coefficients for Abundance and Scarcity will represent the difference between the value of the response variable among Abundance (Scarcity) participants and Control participants at the end of Phase 1.

In the seventh and eighth rows, we find the coefficients for the Abundance × Phase 2 interaction, $\beta_5 = 0.20$ (*s.e.* = 0.60), and for the Scarcity × Phase 2 interaction, $\beta_6 = 1.79$ (*s.e.* = 0.59). The coefficient for the Abundance × Phase 2 interaction is the *difference* between the change in Number of Platforms Pitched by *Abundance* participants in Phase 2 versus Phase 1 and the change in Number of Platforms Pitched by *Control* participants in Phase 2 versus Phase 1. Abundance participants explored about 15.58 (= $\beta_0 + \beta_1 + \beta_3 + \beta_5 = 15.63 - 0.26 + 0.01 + 0.20$)

platforms by the end of Phase 2, which is a (non-significant) decrease of about –0.06 (z = –0.13, p = 0.894) from the number they explored in Phase 1.

The Phase 2 coefficient tells us that the change in the Number of Platforms Pitched between Phases 1 and 2 among Control participants was about –0.26. The Abundance × Phase 2 interaction coefficient tells us that the difference between the change among Control participants and the change among Abundance participants is about 0.20. Adding these two terms together, we get the difference in the number of platforms explored by Abundance participants in Phase 1 versus Phase 2 (–0.26 + 0.20 = –0.06).

The coefficient for the Scarcity × Phase 2 interaction is the *difference* between the change in Number of Platforms Pitched by *Scarcity* participants in Phase 2 versus Phase 1 and the change in Number of Platforms Pitched by *Control* participants in Phase 2 versus Phase 1. Scarcity participants explored about 16.86 (= $\beta_0 + \beta_1 + \beta_4 + \beta_6$ = 15.63 – 0.26 – 0.30 + 1.79) platforms by the end of Phase 2, which is a significant increase of about 1.53 (z = 3.73, p < 0.000) over the number they explored by the end of Phase 1. In all subsequent analyses, the coefficients for the Abundance × Phase 2 and Scarcity × Phase 2 interactions will represent the *difference* between the *change* in the value of the response variable in Phase 2 versus Phase 1 among Abundance (Scarcity) participants and the *change* in the value of the response variable in Phase 2 versus Phase 1 among Control participants.

The number of platforms Abundance participants explored in Phase 2 was not significantly different than the number explored by Controls (Abundance Phase 2 – Control Phase 2 = 0.21, z = 0.36, p = 0.721). But, the number of platforms Scarcity participants explored in Phase 2 was significantly higher than the number explored by Controls (Scarcity Phase 2 – Control Phase 2 = 1.49, z = 2.53, p = 0.012).

In the ninth and tenth rows, we find the coefficients for the Abundance × Phase 3 interaction, $\beta_7 = 0.68$ (*s.e.* = 0.60), and for the Scarcity × Phase 3 interaction, $\beta_8 = –0.04$ (*s.e.* = 0.59). The coefficient for the Abundance (Scarcity) × Phase 3 interaction is the *difference* between the change in Number of Platforms Pitched by *Abundance* participants in Phase 3 versus Phase 2 and the change in Number of Platforms Pitched by *Control* participants in Phase 3 versus Phase 2. Abundance participants explored about 15.37 (= $\beta_0 + \beta_1 + \beta_2 + \beta_3 + \beta_5 + \beta_7 =$ 15.63 – 0.26 – 0.89 + 0.01 + 0.20 + 0.68) platforms by the end of Phase 3, which is a decrease of about –0.21 from the number they explored in Phase 2, but this decrease was not significant (z = –0.49, p = 0.625).

Scarcity participants explored about 15.93 (= $\beta_0 + \beta_1 + \beta_2 + \beta_4 + \beta_6 + \beta_8$ = 15.63 – 0.26 – 0.89 – 0.30 + 1.79 – 0.04) platforms by the end of Phase 3, which is a significant decrease of –0.93 (z = –2.27, p = 0.023) from the number they explored by the end of Phase 2. In all subsequent analyses, the coefficients for the Abundance × Phase 3 and Scarcity × Phase 3 interactions will represent the *difference* between the *change* in the value of the response variable in Phase 3 versus Phase 2 among Abundance (Scarcity) participants and the *change* in the value of the response variable in Phase 3 versus Phase 2 among Control participants.

The number of platforms Abundance participants explored in Phase 3 was higher than the number explored by Controls, but this difference was not significant (Abundance Phase 3 – Control Phase 3 = 0.90, z = 1.28, p = 0.199). Scarcity participants explored a significantly higher number of platforms than did Controls (Scarcity Phase 3 – Control Phase 3 = 1.45, z = 2.11, p = 0.035).

In the eleventh row of Table 1, we find the Level 2 Random Intercept Variance, $\psi_{11}^{(2)}$ = 4.78 (*s.e.* = 0.98). This is the between-subject variance in the Number of Unique Platforms

Pitched by Trial 15 of Phase 1. Participants' random intercepts vary around the average Number of Unique Platforms Pitched by the end of Phase 1 with an estimated standard deviation of 2.19 (= $\sqrt{4.78}$). In the twelfth row of Table 1, we find that the Level 2 Random Slope Variance (Phase), $\psi_{22}^{(2)}$ = 1.31 (*s.e.* = 0.44). This is the between-subject variance in the rate of change in the Number of Unique Platforms Pitched across Phases. Participants' random slopes vary around the average slope across Phases with an estimated standard deviation of 1.14 (= $\sqrt{1.31}$). In the thirteenth row of Table 1, we find that the L1 (Residual) Error Variance θ = 4.11 (*s.e.* = 0.45). This is the within-subject variance in the Number of Unique Platforms Pitched across Phases. The estimated residual standard deviation around the participant-specific regression lines is 2.03 (= $\sqrt{4.11}$).

We can use estimates from the random part of the model to calculate the intraclass correlation coefficient (ICC), ρ , which is the estimated correlation between measurements on the same participant.

$$\hat{\rho}(participant) = \frac{\psi_{11}^{(2)} + \psi_{22}^{(2)}}{\psi_{11}^{(2)} + \psi_{22}^{(2)} + \theta} = \frac{4.78 + 1.14}{4.78 + 1.14 + 4.11} = 0.59$$

4.3.2 Exploitation

Figure 4.2 presents the average number of Personal-Best platforms selected by participants on each Trial in each Phase of Study 1 (the number of platforms selected on the current Trial that have one of the three highest empirical averages of all the platforms the participant has selected on any preceding Trial). In Phase 1, participants in all three Conditions exploited their Personal-Best platforms a similar number of times on each Trial. In Phase 2, Control and Abundance participants exploited their Personal-Best platforms significantly more often than Scarcity participants on most Trials. In Phase 3, Control participants exploited their personal-best platforms significantly more often than both Scarcity and Abundance participants on most Trials.

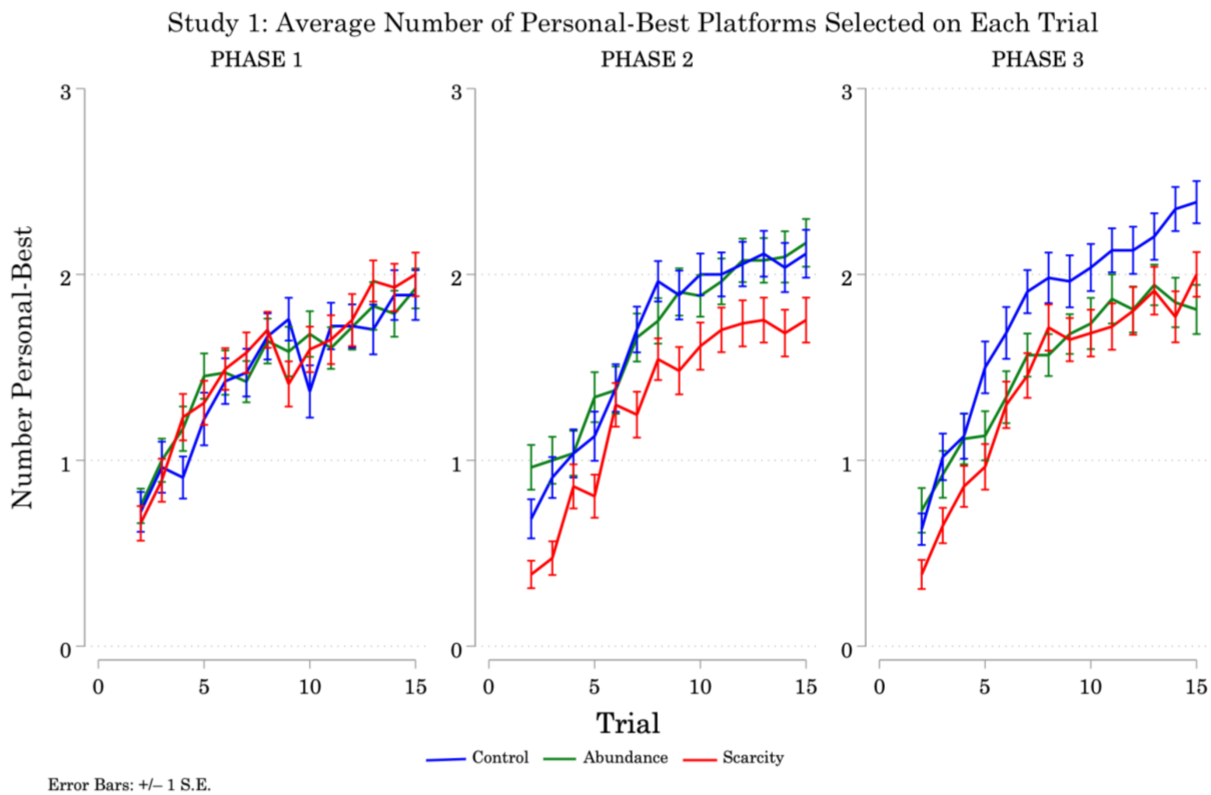


Figure 4.2. Study 1: Exploitation. Average number Personal-Best platforms selected on each Trial, by Phase and Condition. Error bars = +/– 1 S.E. N = 164. Green = Abundance (N = 53); Blue = Control (N = 54); Red = Scarcity (N = 57). Note that the curves begin on Trial 2. On Trial 1, all of the platforms selected have no empirical history. In Phase 1, participants in all three Conditions exploited their Personal-Best platforms a similar number of times on each Trial. In Phase 2, Control and Abundance participants exploited their Personal-Best platforms significantly more often than Scarcity participants on most Trials. In Phase 3, Control participants exploited their personal-best platforms significantly more often than both Scarcity and Abundance participants on most Trials.

Since we are most interested in differences between Conditions, and across Phases, we will look at the cumulative number of times participants exploited their Personal-Best platforms across Trials 2–15 of each Phase. The cumulative number of times participants exploited their top-three Personal-Best platforms ranges from 0 (the participant never exploited any of their personal-best platforms on any Trial) to 42 (the participant selects three platforms on Trial 1, these three platforms are the participant's personal-best going into Trial 2, and the participant exploits these same three platforms from Trial 1 on Trials 2–15).

Table 4.2. Study 1: Exploitation. Maximum likelihood estimates of Two-Level Random-Coefficient models for the cumulative number of times participants exploited their Personal-Best platforms across Trials 2–15 of each Phase. Model 1: Intercept-Slope; Model 2: Main Effects; Model 3: Design Interactions. N = 164.

	Model 1		Model 2		Model 3	
	Est	(SE)	Est	(SE)	Est	(SE)
Fixed Effects						
Intercept β_0	20.80***	0.62	22.00***	0.98	20.41***	1.08
Phase 2 β_1	0.65	0.60	0.65	0.60	2.61**	1.00
Phase 3 β_2	0.48	0.60	0.48	0.60	2.04*	1.00
Abundance β_3			–0.79	1.31	0.55	1.53
Scarcity β_4			–2.73*	1.28	0.61	1.50
Abundance × Phase 2 β_5					–0.35	1.43
Scarcity × Phase 2 β_6					–5.31***	1.40
Abundance × Phase 3 β_7					–4.23**	1.43
Scarcity × Phase 3 β_8					–0.55	1.40
Random Effects						
L2 Random Intercept Variance $\psi_{11}^{(2)}$	36.48	6.96	37.31	7.15	37.86	6.86
L2 Random Slope Variance $\psi_{22}^{(2)}$	5.27	2.55	5.27	2.55	4.74	2.34
L1 (Residual) Error Variance θ	26.91	2.97	26.91	2.97	24.81	2.74
Log likelihood	–1670		–1668		–1655	
AIC | *BIC*	3355 | 3385		3355 | 3393		3336 | 3390	

* $p \leq 0.05$; ** $p \leq 0.01$; *** $p \leq 0.001$; SE = standard error of the mean

Table 2 presents the parameter estimates and fit statistics from three different Two-Level Random Coefficient models for the cumulative number of times participants selected their Personal-Best platforms across Trials 2–15 in a given Phase. Model 1 is the baseline model. The fixed part of Model 1 includes an intercept and piecewise linear slopes for Phases 2 and 3.

The random part of Model 1 includes a random intercept and a random linear slope for Phase at the Participant level (Level 2). Model 2 includes Condition as a fixed effect. Model 3 introduces two-way interactions between elements of the experimental design (Condition, Phase). Model 3 provides a significantly better fit than Model 2 [$LR\ \chi^2(4) = 27.83$, $p < 0.000$] and Model 1 [$LR\ \chi^2(6) = 32.30$, $p < 0.000$], so I will focus on the predictions from Model 3.

In Phase 1, Control participants exploited their Personal-Best platforms 20.41 ($z = 18.94$, $p < 0.000$) times on average. Abundance and Scarcity participants exploited their Personal-Best platforms about the same number of times as did Controls ($\beta_3 = 0.55$, $z = 0.36$, $p = 0.717$; $\beta_4 = 0.61$, $z = 0.41$, $p = 0.685$).

In Phase 2, Control participants exploited their Personal-Best platforms about 23.02 times on average, which is a significant increase over the number of times they exploited their Personal-Best platforms in Phase 1 ($\beta_2 = 2.61$, $z = 2.60$, $p = 0.009$). Abundance participants exploited their Personal-Best platforms about the same number of times as did Controls (Abundance Phase 2 – Control Phase 2 = 0.21, $z = 0.36$, $p = 0.892$), which was a significant increase over the number of times they exploited their Personal-Best platforms in Phase 1 (Abundance Phase 2 – Abundance Phase 1 = 2.26, $z = 2.24$, $p = 0.025$). Scarcity participants exploited their Personal-Best platforms significantly less often than did Controls (Scarcity Phase 2 – Control Phase 2 = –4.70, $z = –3.13$, $p = 0.002$), which was a significant decrease from the number of times they exploited their Personal-Best platforms in Phase 1 (Scarcity Phase 2 – Scarcity Phase 1 = –2.70, $z = –2.77$, $p = 0.006$).

In Phase 3, Control participants exploited their Personal-Best platforms about 25.06 times on average, which is a significant increase over the number of times they exploited their Personal-Best platforms in Phase 1 ($\beta_3 = 2.04$, $z = 2.03$, $p = 0.042$). Abundance participants exploited their Personal-Best platforms significantly less often than did Controls (Abundance Phase 3 – Control Phase 3 = –4.02, z = –2.45, p = 0.014), which was a significant decrease from the number of times they exploited their Personal-Best platforms in Phase 2 (Abundance Phase 3 – Abundance Phase 2 = –2.19, z = –2.16, p = 0.031). Scarcity participants exploited their Personal-Best platforms significantly less often than did Controls (Scarcity Phase 3 – Control Phase 3 = –5.25, z = –3.26, p = 0.001). The number of times Scarcity participants exploited their Personal-Best platforms was about the same as in Phase 2 (Scarcity Phase 3 – Scarcity Phase 2 = 1.49, z = 1.53, p = 0.127).

4.3.3 Mental Models

Recall that participants in Study 1 were asked to estimate the average value of each platform after the 8th and 15th Trials of each Phase. Here we will focus on the estimates participants made at the end of each Phase, following Trial 15. Figure 4.3 plots the average estimated value of each platform against that platform's true value. The red, dotted 45-degree lines indicate what the shape of each curve would look like if there was perfect agreement between the average estimated values reported by participants and the true values of each platform. One way to think about the accuracy of participants' estimates is to consider the proximity of the estimates curve to the 45-degree line.

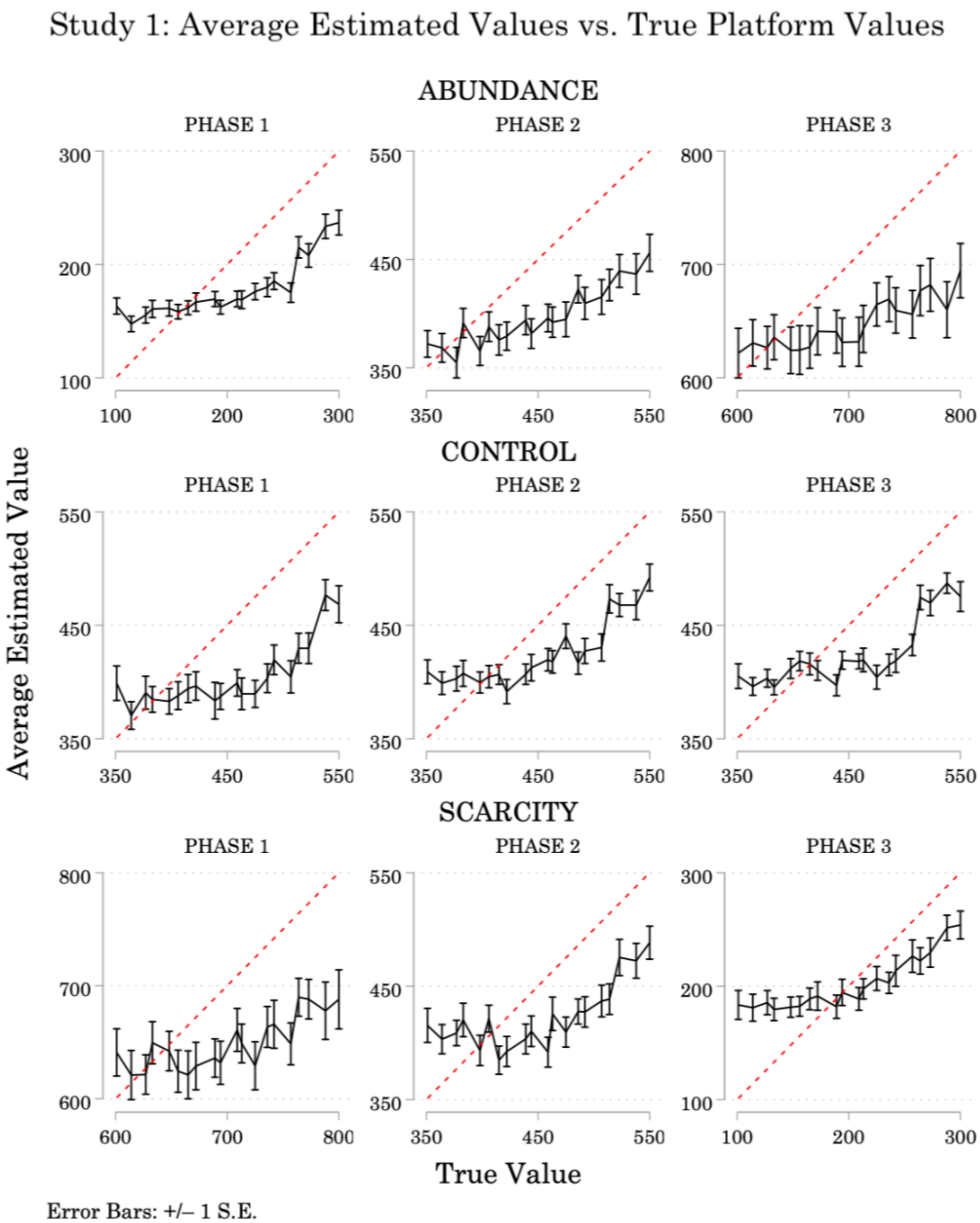


Figure 4.3. Study 1: Mental Models. Average estimated values versus true platform values, by Phase and Condition. N = 161.[3] Top Row = Abundance (N = 53); Middle Row = Control (N = 53); Bottom Row = Scarcity (N = 55). Results for second estimate made by participants (following Trial 15 of each Phase). Error bars = +/– 1 S.E. Average participant estimates on y-axes. True platform values on the x-axes. Red dotted 45-degree lines mark "perfect agreement" between participants' average estimates of each platform's value and each platform's true value.

[3] Two participants (Control Condition = 1, Scarcity Condition = 1) were dropped because they failed to submit their estimates before time expired on Trial 15 of all three Phases. One participant in the Scarcity Condition was dropped because at least 4 of their estimates were extreme outliers. (Extreme outliers are defined as estimates that fall more than three times the size of the interquartile range above the 75th percentile, or more than three times the size of the interquartile range below the 35th percentile.)

Control participants' average error decreases slightly between Phases 1 and 2, and is about the same in Phase 3 as in Phase 2. Abundance participants' average error increases significantly across Phases 1– 3. Scarcity participants' average error decreases significantly between Phases 1 and 2, and decreases again slightly between Phases 2 and 3. Abundance and Scarcity participants' average errors are similar to that of Controls in Phases 1 and 2. In Phase 3, Abundance participants' average error is significantly higher than Controls, and Scarcity participants' average error is similar to Controls.

Table 3 presents the parameter estimates and fit statistics from three different Two-Level Random Coefficient models for the Mean Absolute Difference between participants' estimates of each platform's average value on Trial 15 of each Phase, and the true average value of each platform. Model 1 is the baseline model, and includes an intercept and piecewise linear slopes for Phases 2 and 3. The random part of Model 1 includes a random intercept and random linear slope for Phase at the Participant level (Level 2). Model 2 includes the main effect of Condition. Model 3 introduces interactions among elements of the experimental design (Condition, Phase). Model 3 provides a significantly better fit than Model 2 $LR\ \chi^2(4) = 22.07$, $p = 0.000$] and Model 1 [$LR\ \chi^2(6) = 22.65$, $p = 0.001$], so I will focus on the predictions from Model 3.

Table 4.3. Study 1: Mental Models. Maximum likelihood estimates of Two-Level Random-Coefficient models for the Mean Absolute Difference between participants' estimates of the platform values on Trial 15 of each Phase and the true average value of each platform. Model 1: Intercept-Slope; Model 2: Main Effects; Model 3: Design Interactions. N =161.

	Model 1		Model 2		Model 3	
	Est	(SE)	Est	(SE)	Est	(SE)
Fixed Effects						
Intercept β_0	74.16***	5.79	69.11***	8.81	76.50***	9.88
Phase 2 β_1	–1.36	4.23	–1.38	4.23	–11.01	7.06
Phase 3 β_2	–0.13	4.25	–0.13	4.25	–3.88	7.07
Abundance β_3			7.24	11.45	–22.12	13.98
Scarcity β_4			7.84	11.35	14.64	13.87
Abundance × Phase 2 β_5					36.00***	9.95
Scarcity × Phase 2 β_6					–6.54	9.86
Abundance × Phase 3 β_7					20.22*	9.99
Scarcity × Phase 3 β_8					–8.53	9.90
Random Effects						
L2 Rand Intercept Var $\psi_{11}^{(2)}$	4792.99	590.73	4806.60	609.82	4593.17	566.90
L2 Rand Slope Var $\psi_{22}^{(2)}$	1738.63	235.89	1743.02	236.77	1505.33	208.33
Level-1 Error Variance θ	505.44	58.97	505.44	58.97	496.44	57.92
Log likelihood	–2485		–2485		–2473	
AIC | *BIC*	4984 | 5013		4987 | 5024		4973 | 5027	

* $p \leq 0.05$; ** $p \leq 0.01$; *** $p \leq 0.001$

In Phase 1, Control participants' average error was 76.50 (z = 7.74, p < 0.000). Abundance participants' error was lower than Controls, but this difference was not significant (β_3 = –22.12, z = –1.58, p = 0.113). Scarcity participants' error was higher than Controls, but this difference was not significant either (β_4 = 14.64, z = 1.06, p = 0.291).

In Phase 2, Control participants' average error was 65.39, which is lower than their error in Phase 1, but this decrease was not significant (β_1 = –11.01, z = –1.56, p = 0.119). Abundance and Scarcity participants' errors were higher than Controls, but this difference was not significant in either case (Abundance Phase 2 – Control Phase 2 = 13.88, z = 1.15, p = 0.251;

(Scarcity Phase 2 – Control Phase 2 = 8.09, $z = 0.68$, $p = 0.499$). Abundance participants' error Phase 2 was significantly higher than in Phase 1 (Abundance Phase 2 – Abundance Phase 1 = 24.99, $z = 3.57$, $p < 0.000$). Scarcity participants' error in Phase 2 was significantly lower than in Phase 1 (Scarcity Phase 2 – Scarcity Phase 1 = –17.56, $z = -2.55$, $p = 0.011$).

In Phase 3, Control participants' average error was 61.51, which is slightly lower than in Phase 2, but this decrease was not significant ($\beta_2 = -3.88$, $z = -0.55$, $p = 0.583$). Abundance participants' error in Phase 3 was significantly higher than Controls (Abundance Phase 3 – Control Phase 3 = 34.10, $z = 2.35$, $p = 0.019$), and significantly higher than in Phase 2 (Abundance Phase 3 – Abundance Phase 2 = 16.34, $z = 2.31$, $p = 0.021$). Scarcity participants' error in Phase 3 was about the same as Controls (Scarcity Phase 3 – Control Phase 3 = –0.44, $z = -0.03$, $p = 0.976$). Scarcity participants' error in Phase 3 was lower than in Phase 2, but this decrease was not significant (Scarcity Phase 3 – Scarcity Phase 2 = –12.41, $z = -1.79$, $p = 0.074$).

We need to exercise caution when interpreting differences in the amount of error participants exhibit between Conditions and across Phases. While neither Abundance nor Scarcity participants' errors were significantly different than Controls in Phase 1, they *were* significantly different from *each other*. Figure 4.4 presents the adjusted marginal predictions for the Mean Absolute Difference between participants' estimates and the true average value of each platform. Abundance participants' error is significantly lower than Scarcity participants' in Phase 1 (Abundance Phase 1 – Scarcity Phase 1 = –36.76, $z = -2.65$, $p = 0.008$).

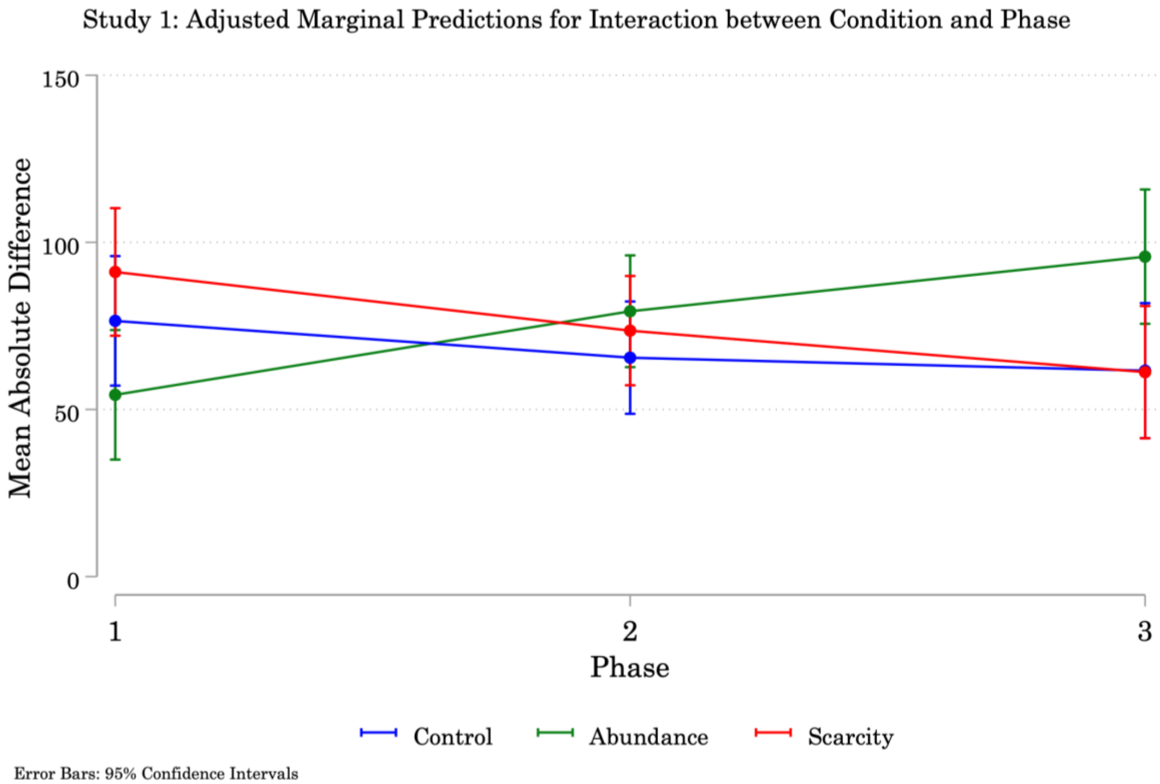


Figure 4.4. Study 1: Mental Models Interaction. Adjusted marginal predictions for the interaction between Condition and Phase. N = 161. Error bars = 95% Confidence Interval. Green = Abundance (N = 53); Blue = Control (N = 53); Red = Scarcity (N = 55). Results for second estimate made by participants (following Trial 15 of each Phase). In Phase 1, Abundance participants' error is significantly lower than Scarcity participants' error.

Abundance participants face the Low range, [100, 300], of platform values in Phase 1, and Scarcity participants face the High range, [600, 800]. I did not anticipate differences in participants' ability to learn the average platform values in each range *a priori*. The length of each range is the same in both Conditions (200 points). The amount of noise around each platform's average value is the same in both Conditions (on each Trial, platform values are drawn from a normal distribution around each platform's true average value with a standard deviation of 20 points). During the instructions and practice trial, participants in both Conditions were exposed to values from the same range they faced in Phase 1 (Abundance participants were exposed to Low range values; Scarcity participants were exposed to High range values). Aside from these considerations, it did not occur to me that any other factors might differentially affect participants' ability to learn the average platform values.

There are (at least) two potential explanations for Phase 1 differences in error across Conditions. First, there is evidence that humans process numbers of lower magnitude faster than numbers of higher magnitude (Li & Cai, 2014; Schwarz & Eiselt, 2008). The experimental evidence supporting this phenomenon compares processing speeds for numbers with the same amount of digits. For example, Schwarz and Eiselt (2008) compare response times for single-digit pairs such as "1" and "9" (with "9" being the higher-magnitude number in the pair). Given the time limits imposed in the present experiment, faster processing speeds for numbers of smaller magnitude could advantage participants when they are faced with the Low range.

Second, humans exhibit increased learning rates as distance increases between the expected value of a given reward and the realized value of that reward (Rouhani et al., 2019). The bigger the prediction error, the more learning. Previous experimental investigations into the effect of prediction error on learning rates focus on the absolute size of a given prediction error. For example, if the participant expects a reward of 100 points, and observes a realized reward of 150 points, then the prediction error is coded as 50. However, we can also think about the size of a prediction error as a proportion of the true average value of a reward.

On each Trial in the present experiment, the point value for a given platform is drawn from a normal distribution around that platform's average value with a standard deviation of 20 points. On a given Trial, the absolute size of the difference between the realized point value of a given platform and that platform's true average value is consistent across the ranges of platform values (Low = [100, 300]; Medium = [350, 550]; High = [600, 800]). However, the size of the difference between the realized point value and the platform's true average value is not consistent if we think of this difference as a proportion of the platform's average value. A concrete example will help clarify.

Consider Platform X whose true average value is 100 points for participants facing the Low range (e.g. Abundance participants in Phase 1), and whose true average value is 600 points for participants facing the High range (e.g. Scarcity participants in Phase 1). Suppose Participant *i* is facing the Low range, and Participant *j* is facing the High range. And, suppose that both Participant *i* and Participant *j* have perfectly accurate beliefs about the true average value of Platform X (Participant *i* believes Platform X's true average value is 100 points; Participant *j* believes Platform X's true average value is 600 points).

On Trial *t*, the realized value of Platform X is equal to the true average value plus 10 points. So, Participant *i* observes a realized value of 110 points, and Participant *j* observes a realized value of 610 points. The absolute size of the difference between the realized values and each participant's expectation is the same (+10 points). But the relative size, or the size of the error as proportion of expected value, is different. For Participant *i*, who (accurately) believes the true average value of Platform X is 100 points, an error of +10 points is 1/10th the size of the true average value of Platform X. For Participant *j*, who (accurately) believes the true average value of Platform X is 600 points, an error of +10 points is only 1/60th the size of the true average value of Platform X.

If the size of the prediction error is represented as a proportion of the expected value of the reward, then the size of the prediction error is larger for Participant *i* than for Participant *j*. As a result, Participant *i*'s learning rate for the value of Platform X will be higher than Participant *j*'s learning rate. My suggestions here are purely speculative. To my knowledge, researchers investigating the effect of prediction errors on learning have only considered the absolute size of a prediction error, not the size of the error as a proportion of the true value of the reward.

Exploring the effect of numerical magnitude on learning rates was not the goal of the present experiment, and the experimental design does not allow us to directly test any hypotheses about the cause of the Phase 1 asymmetry between Abundance and Scarcity participants' errors.

If we compare Abundance and Scarcity participants' error when they are faced with the *same* distribution, we find no significant differences. Scarcity participants' error when they face the Low distribution in Phase 3 is slightly higher than Abundance participants' error when they face the Low distribution in Phase 1, but this difference is not significant (Scarcity Phase 3 – Abundance Phase 1 = 12.99, $z = 1.11$, $p = 0.268$). Scarcity participants' error when they face the High distribution in Phase 1 is slightly lower than Abundance participants' error when they face the High distribution in Phase 3, but this difference is not significant either (Scarcity Phase 1 – Abundance Phase 3 = –10.16, $z = -0.85$, $p = 0.393$).

The only comparison that is not subject to the apparent effect of range magnitude (e.g. High range versus Low range) occurs in Phase 2, when participants in all three Conditions face the Medium range. Both Scarcity and Abundance participants are exposed to the Medium range for the first time in Phase 2, so neither has an advantage in terms of the accuracy of their prior beliefs over the range of platform values they will encounter in Phase 2. The difference between Scarcity and Abundance participants' average error in Phase 2 is not significant (Scarcity Phase 2 – Abundance Phase 2 = –5.79, $z = -0.85$, $p = 0.393$).

4.3.4 Rewards

Figure 4.5 presents participants' Standardized Achievement Scores on each Trial in each Phase of Study 1. We see evidence that participants' are learning in the significant increase in participants' scores across Trials 1–15 in each Phase.

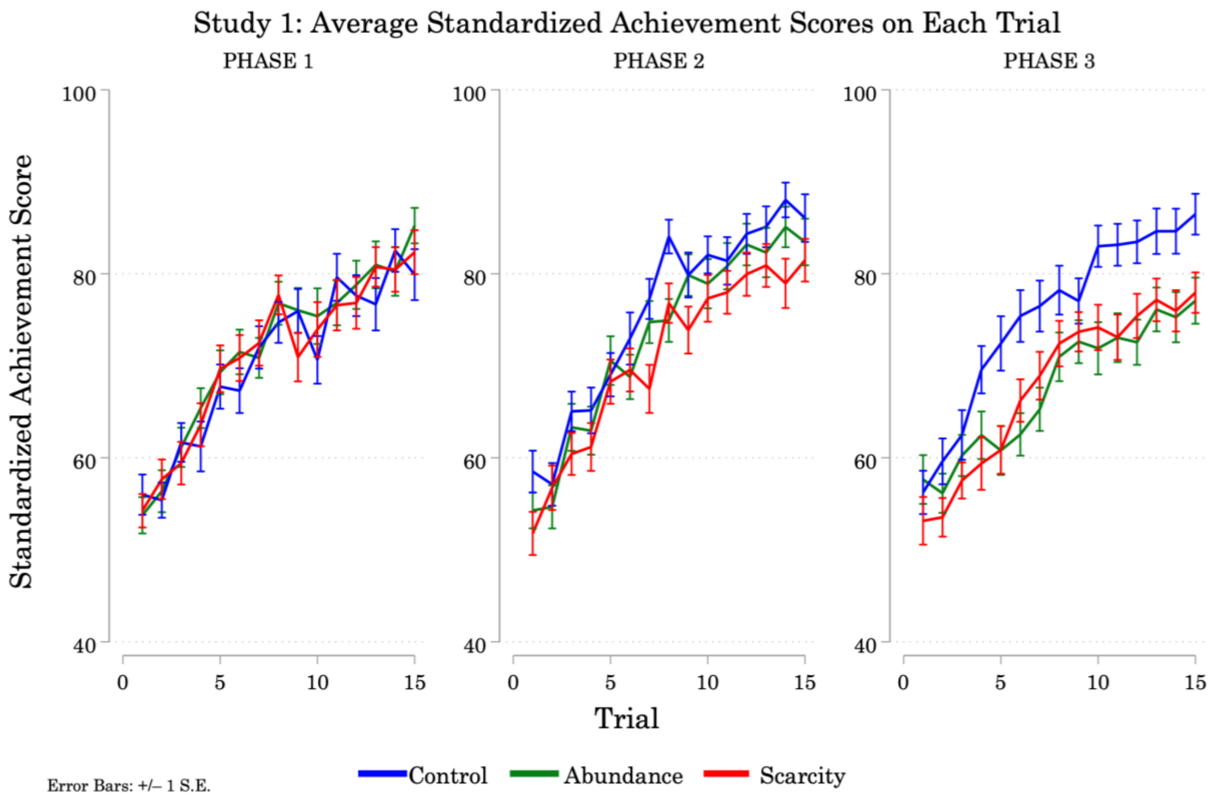


Figure 4.5. Study 1: Rewards. Average Standardized Achievement Scores on each Trial, by Phase and Condition. Error bars: +/– 1 S.E. N = 164. Green = Abundance (N = 53); Blue = Control (N = 54); Red = Scarcity (N = 57). Standardized Achievement Scores range from 7 (participant selects the 3 lowest-valued platforms) to 100 (participant selects the 3 highest-valued platforms). In Phase 1, there are no significant differences between Conditions across Trials. Toward the end of Phase 2, we see that Control participants' start to achieve slightly higher scores than Scarcity participants. Starting around Trial 4 in Phase 3, Control participants achieve significantly higher scores than Scarcity and Abundance participants across almost every Trial.

In Phase 1, there are no significant differences between Conditions across Trials. Toward the end of Phase 2, we see that Control participants' start to achieve slightly (but not significantly) higher scores than Scarcity participants. Starting around Trial 4 in Phase 3, Control participants achieve significantly higher scores than Scarcity and Abundance participants across almost every Trial.

Table 4.4. Study 1: Rewards. Maximum likelihood estimates of Two-Level Random-Coefficient models for participants' Cumulative Standardized Achievement Scores at the end of each Phase. Model 1: Intercept-Slope; Model 2: Main Effects; Model 3: Design Interactions. N = 164.

	Model 1		Model 2		Model 3	
	Est	(SE)	Est	(SE)	Est	(SE)
Fixed Effects						
Intercept β_0	1063***	11	1098***	18	1058***	20
Phase 2 β_1	33**	12	33**	12	78***	21
Phase 3 β_2	–44***	12	–44***	12	–4	21
Abundance β_3			–43	23	17	28
Scarcity β_4			–59**	22	1	28
Abundance × Phase 2 β_5					–58*	29
Scarcity × Phase 2 β_6					–75**	29
Abundance × Phase 3 β_7					–80**	30
Scarcity × Phase 3 β_8					–41	29
Random Effects						
L2 Random Intercept Var $\psi_{11}^{(2)}$	10781	1194	11438	2528	10733	2386
L2 Random Slope Var $\psi_{22}^{(2)}$	2192	1030	2192	1030	1330	947
Level-1 Error Var θ	10814	1194	10815	1302	10727	1185
Log likelihood	–3125		–3122		–3111	
AIC | *BIC*	6264 | 6294		6262 | 6299		6247 | 6302	

* $p \leq 0.05$; ** $p \leq 0.01$; *** $p \leq 0.001$

Table 4.4 presents the parameter estimates and fit statistics from three different Two-Level Random Coefficient models for the participants' cumulative Standardized Achievement Scores at the end of each Phase in Study 1. Model 1 is the baseline model, and includes two piecewise slopes for Phases 2 and 3. The random part of Model 1 includes a random intercept and a random linear slope for Phase at the Participant level (Level 2). Model 2 includes Condition as a fixed effect. Model 3 includes interactions among elements of the experimental design (Condition, Phase). Model 3 provides a significantly better fit than Model 2 [$LR\ \chi^2(4) = 22.16$, $p = 0.000$] and Model 1 [$LR\ \chi^2(6) = 28.66$, $p = 0.000$], so I will focus on the predictions from Model 3.

In Phase 1, Control participants accumulated standardized scores of 1057.66 ($z = 53.06$, $p < 0.000$) on average. Abundance participants accumulated slightly higher scores in Phase 1 than did Controls, but this difference was not significant ($\beta_3 = 16.98$, $z = 0.60$, $p = 0.549$). Scarcity participants' scores at the end of Phase 1 were pretty much the same as Controls ($\beta_4 = 0.59$, $z = 0.02$, $p = 0.983$).

In Phase 2, Control participants accumulated standardized scores of 1135.97 on average, which is significantly higher than the scores they accumulated by the end of Phase 1 ($\beta_1 = 78.32$, $z = 3.81$, $p < 0.000$). Abundance participants' scores were lower than Controls, but this difference was not significant (Abundance Phase 2 – Control Phase 2 = –41.01, $z = -1.46$, $p = 0.144$). Abundance participants' scores at the end of Phase 2 were higher than what they accumulated by the end of Phase 1, but this increase was not significant (Abundance Phase 2 – Abundance Phase 1 = 20.73, $z = 0.98$, $p = 0.327$). Scarcity participants scores at the end of Phase 2 were significantly lower than the scores accumulated by Controls (Scarcity Phase 2 – Control Phase 2 = –74.55, $z = -2.70$, $p = 0.007$). Scarcity participants' scores at the end of Phase 2 were pretty much the same as what they accumulated by the end of Phase 1 (Scarcity Phase 2 – Scarcity Phase 1 = 3.17, $z = 0.16$, $p = 0.874$).

In Phase 3, Control participants' accumulated similar scores as in Phase 2 ($\beta_2 = -4.17$, $z = -0.20$, $p = 0.839$). Abundance participants' scores were significantly lower than Controls

(Abundance Phase 3 – Control Phase 3 = –120.81, z = –4.08, $p < 0.000$), and significantly lower than what they accumulated by the end of Phase 2 (Abundance Phase 3 – Abundance Phase 2 = –83.97, z = –4.05, $p < 0.000$). Scarcity participants' scores at the end of Phase 3 were also significantly lower than Controls (Scarcity Phase 3 – Control Phase 3 = –115.87, z = –3.99, $p < 0.000$), and significantly lower than what they accumulated by the end of Phase 2 (Scarcity Phase 3 – Scarcity Phase 2 = –45.49, z = –2.28, $p = 0.023$).

4.3.5 Discovery

Figure 4.6 presents the average number of True Top Three platforms participants on each Trial in each Phase of Study 1 (the number of platforms in the current pitch that have one of the three highest true average values). In Phases 1 and 2, participants in all three Conditions selected True Top Three platforms a similar number of times (though there is a hint that Control participants had slightly higher discovery rates in Phase 2 than participants in the other two Conditions). In Phase 3, Control participants selected True Top Three platforms significantly more often than Abundance and Scarcity participants starting around Trial 3.

Since we are most interested in differences between Conditions, across Phases, we will look at the cumulative number of times participants selected True Top Three platforms across Trials 1–15 of each Phase. The cumulative number of times participants select True Top Three platforms ranges from 0 (the participant never selects any of the True Top Three platforms on any Trial) to 45 (the participant selects all of the True Top Three platforms on every Trial).

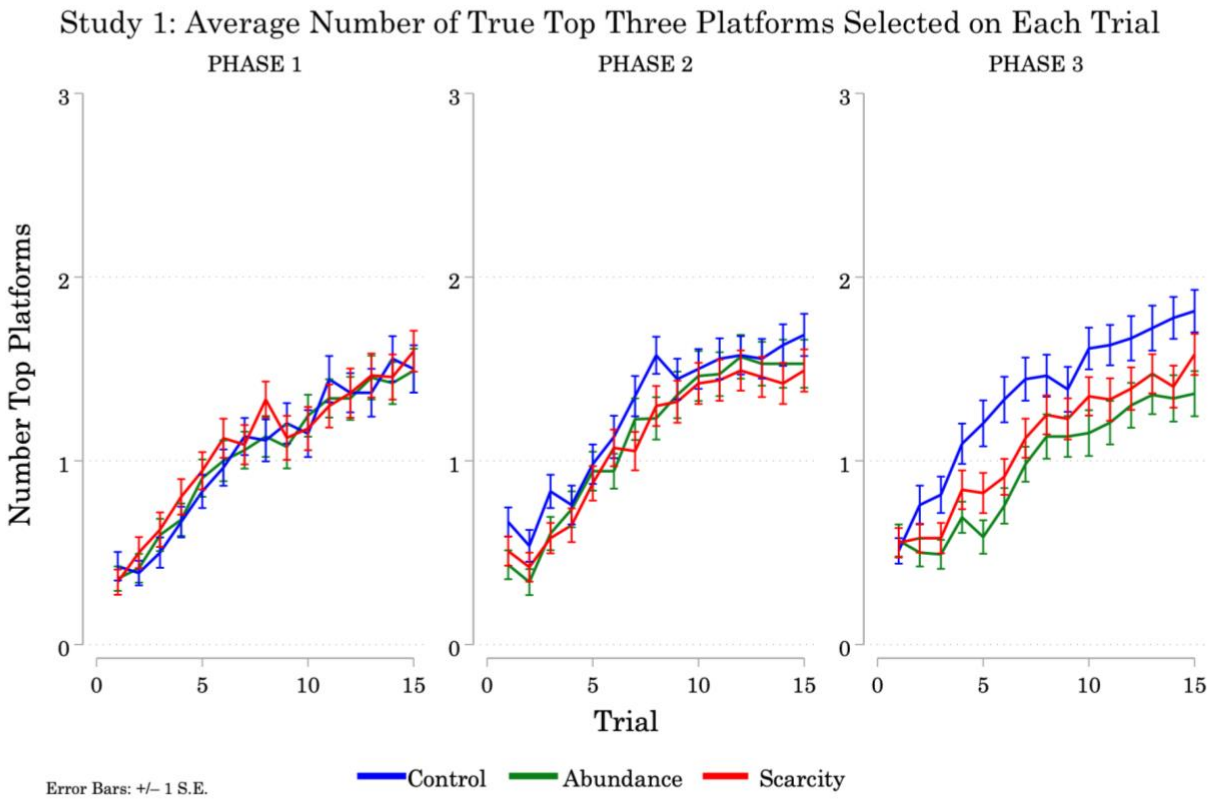


Figure 4.6. Study 1: Discovery. Average number of True Top Three platforms selected on each Trial, by Phase and Condition. Error bars = +/– 1 S.E. N = 164. Green = Abundance (N = 53); Blue = Control (N = 54); Red = Scarcity (N = 57). In Phases 1 and 2, participants in all three Conditions selected True Top Three platforms a similar number of times (though there is a hint that Control participants had slightly higher discovery rates in Phase 2 than participants in the other two Conditions). In Phase 3, Control participants selected True Top Three platforms significantly more often than Abundance and Scarcity participants starting around Trial 3.

Table 4.5 presents the parameter estimates and fit statistics from three different Two-Level Random Coefficient models of the cumulative number of times participants select True Top Three platforms across Trials 1–15 in a given Phase. Model 1 is the baseline model. The fixed part of Model 1 includes an intercept and piecewise linear slopes for Phases 2 and 3. The random part of Model 1 includes a random intercept and a random linear slope for Phase at the Participant level (Level 2). Model 2 includes Condition as a fixed effect. Model 2 failed to converge when both a random intercept and random slope were included, so the random slope was dropped from this model. Model 3 introduces two-way interactions between elements of the experimental design (Condition, Phase), and includes both a random intercept and a random linear slope for Phase at the Participant level. Model 3 provides a better fit than Model 2 [LR $\chi^2(4) = 11.33$, $p = 0.023$] and Model 1 [LR $\chi^2(6) = 15.98$, $p = 0.014$], so I will focus on the predictions from Model 3.

Table 4.5. Study 1: Discovery. Maximum likelihood estimates of Two-Level Random-Coefficient models for the cumulative number of times participants selected True Top-Three platforms in each Phase. Model 1: Intercept-Slope; Model 2: Main Effects; Model 3: Design Interactions. N = 164.

	Model 1		Model 2		Model 3	
	Est	(SE)	Est	(SE)	Est	(SE)
Fixed Effects						
Intercept β_0	15.95***	0.60	17.26***	0.87	15.65***	1.05
Phase 2 β_1	1.46	0.77	1.46	0.77	3.13*	1.32
Phase 3 β_2	–0.24	0.77	–0.24	0.77	1.50	1.32
Abundance β_3			–2.34*	1.07	–0.03	1.49
Scarcity β_4			–1.59	1.05	0.90	1.47
Abundance × Phase 2 β_5					–1.79	1.87
Scarcity × Phase 2 β_6					–3.15	1.84
Abundance × Phase 3 β_7					–3.78*	1.87
Scarcity × Phase 3 β_8					–1.50	1.84
Random Effects						
L2 Random Intercept Var $\psi_{11}^{(2)}$	11.31	4.77	12.18	5.15	12.91	5.03
L2 Random Slope Var $\psi_{22}^{(2)}$	0.35	0.64	0.10	0.37	0.08	0.31
L1 (Residual) Error Var θ	48.25	3.77	48.51	3.79	46.87	1.75
Log likelihood	–1708		–1708		–1700	
AIC | *BIC*	3430 | 3460		3430 | 3467		3426 | 3481	

* $p \leq 0.05$; ** $p \leq 0.01$; *** $p \leq 0.001$; SE = standard error of the mean

† Model 2 failed to converge when both a random intercept and random slope were included, so the random slope was dropped from this model.

In Phase 1, Control participants selected True Top Three platforms 15.65 ($z = 14.87$, $p <$ 0.000) times on average. Abundance and Scarcity participants selected True Top Three platforms about the same number of times as did Controls (β_3 = –0.03, z = –0.02, p = 0.986; β_4 = 0.90, z = 0.61, p = 0.542).

In Phase 2, Control participants selected True Top Three platforms about 18.78 times on average, which is a significant increase over the number of times they selected True Top Three platforms in Phase 1 (β_2 = 3.13, z = 2.37, p = 0.018). Abundance and Scarcity participants selected True Top Three platforms about the same number of times as did Controls (Abundance Phase 2 – Control Phase 2 = –1.82, z = –1.19, p = 0.233; Scarcity Phase 2 – Control Phase 2 = –2.25, z = –1.51; p = 0.132), which was about the same as the number of times they each selected True Top Three platforms in Phase 1 (Abundance Phase 2 – Abundance Phase 1 = 1.34, z = 1.01, p = 0.314; Scarcity Phase 2 – Scarcity Phase 1 = –0.02, z = –0.01, p = 0.989).

In Phase 3, Control participants selected True Top Three platforms about 20.28 times on average, which is about the same as the number of times they selected True Top Three platforms in Phase 1 (β_3 = 1.50, z = 1.14, p = 0.255). Abundance and Scarcity participants selected True Top Three platforms significantly less often than did Controls (Abundance Phase 3 – Control Phase 3 = –5.60, z = –3.61, p < 0.000; Scarcity Phase 3 – Control Phase 3 = –3.75, z = –2.46, p = 0.014), and about the same number of times they each selected top-three platforms in Phase 2 (Abundance Phase 3 – Abundance Phase 2 = –2.28, z = –1.72, p = 0.086; Scarcity Phase 3 – Scarcity Phase 2 = 0.00, z = 0.00, p = 1.000).

4.4 Discussion

In Study 1, participants could only learn about the platform values through Exploration (directly sampling platform values by including platforms in their pitch on each Trial). The purpose of Study 1 was to establish a baseline for participant behavior. In particular, I am interested in comparing behavior in Phase 1, before any resource shock occurs, with behavior in Phase 2, after Abundance and Scarcity participants experience the first resource shock. I find significant effects of *negative* resource shocks on 4 out of 5 of the focal dependent variables in Phase 2. The effects of *positive* resource shocks in Phase 2 are mixed. In Phase 3, the effects of both negative and positive resource shocks are mixed.

I am going to focus on the effects observed in Phase 2, when participants in all three Conditions face the Medium range of platform values. Control participants experience *no change* in platform values between Phases 1 and 2 (they face the Medium range in every Phase of the experiment). Abundance participants experience a *positive* resource shock in Phase 2 (the Medium range platform values are *higher* than the Low range platform values they faced in Phase 1). Scarcity participants experience a *negative* resource shock in Phase 2 (the Medium range platform values are *lower* than the High range platform values they faced in Phase 1).

4.4.1 Exploration

Exploration is defined as the total number of unique platforms participants explored across Trials 1–15 of a given Phase. In other words, Exploration is the number of platforms (out of 20) that the participant included in her pitch on at least one Trial. Control participants explored the same number of platforms in Phase 2 as they did in Phase 1. Abundance participants also explored the same number of platforms in Phase 2 as they did in Phase 1. Scarcity participants explored a larger number of platforms in Phase 2 than they did in Phase 1.

No change in platform values produced *no change* in Exploration. An *increase* in platform values produced *no change* in Exploration. A *decrease* in platform values produced an *increase* in Exploration.

4.4.2 Exploitation

Exploitation is defined as the total number of times that a participant selected Personal-Best platforms (those with the top three highest empirical averages) across Trials 2–15 of a given Phase. A platform's "empirical average" is the average of the *realized* values that the participant has observed for that platform over all preceding Trials. Control participants exploited their Personal-Best platforms significantly *more* often in Phase 2 than they did in Phase 1. Abundance participants also exploited their Personal-Best platforms significantly *more* often in Phase 2 than they did in Phase 1. Scarcity participants exploited their Personal-Best platforms significantly *less* often than they did in Phase 1.

No change in platform values produced an *increase* in Exploitation. An *increase* in platform values also produced an *increase* in Exploitation. A *decrease* in platform values produced a *decrease* in Exploitation.

4.4.3 Mental Models

Mean Absolute Difference is defined as the average absolute value of the difference between participants' estimates of the platform values at the end of each Phase and the true average values of each platform. We'll refer to the Mean Absolute Difference as "average error." Control participants' average error was slightly lower in Phase 2 than in Phase 1, but this difference was not significant. Abundance participants' average error in Phase 2 was significantly higher than in Phase 1. Scarcity participants' average error in Phase 2 was lower than in Phase 1, but this difference was not significant.

No change in platform values produced *no change* in average error. An *increase* in platform values produced an *increase* in average error. A *decrease* in platform values produced a *decrease* in average error. (But note that there was no difference between Scarcity and Abundance participants' average error in Phase 2. The observed increase in error among Abundance participants, and the corresponding decrease in error among Scarcity participants, may result from differences in reward magnitudes – the smaller platform values in the Low range may be easier for participants to learn for the reasons discussed in Section 4.3.)

4.4.4 Rewards

A participant's Cumulative Standardized Achievement Score is the sum of the Standardized Achievement Scores a participant earns across Trials 1–15 of a given Phase. Control participants earned significantly higher Cumulative Standardized Achievement Scores in Phase 2 than they did in Phase 1. Abundance participants' scores in Phase 2 were higher than in Phase 1, but this difference was not significant. An *increase* in platform values resulted in a (non-significant) *increase* in Cumulative Standardized Achievement scores, and this increase was smaller than that exhibited by Control participants. Scarcity participants' scores in Phase 2 were the same as in Phase 1. A *decrease* in platform values produced *no improvement* in Cumulative Standardized Achievement scores.

No change in platform values produced an *increase* in Cumulative Standardized Achievement. An *increase* in platform values produced *no change* in Cumulative Standardized Achievement. A *decrease* in platform values produced *no change* in Cumulative Standardized Achievement.

4.4.5 Discovery

Discovery is defined as the number of times a participant selected any of the true top-three highest-valued platforms across Trials 1–15 of a given Phase. In Phase 2, Control participants selected True Top-Three platforms significantly more often than they did in Phase 1. Abundance and Scarcity participants selected top-three platforms in Phase 2 with similar frequency to Phase 1.

No change in platform values produced a significant *increase* in Discovery. An *increase* in platform values produced *no change* in Discovery. A *decrease* in platform values produced *no change* in Discovery.

4.4.6 Take-Aways from Study 1

The biggest take-away from Study 1 is that a *negative* resource shock (Scarcity Condition) *increases* Exploration and *decreases* Exploitation. This pattern is consistent with behavior observed in similar studies where participants engaged in a explore-exploit task are exposed to a "low value" or "loss" environment following a "high value" or "gain" environment (Cooper, Blanco, & Maddox 2017; Garrett & Daw, 2020; Huijsmans et al., 2019).

We see signs of learning across Trials within each Phase (e.g. in the increase in Standardized Achievement Scores across Trials). Participants comprehend the task and are behaving "strategically" (their decisions may not be "optimal," but they do manage to discover higher-valued platforms and increase their rewards across Trials).

Participants also update their beliefs about the distribution of platform values across Phases. Though there is still a good amount of error in their estimates of each individual platform's average value, their estimates do tend to fall within the true range of average values within each Phase.

We also found that responses to the *second* resource shock in Phase 3 are not consistent with responses to the *first* resource shock in Phase 2. In Phase 3, Scarcity participants' rate of Exploration *decreases* (compared to Phase 2), and there is no change in their rate of Exploitation.

There are (at least) two explanations for inconsistency across Phases 2 and 3. First, the expectation of a shift in values could lead Scarcity participants to place more weight on the platform values they observe over the first few Trials of Phase 3. As a result, Scarcity participants' posterior beliefs over the platform value distribution in Phase 3 would converge more quickly to the true distribution of platform values. Second, a reduction in Exploration may be a sign of fatigue, or boredom. The latter explanation is consistent with the decline in Exploration and Rewards that we observe across all three Conditions in Phase 3. Going forward, we'll focus on the *initial* shift from Phase 1 to Phase 2 in order to avoid confusing boredom or fatigue with "effects" in Phase 3.

5 STUDIES 2A & 2B: SOLO PARTICIPANTS WITH SIDE OBSERVATIONS

5.1 Study 2A: Solo Participants with Random Side Observations

Study 2A is designed to investigate the effect of resource shocks on strategic decision-makers' appetite for side observations of the platform values that are randomly sampled from the environment. A *side observation* is a sample of the true state of the environment that does not directly affect an agent's payoffs. In the present context, a side observation is an opportunity for the participant to observe a realization of the platform values *before* selecting which platforms to include in her pitch. The primary purpose of study 2A is to establish a benchmark for participants' interest in viewing side observations of the platform values when these observations *are not* generated by the actions of an intentional, social agent. This benchmark allows me to separate participants' *general* interest in cost-free information about the platform values from their *specific* interest in *social* information when I introduce social information for the first time in Study 2B.

Starting on Trial 2 of each Phase, participants have the option to view up to 5 Random Pitches. A new set of 5 Random Pitches is available on each Trial. On each Trial, each Random Pitch contains three randomly-sampled platforms. Point values for each platform are randomly drawn from a normal distribution around each platform's true average value with a standard deviation equal to 20 points. There is no cost to view each Random Pitch (aside from time and cognitive load). Participants can view each Random Pitch as many times as they wish, but they can only view one Random Pitch at a time).

Study 2A also allows me to test whether access to side observations moderates the effect of resource shocks on participants' explore-exploit strategies. In Study 1, we found that participants in the Scarcity Condition *increased* Exploration and *decreased* Exploitation following a *decrease* in platform values. We did not observe a change in explore-exploit strategies among Abundance participants following an *increase* in platform values. This pattern is consistent with the sort of asymmetric updating observed by Garrett and Daw (2020), who found that participants were faster to update their beliefs about the distribution of potential reward values following a better-than-expected outcome than a worse-than-expected outcome.[1]

Access to side observations increases Scarcity participants' exposure to the new, downward-shifted, distribution of platform values in Phases 2 and 3. This increased exposure may speed up the convergence of Scarcity participants' posterior beliefs toward the true distribution of platform values, allowing them to "catch up" to Abundance participants. If this occurs, Scarcity participants' Exploration and Exploitation rates should be closer to those of Abundance and Control participants in Phases 2 and 3.

5.1.1 Participants

159 people participated in Study 2A (Female = 85; Average Age: 41, SD = 12). All participants were recruited through Amazon Mechanical Turk (MTurk). Participants were paid a $6.00 base

[1] Note that this pattern can be obtained even if the updating process is unbiased, but the prior beliefs over the distribution of rewards are inflated (which is the situation that Scarcity participants find themselves in when the platform values shift downward on each subsequent Phase of the experiment). Consider a basic epsilon-greedy algorithm that exploits with probability p (samples the option with the highest average value) and explores with probability $1 - p$ (selects an option at random). Imagine there are five options, and the true value of each option is [60, 80, 100, 120, 140]. In each time period, the realized values of each option are drawn from a normal distribution with mean equal to the true value of each option, and standard deviation equal to 5 points. Suppose we initialize the algorithm with prior beliefs over the mean of the distribution of option values. Suppose further than this mean is inflated, such that the agent believes the mean of the distribution is 200. Before sampling any of the options, the agent's best guess for the true value of each option is the mean of the distribution. So, at time $t = 0$, the agent believes that the true values of the options are [200, 200, 200, 200, 200]. We would then observe excessive exploration for some number of time periods (depending on the value of p). The reason this happens is that each time the agent samples an option, the realized value of that option will be lower than the initialized value (prior belief) more than 95% of the time. As a result, the agent updates his belief over each sampled option downward, and his prior beliefs over the unsampled options end up being higher than the sampled options. So, when the agent decides to "exploit," instead of selecting whichever *sampled* option has the highest *empirical* average, he ends up selecting one of the *unsampled* options. This results in the agent continuing to select unsampled options until every option has been sampled at least once, which results in "over"-exploration.

fee upon completion of the focal procedure, and earned a variable performance-based bonus (Average Bonus: \$6.69, SD = \$0.68). Participants also earned an Active Participation Bonus of \$4.00 if they consistently submitted their responses before the time limits (described in *3.1.1 Recruitment and Compensation*).

Participants were randomly assigned to one of three experimental Conditions: Control (N = 51), Abundance (N = 59), Scarcity (N = 49). Control, Scarcity, and Abundance carry the same meaning as before, and refer to the trends in platform values described in *Section 3 Common Design Elements* (Control = constant; Abundance = increasing; Scarcity = decreasing).

5.1.2 Procedure

The focal experimental procedure is identical to that described in *3.1.3 Procedure,* with the addition of one critical element. In Study 2A, participants have the option to view 5 Random Pitches starting on Trial 2 of each Phase. Each Random Pitch contains 3 randomly selected platforms. A point value for each randomly selected platform is drawn from a normal distribution around that platform's average value and a standard deviation of 20 points. A new set of 5 Random Pitches is available on each Trial. Each Random Pitch is represented by a button on the pitch selection screen (see Figure 5.1).

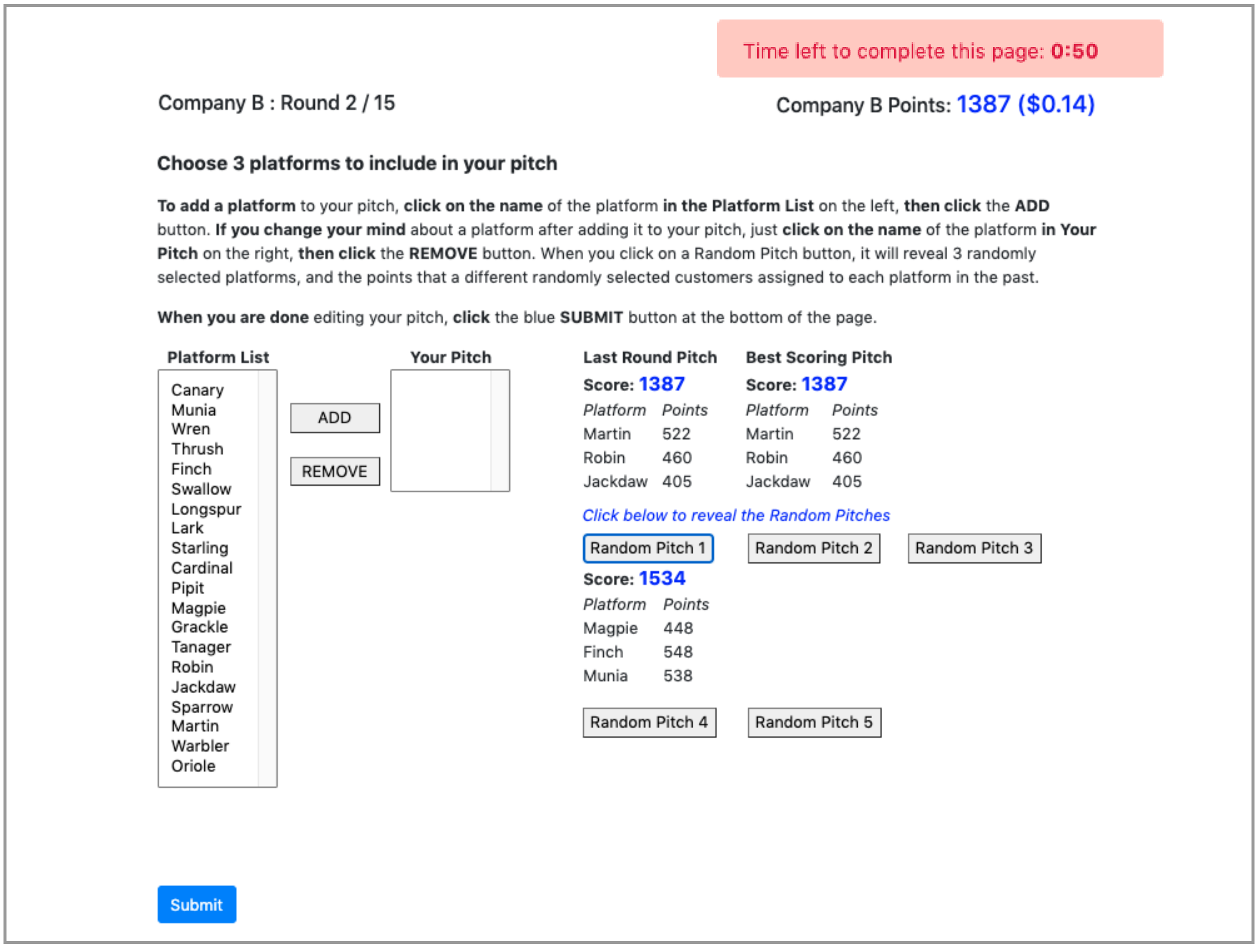


***Figure 5.1*. Screenshot of Pitch Selection Screen on Trials 2-15 of each Phase.** Taken from the perspective of a participant in the Control Condition on Trial 2 of Phase 1. Starting on the second Trial of each Phase, participants can choose to view the point values assigned to 5 randomly drawn pitches. A new set of Random Pitches is presented on each Trial. Each Random Pitch is represented by a button on the pitch selection screen. Participants click a Random Pitch button to view the randomly drawn point values assigned to the three randomly drawn platforms in that pitch. Only one Random Pitch can be viewed at a time. Participants can view each Random Pitch as many times as they wish.

In the instructions, the Random Pitches are described to the participants as follows:

In the real world, companies usually record the outcomes of sales pitches, and make those records available to their salesforce to help salespeople decide what to pitch to customers in the future. In The Sales Game, you'll have access to a similar record of past sales pitches. Starting with your second pitch for each company, you'll be able to look at 5 different Random Pitches. Each Random Pitch contains 3 randomly selected platforms. For each of the 3 platforms in a Random Pitch, we will show you the points that a different, randomly selected customer assigned to that platform in the past. Each round

> you'll have access to a new set of 5 Random Pitches. You can use this information to learn about the average value of each platform.

When participants click a Random Pitch button, the platforms in that Pitch are displayed along with their associated point values. Only one Random Pitch can be viewed at a time. Participants can view each Random Pitch as many times as they wish. There is no cost to view this information other than time and cognitive load. As before, participants have 60 seconds to submit their pitch. After 60 seconds, the procedure automatically advances to the results screen. If the participant fails to enter his pitch before time runs out, an empty pitch is recorded, and no points are earned for the current Trial.

After completing the focal procedure, participants in Study 2A complete the Debrief Questionnaire described in *3.1.3 Procedure.*

5.1.3 Results

I exclude participants who were marked as dropouts after repeatedly failing to submit their responses before the time limits. 2 participants met this exclusion criteria (Abundance Condition = 1; Scarcity Condition = 1). I also exclude Trials on which participants failed to submit their response before the time limit expired (timeouts).

5.1.3.1 Exploration

Figure 5.2 presents the average number of Never-Seen platforms participants selected on each Trial, in each Phase of Study 2A. There are no significant differences between Conditions in Phase 1. On the second Trial of Phase 2, Scarcity participants select a higher number of Never-

Seen platforms than participants in the Abundance and Control Conditions.[2] There are no significant differences between Conditions across the later Trials in Phase 2. In Phase 3, there are no significant differences between Conditions.

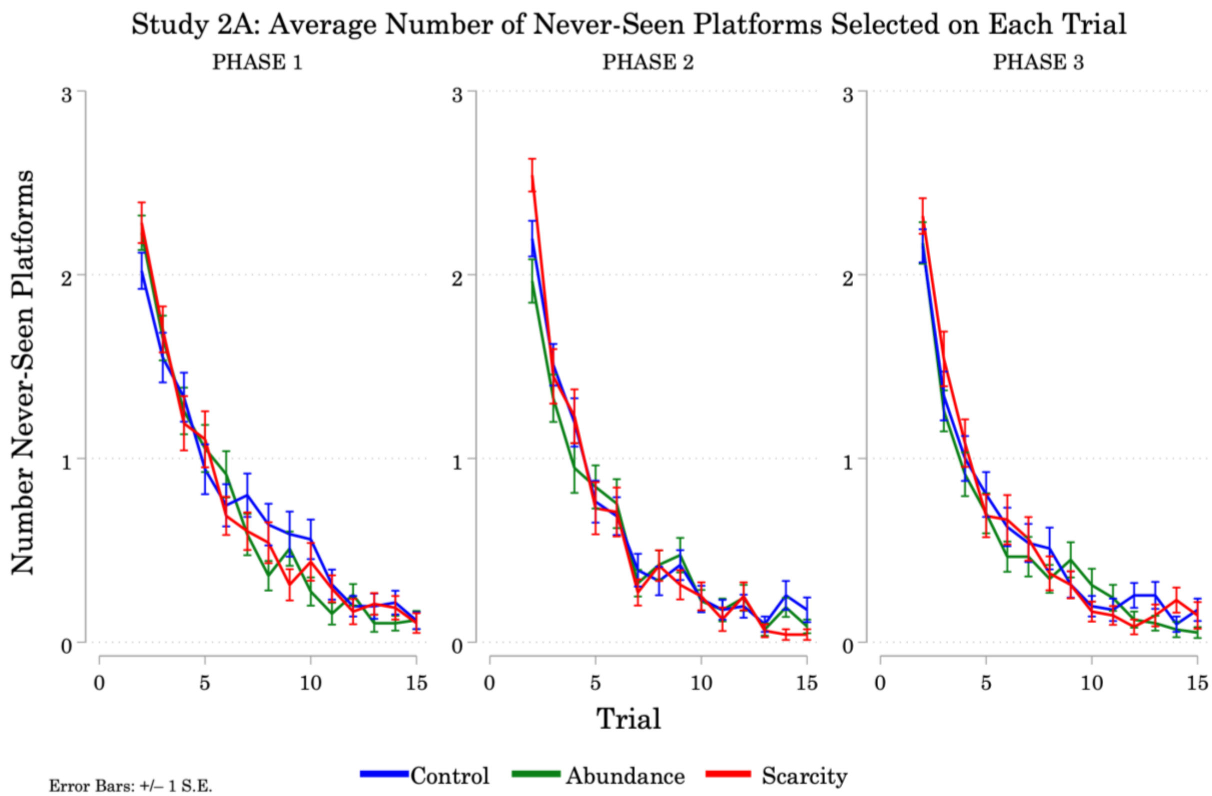


Figure 5.2. Study 2A: Exploration. Average number of Never-Seen platforms selected on each Trial, by Phase and Condition. Error bars = +/– 1 S.E. N = 157. Green = Abundance (N = 58); Blue = Control (N = 51); Red = Scarcity (N = 48). Note that the curves begin on Trial 2, the first opportunity to observe differences (the number of Never-Seen platforms on Trial 1 is always 3 for every participant). There are no significant differences between Conditions in Phase 1. On the second Trial of Phase 2, Scarcity participants select a higher number of Never-Seen platforms than participants in the Abundance and Control Conditions. By Trial 3 of Phase 2, there is no significant difference between Scarcity participants and those in the other two Conditions. In Phase 3, there are no significant differences between Conditions.

[2] Between-Condition differences on Trial 2 (two-sample t-tests): Scarcity Trial 2 – Abundance Trial 2 = 0.58, t = 3.77, p = 0.000; Scarcity Trial 2 – Control Trial 2 = 0.35, t = 2.61, p = 0.010.

Table 5.1 presents the parameter estimates and fit statistics from three different Two-Level Random Coefficient models for the total number of unique platforms participants explored across Trials 1–15 of each Phase in Study 2A. Model 1 is the baseline model, and includes an intercept and piecewise linear slopes for Phases 2 and 3 (in the form of two linear spline functions for the change between Phases 1 and 2, and between Phases 2 and 3). The random part of Model 1 includes a random intercept and a random linear slope for Phase at the Participant level (Level 2).[3]

Model 2 includes the main effect of Condition, and Model 3 introduces interactions among elements of the experimental design (Condition, Phase). Model 3 did not provide a significant improvement over Model 2 [$LR\ \chi^2(4) = 1.17$, $p = 0.884$], nor did Model 2 provide a significant improvement over Model 1 [$LR\ \chi^2(2) = 0.49$, $p = 0.784$]. It seems that there was no main effect of Condition, nor was there a significant interaction between Condition and Phase.

From the Model 1 estimates, we see that participants explored about 12.63 ($z = 37.75$, $p < 0.000$) platforms by the end of Phase 1. By the end of Phase 2, participants explored significantly fewer platforms than they did by the end of Phase 1 ($\beta_1 = -1.31$, $z = -6.28$, $p < 0.000$). By the end of Phase 3, participants explored a similar number of platforms to what they did by the end of Phase 2, but this decrease was not significant ($\beta_2 = -0.20$, $z = -0.95$, $p = 0.342$).

[3] Including a single linear slope in the random part of the model is more computationally efficient than estimating two separate slopes for each of the linear spline functions, and produces similar estimates.

Table 5.1. Study 2A: Exploration. Maximum likelihood estimates of Two-Level Random-Coefficient models for the total number of unique platforms explored across Trials 1–15 of each Phase. Model 1: Intercept-Slope; Model 2: Main Effects; Model 3: Design Interactions. N = 157.

	Model 1		Model 2		Model 3	
	Est	(SE)	Est	(SE)	Est	(SE)
Fixed Effects						
Intercept β_0	12.63***	0.33	12.88***	0.57	12.84***	0.59
Phase 2 β_1	–1.31***	0.21	–1.31***	0.21	–1.22***	0.36
Phase 3 β_2	–0.20	0.21	–0.20	0.21	–0.24	0.36
Abundance β_3			–0.53	0.77	–0.38	0.80
Scarcity β_4			–0.20	0.80	–0.24	0.84
Abundance × Phase 2 β_5					–0.25	0.50
Scarcity × Phase 2 β_6					0.01	0.52
Abundance × Phase 3 β_7					–0.11	0.50
Scarcity × Phase 3 β_8					0.26	0.52
Random Effects						
L2 Random Intercept Var $\psi_{11}^{(2)}$	14.67	1.95	14.65	1.95	14.65	1.95
L2 Random Slope Var $\psi_{22}^{(2)}$	0.97	0.32	0.97	0.32	0.95	0.32
L1 (Residual) Error Var θ	2.90	0.33	2.90	0.33	2.90	0.33
Log likelihood	–1180		–1179		–1179	
AIC | *BIC*	2373 | 2402		2377 | 2414		2383 | 2437	

* $p \leq 0.05$; ** $p \leq 0.01$; *** $p \leq 0.001$

5.1.3.2 Exploitation

Figure 5.3 presents the average number of Personal-Best Platforms selected by participants on Trials 2–15 of Study 2A (the number of platforms in the current pitch that have one of the three highest empirical averages based on what the participant has seen so far in the current Phase).

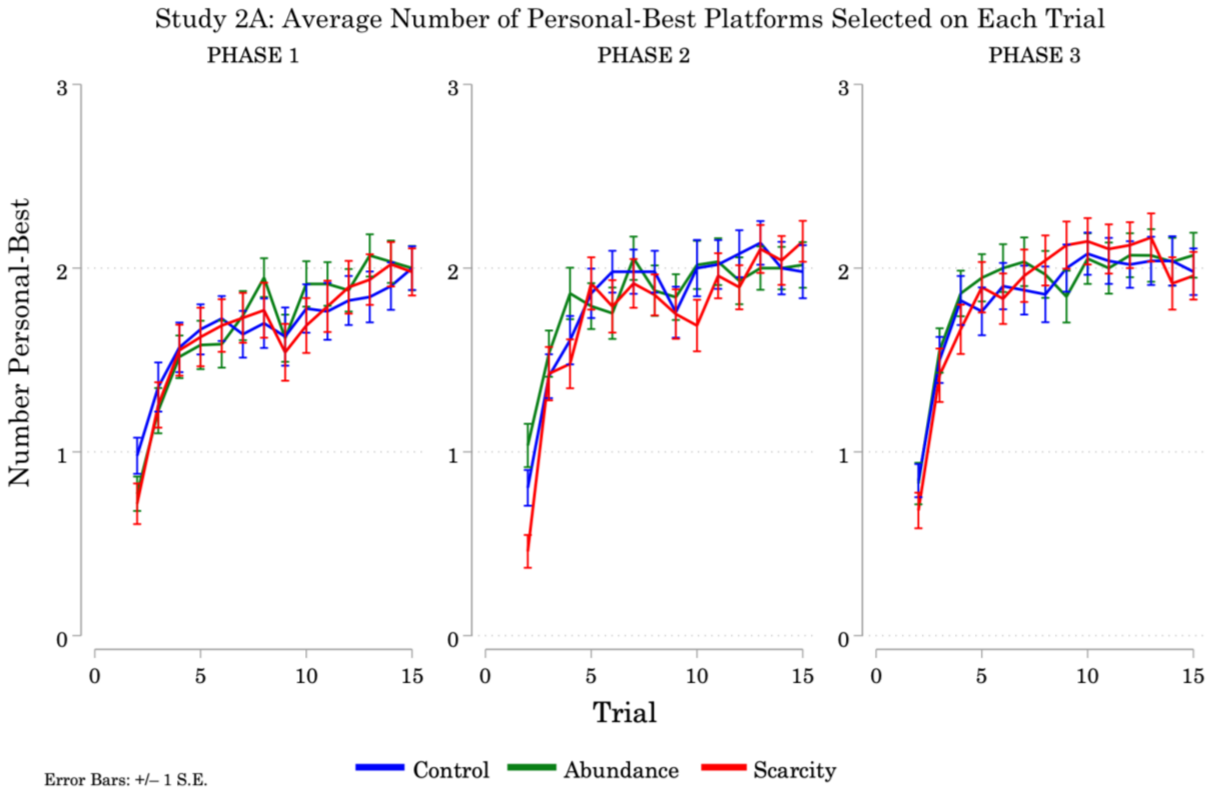


Figure 5.3. Study 2A: Exploitation. Average number of Personal-Best platforms selected on each Trial, by Phase and Condition. Error bars = +/– 1 S.E. N = 157. Green = Abundance (N = 58); Blue = Control (N = 51); Red = Scarcity (N = 48). Note that the curves begin on Trial 2. On Trial 1, all of the platforms selected have no empirical history. There are no differences between Conditions in any Phase of the experiment. Participants in all three Conditions exploit their Personal-Best platforms significantly more often in Phase 2 than they do in Phase 1.

Participants in all three Conditions exploited a similar number of Personal-Best platforms across Trials in Phase 1. On Trial 2 of Phase 2, Scarcity participants exploited significantly fewer Personal-Best platforms than Control and Abundance participants, but participants in all three Conditions exploited a similar number of Personal-Best platforms across the later Trials.[4] In Phase 3, participants in all three Conditions exploited their Personal-Best platforms with similar frequency across Trials.

[4] Between-Condition differences on Trial 2 (two-sample t-tests): Scarcity Trial 2 – Abundance Trial 2 = –0.58, $t = -3.77$, $p = 0.000$; Scarcity Trial 2 – Control Trial 2 = –0.35, $t = -2.61$, $p = 0.010$.

As before, we will look at the cumulative number of times participants exploited any of their top-three Personal-Best platforms across Trials 2–15 of each Phase. Table 5.2 presents the parameter estimates and fit statistics from three different Two-Level Random Coefficient models for the cumulative number of times participants selected their Personal-Best platforms across Trials 2–15 in a given Phase.

Table 5.2. Study 2A: Exploitation. Maximum likelihood estimates of Two-Level Random-Coefficient models for the number of times participants selected any of their Personal-Best platforms across Trials 2–15 of each Phase. Model 1: Intercept-Slope; Model 2: Main Effects; Model 3: Design Interactions. N = 157.

	Model 1		Model 2		Model 3	
	Est	(SE)	Est	(SE)	Est	(SE)
Fixed Effects						
Intercept β_0	23.32***	0.74	23.33***	1.25	23.49***	1.31
Phase 2 β_1	1.88***	0.54	1.88***	0.54	2.59**	0.96
Phase 3 β_2	0.76	0.54	0.76	0.54	–0.02	0.96
Abundance β_3			0.30	1.69	0.53	1.79
Scarcity β_4			–0.38	1.77	–0.09	1.88
Abundance × Phase 2 β_5					–0.76	1.31
Scarcity × Phase 2 β_6					–1.23	1.37
Abundance × Phase 3 β_7					0.85	1.31
Scarcity × Phase 3 β_8					1.71	1.37
Random Effects						
L2 Random Intercept Var $\psi_{11}^{(2)}$	63.82	9.56	63.72	9.55	64.64	9.64
L2 Random Slope Var $\psi_{22}^{(2)}$	1.47	1.92	1.47	1.92	1.76	1.94
L1 (Residual) Error Var θ	22.54	2.54	22.54	2.54	22.46	2.54
Log likelihood	–1595		–1597		–1596	
AIC | *BIC*	3209 | 3238		3212 | 3250		3219 | 3273	

* $p \leq 0.05$; ** $p \leq 0.01$; *** $p \leq 0.001$; SE = standard error of the mean

Model 1 is the baseline model. The fixed part of Model 1 includes an intercept and piecewise linear slopes for Phases 2 and 3. The random part of Model 1 includes a random intercept and a random linear slope for Phase at the Participant level (Level 2). Model 2 includes

Condition as a fixed effect. Model 3 introduces two-way interactions between elements of the experimental design (Condition, Phase). Model 3 did not provide a significant improvement over Model 2 [$LR\ \chi^2(4) = 1.42$, $p = 0.841$], nor did Model 2 provide a significant improvement over Model 1 [$LR\ \chi^2(2) = 0.16$, $p = 0.924$]. Again we find no main effect of Condition, nor do we find a significant interaction between Condition and Phase, so we'll focus on the Model 1 estimates.

In Phase 1, participants exploited their personal-best platforms 23.32 ($z = 31.45$, $p < 0.000$) times on average. In Phase 2, participants exploited their personal-best platforms about 25.20 times, a significant increase of over the number of times they exploited their personal-best platforms in Phase 1 ($\beta_1 = 1.88$, $z = 3.45$, $p = 0.001$). In Phase 3, participants exploited their personal-best platforms about the same number of times as they did in Phase 2 ($\beta_2 = 0.76$, $z = 1.40$, $p = 0.160$).

5.1.3.3 Mental Models

Recall that participants in Study 2A were asked to estimate the average value of each platform after the 8th and 15th Trials of each Phase. Here we will focus on the estimates participants made following Trial 15. Figure 5.4 plots the average estimated value of each platform against that platform's true value. The red, dotted 45-degree lines indicate what the shape of each curve would look like if there was perfect agreement between the average estimated values reported by participants and the true values of each platform. One way to think about the accuracy of participants' estimates is to consider the proximity of the estimates curve to the 45-degree line.

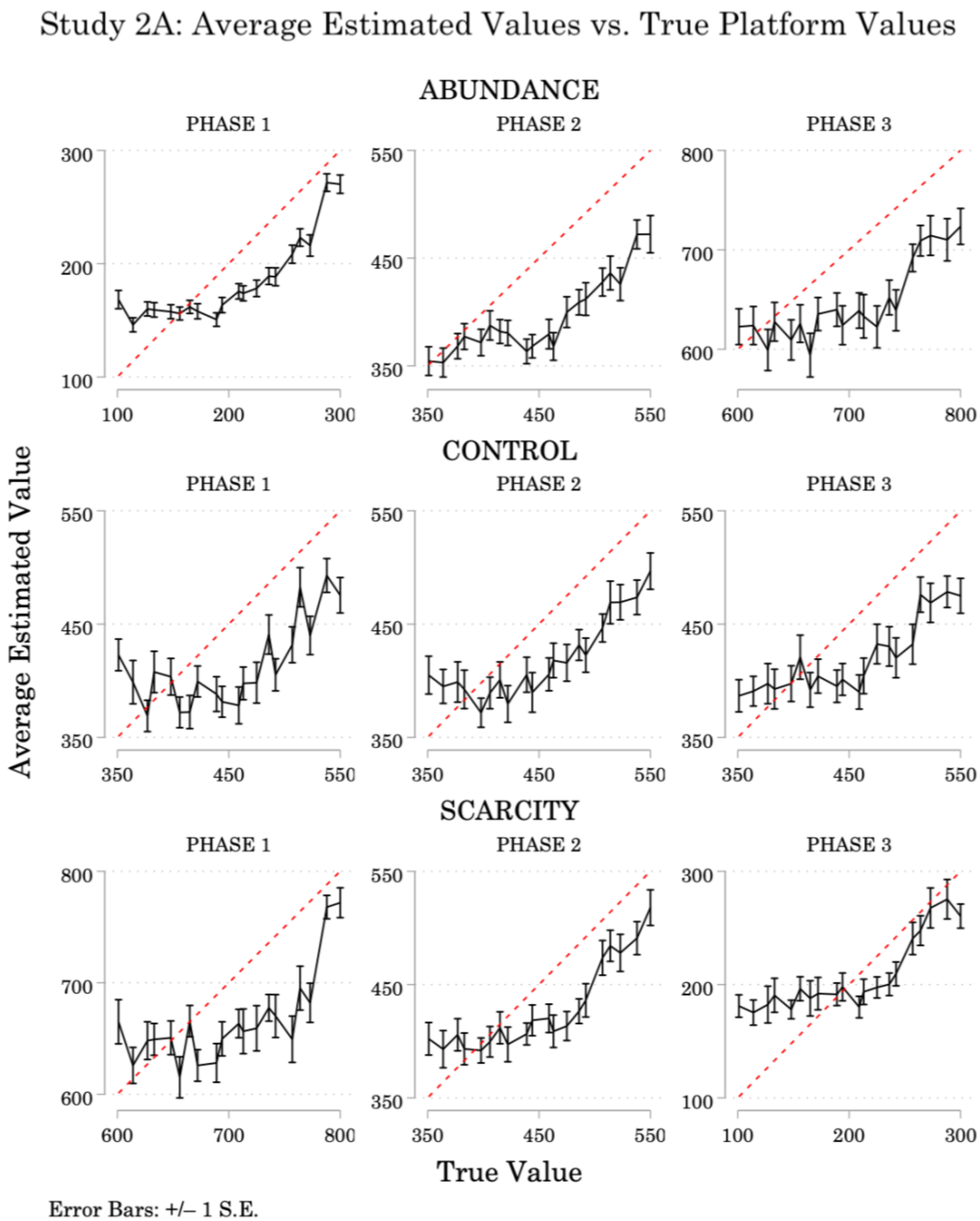


Figure 5.4. Study 2A: Mental Models. Average estimated values submitted by participants following Trial 15 of each Phase versus the true average values of each platform, by Phase and Condition. Error bars = +/– 1 S.E. N = 154.[5] Top Row = Abundance (N = 58); Middle Row = Control (N = 49); Bottom Row = Scarcity (N = 47). Average participant estimates on y-axes. True platform values on the x-axes. Red dotted 45-degree lines mark "perfect agreement" between participants' average estimates of each platform's value and each platform's true value. Abundance participants' error increases across Phases 1–3. Scarcity and Control participants' error is similar across Phases 1–3.

[5] 3 participants (Control Condition = 2, Scarcity Condition = 1) were dropped because they failed to submit their estimates before time expired on Trial 15 of all three Phases.

There are only small, non-significant differences between Conditions in any Phase. Abundance participants' average error is slightly higher than Controls in Phases 2 and 3, and Scarcity participants' average error is slightly lower than Controls in Phase 2 and 3. Abundance participants' estimates become *less accurate* across Phases 1–3. Control and Scarcity participants perform similarly across Phases 1–3.

Table 5.3 presents the parameter estimates and fit statistics from three different Two-Level Random Coefficient models for the Mean Absolute Difference between participants' estimates of each platform's average value and the true average value of that platform. Model 1 is the baseline model, and includes an intercept and piecewise linear slopes for Phases 2 and 3. The random part of Model 1 includes a random intercept and random linear slope for Phase at the Participant level (Level 2). Model 2 includes the main effect of Condition. Model 3 introduces interactions among elements of the experimental design (Condition, Phase). Model 3 provides a significantly better fit than Model 2 $LR\ \chi^2(4) = 34.74$, $p < 0.000$] and Model 1 [$LR\ \chi^2(6) = 36.23$, $p < 0.000$], so I will focus on the predictions from Model 3.

In Phase 1, Control participants' average error was 80.47 ($z = 9.91$, $p < 0.000$). Abundance participants' error was significantly lower than Controls ($\beta_3 = -31.26$, $z = -2.83$, $p = 0.005$). Scarcity participants' error was slightly lower than Controls, but this difference was not significant ($\beta_4 = -1.76$, $z = -0.15$, $p = 0.879$).

Table 5.3. Study 2A: Mental Models. Maximum likelihood estimates of Two-Level Random-Coefficient models for Mean Absolute Difference between participants' estimates following Trial 15 of each Phase and the true average value of each platform. Model 1: Intercept-Slope; Model 2: Main Effects; Model 3: Design Interactions. N =154.

	Model 1		Model 2		Model 3	
	Est	(SE)	Est	(SE)	Est	(SE)
Fixed Effects						
Intercept β_0	68.24***	4.70	74.43***	7.82	80.47***	8.12
Phase 2 β_1	6.12	3.74	6.13	3.74	–8.29	6.22
Phase 3 β_2	3.17	3.80	3.15	3.80	3.05	6.28
Abundance β_3			–13.15	10.39	–31.26**	11.05
Scarcity β_4			–4.11	10.92	–1.76	11.61
Abundance × Phase 2 β_5					40.67***	8.47
Scarcity × Phase 2 β_6					–2.73	8.87
Abundance × Phase 3 β_7					10.46	8.59
Scarcity × Phase 3 β_8					–12.58	9.01
Random Effects						
L2 Random Intercept Var $\psi_{11}^{(2)}$	2851.08	381.02	2746.18	375.52	2718.52	362.36
L2 Random Slope Var $\psi_{22}^{(2)}$	1022.57	156.75	1023.68	156.78	837.64	133.40
Level-1 Error Var θ	545.98	64.95	545.68	64.88	512.98	61.09
Log likelihood	–2384		–2383		–2366	
AIC | *BIC*	4782 | 4811		4784 | 4821		4758 | 4811	

* $p \leq 0.05$; ** $p \leq 0.01$; *** $p \leq 0.001$

In Phase 2, Control participants' average error was 72.18, which is lower than in Phase 1, but this decrease was not significant (β_1 = –8.29, z = –1.33, p = 0.183). Abundance participants' error was higher than that among Controls, but this difference was not significant (Abundance Phase 2 – Control Phase 2 = 9.41, z = 0.82, p = 0.411). Abundance participants' error in Phase 2 was significantly higher than in Phase 1 (Abundance Phase 2 – Abundance Phase 1 = 32.38, z = 5.63, p < 0.000). Scarcity participants' error was slightly lower than Controls, but the difference was not significant (Scarcity Phase 2 – Control Phase 2 = –4.49, z = –0.37, p = 0.709). Scarcity participants' error in Phase 2 was lower than in Phase 1, but this decrease was not significant (Scarcity Phase 2 – Scarcity Phase 1 = –11.02, z = –1.74, p = 0.081).

In Phase 3, Control participants' average error was 75.23, which is slightly higher than in Phase 2, but this increase was not significant (β_2 = 3.05, z = 0.49, p = 0.627). Abundance participants' error in Phase 3 was higher than Controls, but this difference was not significant (Abundance Phase 3 – Control Phase 3 = 19.87, z = 1.39, p = 0.164). Abundance participants' error in Phase 3 was significantly higher than in Phase 2 (Abundance Phase 3 – Abundance Phase 2 = 13.52, z = 2.31, p = 0.021). Scarcity participants' error in Phase 3 was lower than that among Controls, but this difference was not significant (Scarcity Phase 3 – Control Phase 3 = –17.07, z = –1.14, p = 0.256). Scarcity participants' error in Phase 3 was lower than in Phase 2, but this decrease was not significant (Scarcity Phase 3 – Scarcity Phase 2 = –9.52, z = –1.47, p = 0.141).

Figure 5.5 presents the adjusted marginal predictions for the Mean Absolute Difference between participants' estimates and the true average value of each platform. Notice that Abundance participants' average error is significantly lower than Scarcity participants' in Phase 1 (Abundance Phase 1 – Scarcity Phase 1 = –29.50, z = –2.64, p = 0.008). Recall the cautionary discussion we had in Study 1 regarding the potential effects of range magnitude (e.g. High range of platform values versus Low range of platform values) on participants' ability to learn the true average platform values. If we compare Abundance and Scarcity participants' average error when they are faced with the *same* distribution, we find no significant differences.

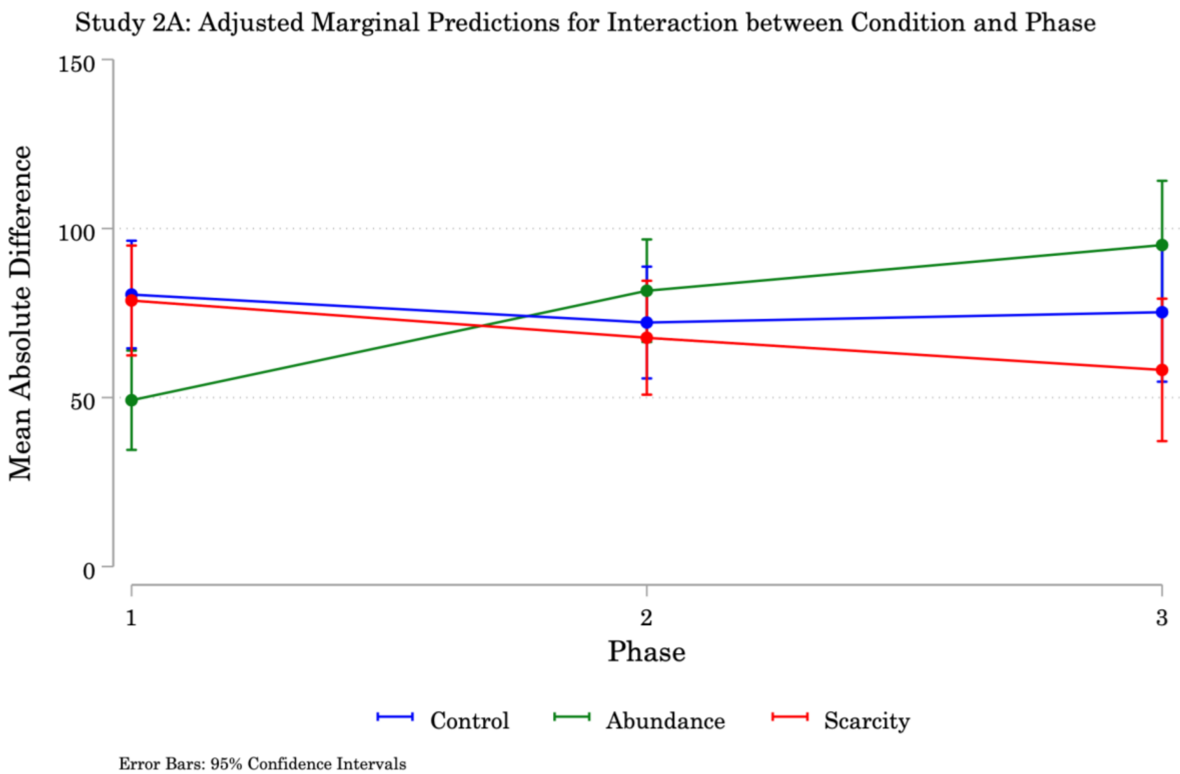


Figure 5.5. Study 2A: Mental Models Interaction. Adjusted marginal predictions for the interaction between Condition and Phase. Error bars = 95% Confidence Interval. N = 154. Green = Abundance (N = 58); Blue = Control (N = 49); Red = Scarcity (N = 47). In Phase 1, Abundance participants' average error is significantly lower than Scarcity participants' average error.

Scarcity participants' error when they face the Low distribution in Phase 3 is slightly higher than Abundance participants' error when they face the Low distribution in Phase 1, but this difference is not significant (Scarcity Phase 3 – Abundance Phase 1 = 9.70, $z = 0.91$, $p = 0.364$). Scarcity participants' error when they face the High distribution in Phase 1 is slightly lower than Abundance participants' error when they face the High distribution in Phase 3, but this difference is not significant either (Scarcity Phase 1 – Abundance Phase 3 = –16.12, $z = –1.33$, $p = 0.182$).

The only comparison that is not subject to the apparent effect of range magnitude (e.g. High range versus Low range) occurs in Phase 2, when participants in all three Conditions face the Medium range. Both Scarcity and Abundance participants are exposed to the Medium range for the first time in Phase 2, so neither has an advantage in terms of the accuracy of their prior beliefs over the range of platform values they will encounter in Phase 2. The difference between Scarcity and Abundance participants' average error in Phase 2 is not significant (Scarcity Phase 2 – Abundance Phase 2 = –13.90, z = –1.20, p = 0.230).

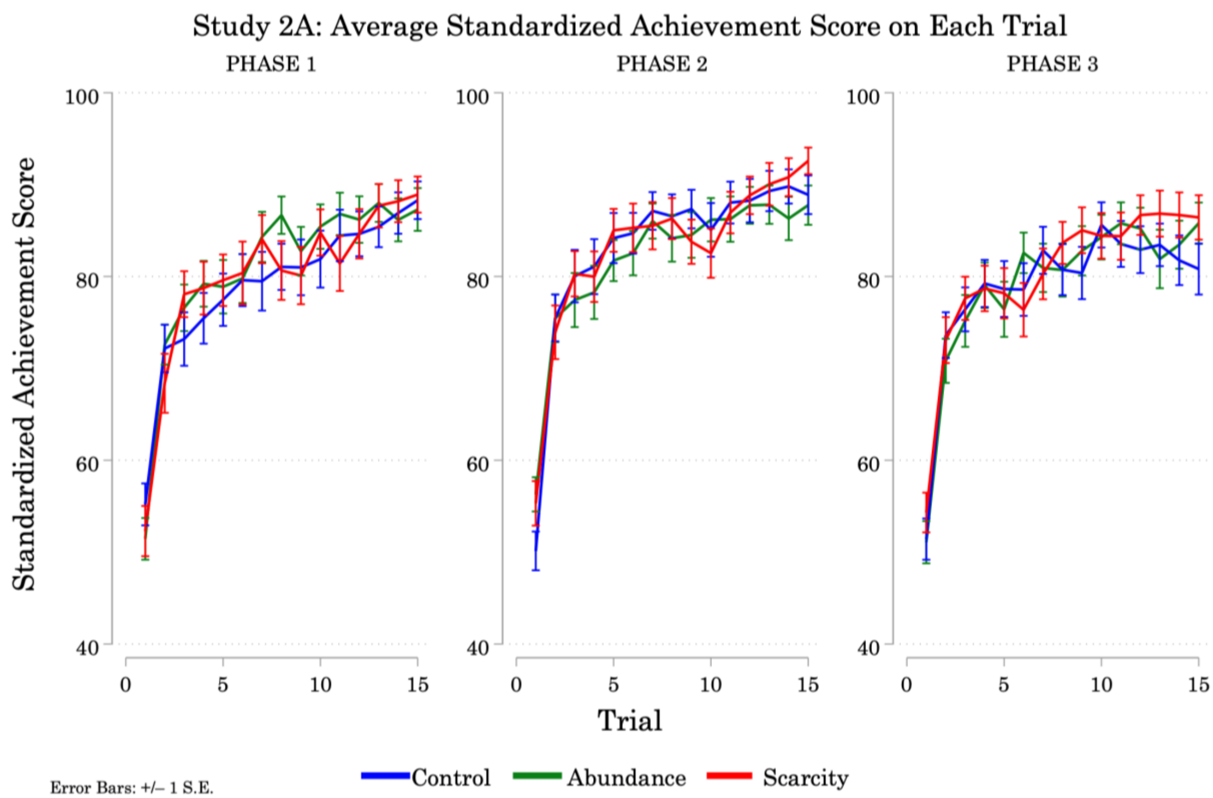


Figure 5.6. Study 2A: Rewards. Average Standardized Achievement Scores on each Trial, by Phase and Condition. Error bars: +/– 1 S.E. N = 157. Green = Abundance (N = 58); Blue = Control (N = 51); Red = Scarcity (N = 48). There are no significant differences between Conditions in any Phase of the experiment. Participants' scores increase dramatically between Trials 1 and 2 of each Phase (participants are able to sample Random Pitches starting on Trial 2). Participants achieve similar scores by the end of Phase 2 as they did by the end of Phase 1. Participants' scores at the end of Phase 3, are significantly lower than those they achieved at the end of Phase 2.

5.1.3.4 Rewards

Figure 5.6 presents participants' Standardized Achievement Scores on each Trial in each Phase of Study 2A. There are no significant differences between Conditions in any Phase of the experiment. Participants' scores increase dramatically between Trials 1 and 2 of each Phase (participants are able to sample Random Pitches starting on Trial 2). Participants achieve slightly (but not significantly) higher scores toward the end of Phase 2 than they did by the end of Phase 1. Participants' scores at the end of Phase 3 are significantly lower than those they achieved at the end of Phase 2.

Table 5.4 presents the parameter estimates and fit statistics from three different Two-Level Random Coefficient models for participants' Cumulative Standardized Achievement Scores at the end of each Phase in Study 2A. Model 1 is the baseline model, and includes two pairwise linear spline functions representing Phase 2 and Phase 3. The random part of Model 1 includes a random intercept and a random linear slope for Phase at the Participant level (Level 2). Model 2 includes Condition as a fixed effect. Model 3 includes interactions among elements of the experimental design (Condition, Phase). Model 3 does not provide a significantly better fit than Model 2 [$LR\ \chi^2(4) = 6.00$, $p = 0.199$] and Model 2 does not provide a significantly better fit than Model 1 [$LR\ \chi^2(2) = 0.15$, $p = 0.928$]. There's no evidence for a main effect of Condition, nor for any interactions between Condition and Phase, so I will focus on the Model 1 estimates.

Table 5.4. Study 2A: Rewards. Maximum likelihood estimates of Two-Level Random-Coefficient models for participants' Cumulative Standardized Achievement Scores at the end of each Phase. Model 1: Intercept-Slope; Model 2: Main Effects; Model 3: Design Interactions. N = 157.

	Model 1		Model 2		Model 3	
	Est	(SE)	Est	(SE)	Est	(SE)
Fixed Effects						
Intercept β_0	1189***	16	1182***	27	1173***	28
Phase 2 β_1	46***	10	46***	10	72***	18
Phase 3 β_2	–51***	10	–51***	10	–71***	18
Abundance β_3			7	36	30	38
Scarcity β_4			15	38	18	40
Abundance × Phase 2 β_5					–55*	24
Scarcity × Phase 2 β_6					–17	26
Abundance × Phase 3 β_7					33	24
Scarcity × Phase 3 β_8					26	26
Random Effects						
L2 Random Intercept Var $\psi_{11}^{(2)}$	32831	4462	32816	4463	32971	4454
L2 Random Slope Var $\psi_{22}^{(2)}$	1610	735	1610	735	1676	724
Level-1 Error Var θ	7456	1272	7456	842	7236	817
Log likelihood	–3006		–3005		–3002	
AIC | *BIC*	6025 | 6054		6029 | 6066		6031 | 6085	

* $p \leq 0.05$; ** $p \leq 0.01$; *** $p \leq 0.001$

In Phase 1, participants accumulated standardized scores of 1189.16 ($z = 74.24$, $p <$ 0.000) on average. In Phase 2, participants accumulated significantly higher scores than they did in Phase 1 ($\beta_1 = 46.41$, $z = 4.52$, $p < 0.000$). In Phase 3, participants accumulated significantly lower scores than they did by the end of Phase 2 ($\beta_2 = –50.51$, $z = –4.92$, $p < 0.000$).

5.1.3.5 Discovery

Figure 5.7 presents the average number of True Top Three platforms selected by participants on each Trial in each Phase of Study 2A (the number of platforms in the current pitch that have one of the three highest true average values). There are no significant differences between Conditions in any Phase of the experiment. Participants' discovery rates do not improve across Phases.

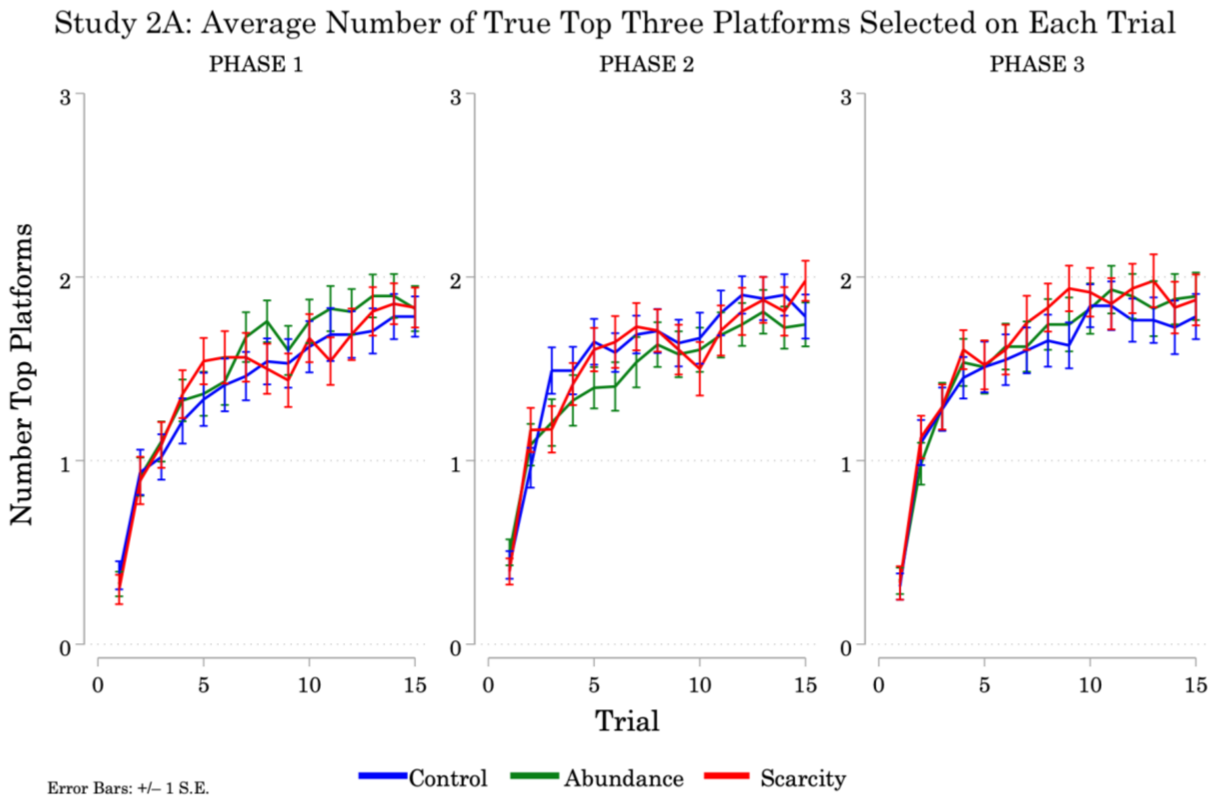


Figure 5.7. Study 2A: Discovery. Average number of True Top Three highest-valued platforms selected on each Trial, by Phase and Condition. Error bars = +/– 1 S.E. N = 157. Green = Abundance (N = 58); Blue = Control (N = 51); Red = Scarcity (N = 48). There are no significant differences between Conditions in any Phase of the experiment. Participants' discovery rates do not improve across Phases.

As before, we will look at the cumulative number of times participants selected one of the True Top Three platforms across Trials 1–15 of each Phase. Table 5.5 presents the parameter estimates and fit statistics from three different Two-Level Random Coefficient models of the cumulative number of times participants selected True Top Three platforms across Trials 1–15 in a given Phase.

Model 1 is the baseline model. The fixed part of Model 1 includes an intercept and piecewise linear slopes for Phases 2 and 3. The random part of Model 1 includes a random intercept and a random linear slope for Phase at the Participant level (Level 2). Model 2 includes Condition as a fixed effect. Model 3 introduces two-way interactions between elements of the experimental design (Condition, Phase). Model 3 does not provide a significantly better fit than Model 2 [$LR\ \chi^2(4) = 4.15$, $p = 0.386$] and Model 2 does not provide a significantly better fit than Model 1 [$LR\ \chi^2(2) = 0.03$, $p = 0.985$]. There's no evidence for a main effect of Condition, nor for any interactions between Condition and Phase, so I will focus on the Model 1 estimates.

Table 5.5. Study 2A: Discovery. Maximum likelihood estimates of Two-Level Random-Coefficient models for the number of times participants selected True Top Three platforms across Trials 1–15 of each Phase. Model 1: Intercept-Slope; Model 2: Main Effects; Model 3: Design Interactions. N = 157.

	Model 1		Model 2		Model 3	
	Est	(SE)	Est	(SE)	Est	(SE)
Fixed Effects						
Intercept β_0	22.05***	0.75	21.88***	1.24	21.49***	1.31
Phase 2 β_1	0.87	0.67	0.87	0.67	2.12	1.17
Phase 3 β_2	0.75	0.67	0.75	0.67	–0.69	1.17
Abundance β_3			0.26	1.66	1.22	1.79
Scarcity β_4			0.25	1.74	0.36	1.88
Abundance × Phase 2 β_5					–2.70	1.61
Scarcity × Phase 2 β_6					–0.81	1.68
Abundance × Phase 3 β_7					2.27	1.61
Scarcity × Phase 3 β_8					1.96	1.68
Random Effects						
L2 Random Intercept Var $\psi_{11}^{(2)}$	52.15	8.92	52.15	8.92	52.34	8.91
L2 Random Slope Var $\psi_{22}^{(2)}$	0.78	0.64	0.78	0.65	0.77	0.64
L1 (Residual) Error Var θ	35.15	2.81	35.15	2.81	34.69	2.77
Log likelihood	–1655		–1655		–1653	
AIC | *BIC*	3325 | 3354		3329 | 3366		3333 | 3387	

* $p \leq 0.05$; ** $p \leq 0.01$; *** $p \leq 0.001$; SE = standard error of the mean

In Phase 1, participants selected True Top Three platforms 22.05 times on average (z = 29.57, $p < 0.000$) on average. In Phase 2, participants selected True Top Three platforms with similar frequency as they did in Phase 1 ($\beta_1 = 0.87$, $z = 1.30$, $p = 0.195$). In Phase 3, participants selected True Top Three platforms with similar frequency as they did in Phase 2 ($\beta_2 = 0.75$, $z = 1.12$, $p = 0.264$).

5.1.3.6 Sampling Side Observations: Random Pitches

Recall that participants in Study 2A had the option to view 5 Random Pitches on Trials 2-15 of each Phase. On each Trial, the three platforms in each Random Pitch were randomly drawn from the list of 20 platforms (without replacement), and the point value of each platform was randomly drawn from a normal distribution with mean equal to that platform's average value, and standard deviation equal to 20 points).

Figure 5.8 presents the average number of Random Pitches participants viewed on each Trial. Participants in all three Conditions chose to view Random Pitches at similar rates across Phases 1–3. In Phase 1, the number of Random Pitches viewed by participants was relatively constant across Phases. In Phases 2 and 3, participants viewed a higher number of Random Pitches over early Trials, and then reduced the number of Random Pitches they viewed across later Trials.

To investigate whether there are differences in participants' overall appetite for side observations of randomly sampled pitches across Conditions, we'll look at the cumulative number of times participants looked at any Random Pitch across Trials 2–15 of a given Phase.

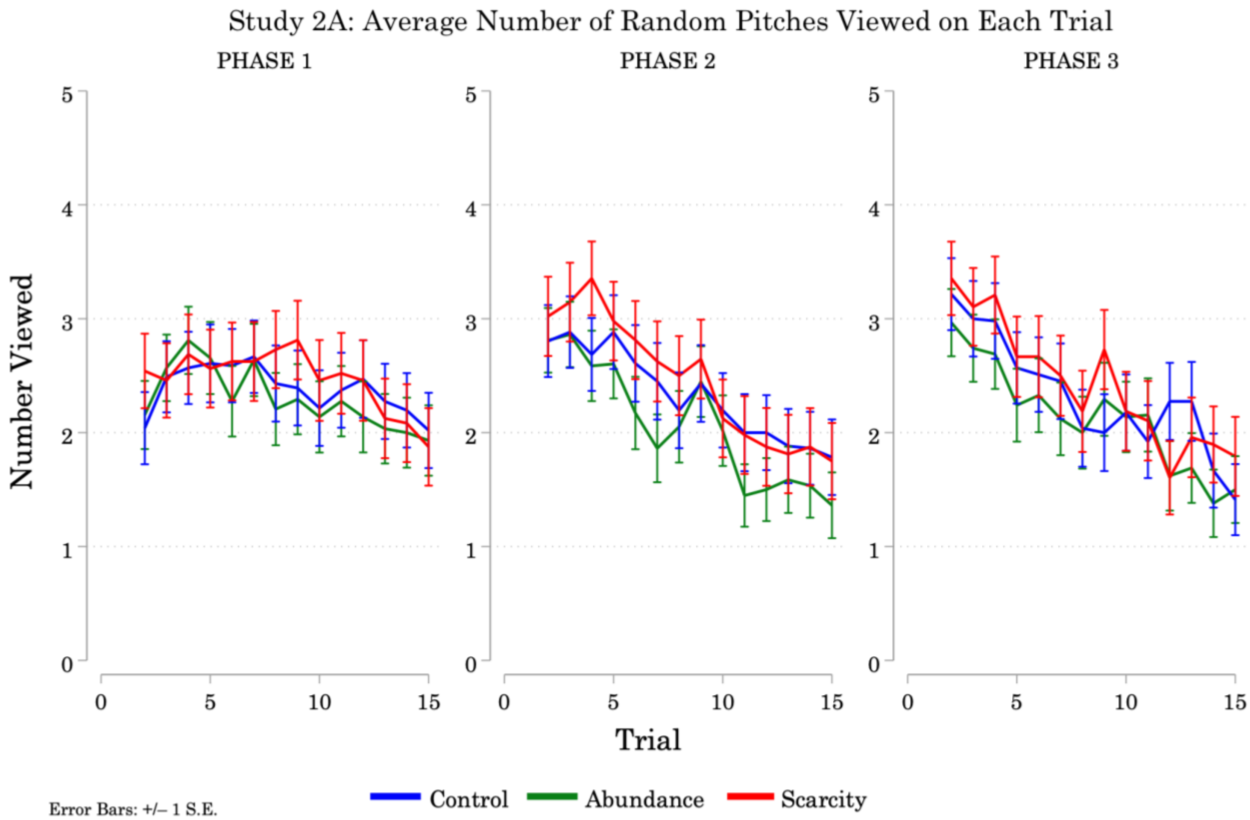


Figure 5.8. Study 2A: Sampling Side Observations. Average number of Random Pitches viewed on each Trial, by Phase and Condition. Error bars = +/– 1 S.E. N = 157. Green = Abundance (N = 58); Blue = Control (N = 51); Red = Scarcity (N = 48). There are no significant differences between Conditions in any Phase of the experiment. Participants chose to view Random Pitches with similar frequency across Phases 1–3.

Table 5.6 presents the parameter estimates and fit statistics from three different Two-Level Random Coefficient models for the cumulative number of times participants viewed Random Pitches in a given Phase. Model 1 is the baseline model. The fixed part of Model 1 includes an intercept and piecewise linear slopes for Phases 2 and 3. The random part of Model 1 includes a random intercept and random linear slope for Phase at the Participant level (Level 2). Model 2 includes Condition as a fixed effect. Model 3 introduces interactions among elements of the experimental design (Condition, Phase).

Table 5.6. Study 2A: Sampling Side Observations. Maximum likelihood estimates of Two-Level Random-Coefficient models for the cumulative number of times participants viewed Random Pitches across Trials 2–15 of each Phase. Model 1: Intercept-Slope; Model 2: Main Effects; Model 3: Design Interactions. N = 157.

	Model 1		Model 2		Model 3	
	Est	(SE)	Est	(SE)	Est	(SE)
Fixed Effects						
Intercept β_0	33.26***	2.04	33.72***	3.43	33.33***	3.57
Phase 2 β_1	–1.45	1.09	–1.45	1.09	–0.67	1.91
Phase 3 β_2	0.15	1.09	0.15	1.09	0.18	1.91
Abundance β_3			–2.49	4.61	–1.21	4.90
Scarcity β_4			1.50	4.83	1.23	5.13
Abundance × Phase 2 β_5					–2.61	2.61
Scarcity × Phase 2 β_6					0.60	2.74
Abundance × Phase 3 β_7					1.19	2.61
Scarcity × Phase 3 β_8					–0.37	2.74
Random Effects						
L2 Random Intercept Var $\psi_{11}^{(2)}$	580.73	72.72	579.06	72.55	579.56	72.52
L2 Random Slope Var $\psi_{33}^{(2)}$	40.86	9.65	40.86	9.65	41.83	9.61
L1 (Residual) Error Var θ	72.89	8.23	72.89	8.23	72.16	8.14
Log likelihood	–1986		–1986		–1985	
AIC | *BIC*	3986 | 4016		3990 | 4027		3996 | 4050	

* $p \leq 0.05$; ** $p \leq 0.01$; *** $p \leq 0.001$; SE = standard error of the mean

Model 3 does not provide a significantly better fit than Model 2 [$LR\ \chi^2(4) = 1.87$, $p = 0.760$] and Model 2 does not provide a significantly better fit than Model 1 [$LR\ \chi^2(2) = 0.75$, $p = 0.687$]. There's no evidence for a main effect of Condition, nor for any interactions between Condition and Phase, so I will focus on the Model 1 estimates. In Phase 1, participants viewed Random Pitches 33.26 times on average ($z = 16.30$, $p < 0.000$) on average. In Phase 2, participants viewed Random Pitches with similar frequency as they did in Phase 1 ($\beta_1 = –1.45$, $z = –1.33$, $p = 0.185$). In Phase 3, participants viewed Random Pitches with similar frequency as they did in Phase 2 ($\beta_2 = 0.15$, $z = 0.14$, $p = 0.888$).

We also want to understand whether participants' choices to view each Random Pitch exhibit a bias toward any particular position on the screen. The Random Pitches were presented as a series of 5 buttons, numbered from one to five (Figure 5.9).

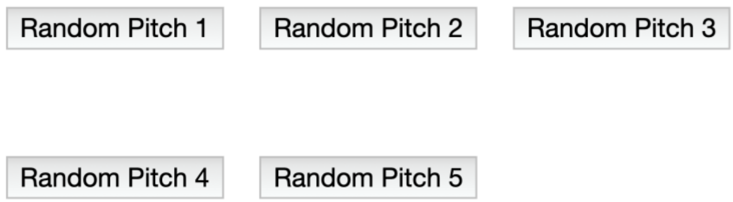


Figure 5.9. Position of Random Pitches in the On-Screen Button Tray. In the top row, buttons are numbered from one to three, starting with the leftmost button. In the second row, the leftmost button is numbered 4, and the center button is numbered 5.

The Random Pitches all have equal value in expectation, so if participants choose to view the Random Pitch in a particular position more frequently, this preference is unlikely to arise from any perceived differences in the average value of the platforms revealed by clicking on that Random Pitch across Trials.

Figure 5.10 presents the number of times participants chose to view each Random Pitch based on the on-screen position of each Random Pitch's button. Participants viewed the top row of Random Pitches (Random Pitches 1–3) significantly more often than they viewed the bottom row of Random Pitches (Random Pitches 4 and 5).[6] In the top row, there was a slight, marginally significant preference for Random Pitch 1 over Random Pitch 2 (RP 2 – RP 1 = –0.25, $z = -1.91$, $p = 0.057$), and a slight, significant preference for Random Pitch 1 over Random Pitch 3 (RP 3 – RP 1 = –0.25, $z = -1.94$, $p = 0.053$).

[6] RP 4 – RP 1 = –0.62, $z = -4.75$, $p < 0.000$; RP 4 – RP 2 = –0.37, $z = -2.84$, $p = 0.004$; RP 4 – RP 3 = –0.37, $z = -2.81$, $p = 0.005$; RP 5 – RP 1 = –0.66, $z = -5.04$, $p < 0.000$; RP 5 – RP 2 = –0.41, $z = -3.13$, $p = 0.002$; RP 5 – RP 3 = –0.41, $z = -3.10$, $p = 0.002$.

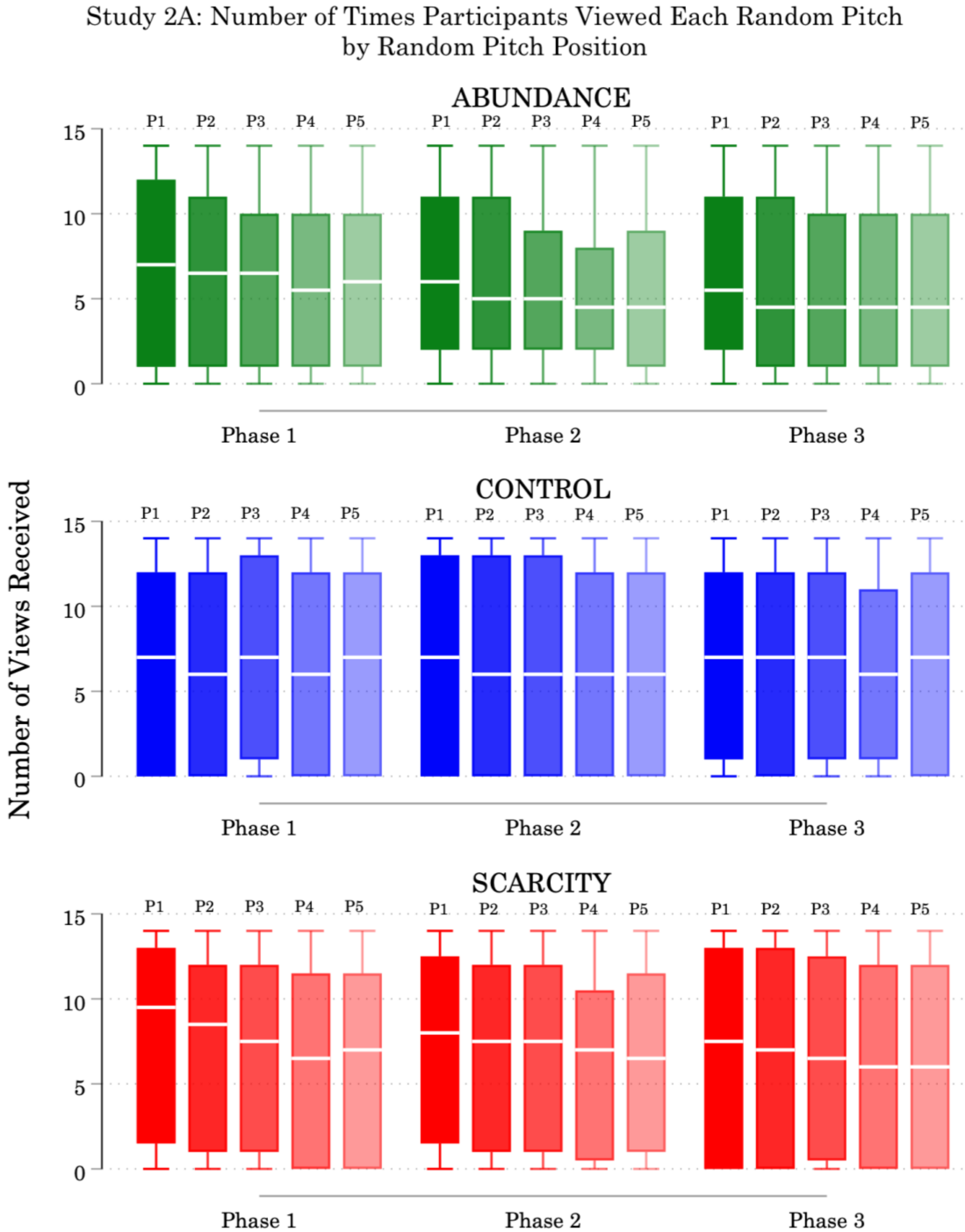


Figure 5.10. Study 2A: Sampling by Position. Number of times participants viewed each Random Pitch by Random Pitch Position (the location of the Random Pitch in the button tray), by Phase and Condition. N = 157. Green = Abundance (N = 58); Blue = Control (N = 51); Red = Scarcity (N = 48). P1 = Top-Left Position, P2 = Top-Middle Position, P3 = Top-Right Position, P4 = Bottom-Left Position, P5 = Bottom-Right Position. Participants in all three Conditions chose to view Random Pitch 1 most often (top-left position), and to view pitches in the top row more often than pitches in the bottom row.

There was no significant difference between the number of times participants viewed Random Pitches 2 and 3, or between the number of times participants viewed Random Pitches 4 and 5. There were no significant differences in participants' preferences between Conditions or between Phases.

5.1.5 Discussion

In Study 2A, participants could learn about the platform values in two ways: 1) through Exploration (sampling platform values by including platforms in their pitch on each Trial), and 2) through side observations (sampling platform values by looking at the Random Pitches). Exploration requires a tradeoff between exploring previously unsampled platforms and exploiting the best platforms encountered on previous Trials. Taking side observations of the platform values by viewing the Random Pitches does not require a tradeoff – viewing Random Pitches does not require participants to forego exploitation of the best platforms encountered on previous Trials. Participants are truthfully informed that the platforms in each Random Pitch are randomly sampled on each Trial. The expected average value of the platforms in each Random Pitch does not increase across Trials.

The purpose of Study 2A was to understand participants' appetite for random samples of the resource distribution. As before, I will focus on the comparison between behavior in Phase 1, before any resource shock occurs, and behavior in Phase 2, after Abundance and Scarcity participants experience the first resource shock. I find no significant effects of *negative* resource shocks on any of the focal dependent variables in Phase 2. *Positive* resource shocks only have a significant effect on one of the focal dependent variables in Phase 2 (average error). For each of the focal dependent variables, I will note the difference between Study 2A and Study 1 (except for Sampling Side Observations, which was not present in Study 1).

As a reminder, Control participants experience *no change* in platform values between Phases 1 and 2 (they face the Medium range in every Phase of the experiment). Abundance participants experience a *positive* resource shock in Phase 2 (the Medium range platform values are *higher* than the Low range platform values they faced in Phase 1). Scarcity participants experience a *negative* resource shock in Phase 2 (the Medium range platform values are *lower* than the High range platform values they faced in Phase 1).

5.1.4.1 Exploration

Exploration is defined as the total number of unique platforms participants explored across Trials 1–15 of a given Phase. In other words, Exploration is the number of platforms (out of 20) that the participant included in her pitch on at least one Trial. There are no significant differences between Conditions. Participants in all three Conditions explored significantly fewer platforms in Phase 2 than they did in Phase 1.

No change in platform values produced a *decrease* in Exploration. An *increase* in platform values also produced a *decrease* in Exploration. A *decrease* in platform values produced a temporary increase in Exploration on Trial 2, followed by a global *decrease* in Exploration.

In every Phase of the experiment, participants in each Condition of Study 2A explored significantly fewer platforms than participants in the corresponding Condition of Study 1.[7]

[7] CONTROL: Study 2A Control Phase 1 – Study 1 Control Phase 1 = –2.57, $z = -3.53$, $p < 0.000$; Study 2A Control Phase 2 – Study 1 Control Phase 2 = –3.74, $z = -5.17$, $p < 0.000$; Study 2A Control Phase 3 – Study 1 Control Phase 3 = –3.09, $z = -3.88$, $p < 0.000$. ABUNDANCE: Study 2A Abundance Phase 1 – Study 1 Abundance Phase 1 = –

5.1.4.2 Exploitation

Exploitation is defined as the total number of times that a participant selected one of the platforms with the top three highest empirical averages across Trials 2–15 of a given Phase. A platform's "empirical average" is the average of the *realized* values that the participant has observed for that platform over all preceding Trials. There were no significant differences between Conditions. Participants in all three Conditions significantly increased the number of times they exploited their Personal-Best platforms in Phase 2 compared to what they did in Phase 1.

No change in platform values produced an *increase* in Exploitation. An *increase* in platform values also produced an *increase* in Exploitation. A *decrease* in platform values produced a temporary decrease in Exploitation on Trial 2, followed by a global *increase* in Exploitation across later Trials.

In every Phase of the experiment, Control participants in Study 2A exploited their Personal-Best platforms with similar frequency to Control participants in Study 1.[8] In Phases 1 and 3 of the experiment, Abundance participants exploited their Personal-Best platforms significantly *more* often than Abundance participants in Study 1. In Phase 2, there was no

3.22, z = –4.55, p < 0.000; Study 2A Abundance Phase 2 – Study 1 Abundance Phase 2 = –4.58, z = –6.50, p < 0.000; Study 2A Abundance Phase 3 – Study 1 Abundance Phase 3 = –4.72, z = –6.09, p < 0.000. SCARCITY: Study 2A Scarcity Phase 1 – Study 1 Scarcity Phase 1 = –2.41, z = –3.31, p = 0.001; Study 2A Scarcity Phase 2 – Study 1 Scarcity Phase 2 = –5.46, z = –7.52, p < 0.000; Study 2A Scarcity Phase 3 – Study 1 Scarcity Phase 3 = –4.51, z = –5.64, p < 0.000.

[8] CONTROL: Study 2A Control Phase 1 – Study 1 Control Phase 1 = 2.13, *z* = 1.22, p = 0.223; Study 2A Control Phase 2 – Study 1 Control Phase 2 = 2.55, *z* = 1.48, p = 0.139; Study 2A Control Phase 3 – Study 1 Control Phase 3 = 0.57, *z* = 0.31, p = 0.754.

difference between Abundance participants in Study 2A and Study 1.[9] In Phases 2 and 3 of the experiment, Scarcity participants exploited their Personal-Best platforms significantly *more* often than Scarcity participants in Study 1. In Phase 1, there was no difference between Scarcity participants in Study 2A and Study 1.[10]

5.1.4.3 Mental Models

Mean Absolute Difference is defined as the average absolute value of the difference between participants' estimates of the platform values at the end of each Phase and the true average values of each platform. We'll refer to the Mean Absolute Difference as "average error." Control participants' average error was slightly lower in Phase 2 than in Phase 1, but this difference was not significant. Abundance participants' average error in Phase 2 was significantly higher than in Phase 1. Scarcity participants' average error in Phase 2 was lower than in Phase 2, but this difference was not significant. There was no difference between Scarcity and Abundance participants' average error in Phase 2, when both faced the Medium range of platform values.

No change in platform values produced *no change* in average error. An *increase* in platform values produced an *increase* in average error. A *decrease* in platform values produced a *decrease* in average error.

Somewhat surprisingly, participants in Study 2A had similar average error to participants in Study 1 in every Phase of the experiment. The opportunity to sample platform values more

[9] ABUNDANCE: Study 2A Abundance Phase 1 – Study 1 Abundance Phase 1 = 3.61, $z = 2.13$, $p = 0.033$; Study 2A Abundance Phase 2 – Study 1 Abundance Phase 2 = 2.33, $z = 1.39$, $p = 0.165$; Study 2A Abundance Phase 3 – Study 1 Abundance Phase 3 = 5.19, $z = 2.92$, $p = 0.004$.
[10] SCARCITY: Study 2A Scarcity Phase 1 – Study 1 Scarcity Phase 1 = 2.13, $z = 1.75$, $p = 0.224$; Study 2A Scarcity Phase 2 – Study 1 Scarcity Phase 2 = 6.08, $z = 3.52$, $p < 0.000$; Study 2A Scarcity Phase 3 – Study 1 Scarcity Phase 3 = 6.21, $z = 3.39$, $p = 0.001$.

frequently (by viewing the Random Pitches) did not result in more accurate estimates of each platform's average value.[11]

5.1.4.4 Rewards

Cumulative Standardized Achievement is the sum of the Standardized Achievement Scores a participant earns across Trials 1–15 of a given Phase. There were no significant differences between Conditions. Participants in all three Conditions earned significantly higher scores in Phase 2 than they did in Phase 1.

No change in platform values produced an *increase* in Cumulative Standardized Achievement scores. The same increase in Cumulative Standardized Achievement scores occurred following an *increase* in platform values and following a *decrease* in platform values.

In every Phase of the experiment, Abundance and Scarcity participants in Study 2A earned significantly higher scores than Abundance and Scarcity participants in Study 1.[12] In Phases 1 and 2, Control participants in Study 2A earned significantly higher scores than Control

[11] CONTROL: Study 2A Control Phase 1 – Study 1 Control Phase 1 = 6.32, $z = 0.54$, $p = 0.593$; Study 2A Control Phase 2 – Study 1 Control Phase 2 = 6.08, $z = 0.53$, $p = 0.594$; Study 2A Control Phase 3 – Study 1 Control Phase 3 = 13.04, $z = 0.89$, $p = 0.372$. ABUNDANCE: Study 2A Abundance Phase 1 – Study 1 Abundance Phase 1 = –8.41, $z = –0.74$, $p = 0.458$; Study 2A Abundance Phase 2 – Study 1 Abundance Phase 2 = 2.18, $z = 0.20$, $p = 0.842$; Study 2A Abundance Phase 3 – Study 1 Abundance Phase 3 = –1.00, $z = –0.07$, $p = 0.943$ SCARCITY: Study 2A Scarcity Phase 1 – Study 1 Scarcity Phase 1 = –10.95, $z = –0.93$, $p = 0.354$; Study 2A Scarcity Phase 2 – Study 1 Scarcity Phase 2 = –5.13, $z = –0.45$, $p = 0.652$; Study 2A Scarcity Phase 3 – Study 1 Scarcity Phase 3 = –3.27, $z = –0.23$, $p = 0.822$.

[12] ABUNDANCE: Study 2A Abundance Phase 1 – Study 1 Abundance Phase 1 = 143.22, $z = 4.19$, $p < 0.000$; Study 2A Abundance Phase 2 – Study 1 Abundance Phase 2 = 124.72, $z = 3.75$, $p < 0.000$; Study 2A Abundance Phase 3 – Study 1 Abundance Phase 3 = 170.76, $z = 4.89$, $p < 0.000$. SCARCITY: Study 2A Scarcity Phase 1 – Study 1 Scarcity Phase 1 = 132.83, $z = 3.77$, $p < 0.000$; Study 2A Scarcity Phase 2 – Study 1 Scarcity Phase 2 = 184.08, $z = 5.36$, $p < 0.000$; Study 2A Scarcity Phase 3 – Study 1 Scarcity Phase 3 = 185.23, $z = 5.15$, $p < 0.000$.

participants in Study 1. In Phase 3, there was no significant difference between Control participants in Study 2A and Control participants in Study 1.[13]

5.1.4.5 Discovery

Discovery is defined as the number of times a participant selected any of the true top-three highest-valued platforms across Trials 1–15 of a given Phase. There were no significant differences between Conditions. Participants in all three Conditions selected True Top Three platforms with the same frequency in Phases 1 and 2.

No change in platform values produced a *no change* in Discovery. No change in Discovery was observed following *increase* in platform values or a *decrease* in platform values.

In every Phase of the experiment, Abundance and Scarcity participants in Study 2A selected the True Top Three platforms significantly more often than Abundance and Scarcity participants in Study 1.[14] In Phases 1 and 2, Control participants in Study 2A selected the True Top Three platforms significantly more often than Control participants in Study 1. In Phase 3, there was no significant difference between Control participants in Study 2A and Control participants in Study 1.[15]

[13] CONTROL: Study 2A Control Phase 1 – Study 1 Control Phase 1 = 92.71, $z = 2.64$, $p = 0.008$; Study 2A Control Phase 2 – Study 1 Control Phase 2 = 108.31, $z = 3.17$, $p = 0.002$; Study 2A Control Phase 3 – Study 1 Control Phase 3 = 41.87, $z = 1.17$, $p = 0.243$.

[14] ABUNDANCE: Study 2A Abundance Phase 1 – Study 1 Abundance Phase 1 = 8.25, $z = 4.67$, $p < 0.000$; Study 2A Abundance Phase 2 – Study 1 Abundance Phase 2 = 4.96, $z = 2.89$, $p = 0.004$; Study 2A Abundance Phase 3 – Study 1 Abundance Phase 3 = 9.04, $z = 5.05$, $p < 0.000$. SCARCITY: Study 2A Scarcity Phase 1 – Study 1 Scarcity Phase 1 = 5.88, $z = 3.23$, $p = 0.001$; Study 2A Scarcity Phase 2 – Study 1 Scarcity Phase 2 = 6.63, $z = 3.74$, $p < 0.000$; Study 2A Scarcity Phase 3 – Study 1 Scarcity Phase 3 = 8.01, $z = 4.33$, $p < 0.000$.

[15] CONTROL: Study 2A Control Phase 1 – Study 1 Control Phase 1 = 4.54, $z = 2.50$, $p = 0.012$; Study 2A Control Phase 2 – Study 1 Control Phase 2 = 4.77, $z = 2.70$, $p = 0.007$; Study 2A Control Phase 3 – Study 1 Control Phase 3 = 2.46, $z = 1.34$, $p = 0.181$.

5.1.4.6 Side Observations: Random Pitches

Sampling Frequency. Starting on Trial 2 of each Phase, participants had the opportunity to sample up to five Random Pitches on each Trial. Therefore, participants had a total of 70 opportunities to sample side observations of the platform values by viewing Random Pitches (70 opportunities = 5 Random Pitches × 14 Trials). There were no differences in sampling frequency between Conditions in any Phase of the experiment. Participants in all three Conditions chose to view Random Pitches at similar rates across Phases 1–3. Participants reduced the number of Random Pitches they viewed across Trials in Phases 2 and 3.

No change in platform values produced *no change* in the frequency of viewing Random Pitches. *No change* in the frequency of viewing Random Pitches was observed following an *increase* in platform values, or following a *decrease* in platform values.

Sampling Bias. Each of the 5 Random Pitches was represented by a button on the participants' screen. Three Random Pitches appeared in the top row of the button tray (in order from left to right: Random Pitch 1, Random Pitch 2, Random Pitch 3). Two Random Pitches appeared in the bottom row of the button tray (in order from left to right: Random Pitch 4, Random Pitch 5). Participants in all three Conditions viewed Random Pitches in the top row of the button tray more often than Random Pitches in the bottom row of the button tray. Random Pitch 1, located in the top-left corner of the button tray, received the highest number of views, on average. (Note that, in expectation, there is no difference between the average values of the platforms contained in each Random Pitch. Viewing Random Pitches in the top row more often than those in the bottom row is not a "bias" in the sense that it is irrational.)

5.1.4.7 Take-Aways from Study 2A

The biggest take-away from Study 2A is that the opportunity to take side observations of the platform values (by viewing Random Pitches) moderates the effect of *negative* resource shocks on Exploration and Exploitation. Following the *first* negative shock in Phase 2, we observe *increased* Exploration and *decreased* Exploitation. But, this effect quickly dissipates. Scarcity participants' rates of Exploration and Exploitation converge toward those of Control and Abundance participants more rapidly in Study 2A than in Study 1.

The opportunity to take side observations dramatically increases learning across Trials within each Phase. The biggest increase in participants' Rewards and Discovery occurs on Trial 2, when they get their first opportunity to view Random Pitches.

Surprisingly, the opportunity to sample the platform values more frequently (through side observations) did not significantly reduce the average error in participants' estimates of the platform values.

We did not observe any differences between Conditions in participants' appetite for random samples of the platform values. Participants chose to view a similar number of Random Pitches following *no shock* (Control), a *positive* shock (Abundance), or a *negative* shock (Scarcity).

Participants did not distribute their attention evenly across Random Pitches. Participants chose to view the Random Pitch in the top-left corner of the button tray most often. The three Random Pitches in the top row of the button tray were viewed significantly more often than the two Random Pitches in the bottom row of the button tray.

5.2 Study 2B: Solo Participants with Social Side Observations

Study 2B is designed to investigate the effect of resource shocks on strategic decision-makers' appetite for *social* information. Following Hoppitt and Laland (2013), I define "social" information in contrast to "asocial" information. *Asocial* information is defined as information about the true state of the environment that an agent obtains by sampling the environment directly (e.g. by visiting a patch of apple trees and observing how much fruit is available). *Social* information is defined as information about the true state of the environment that an agent obtains vicariously from another agent who has sampled the environment directly (e.g. observing the number of apples carried by someone who has just left the patch of apple trees). The primary hypothesis tested in Study 3A is that a *decrease* in resource values *reduces* a person's appetite for social information.

In Study 2A, participants had access to side observations that were generated by a random sampling process. These random samples did not constitute social information, because they were not generated by the actions or decisions of a conscious agent (a person).

In Study 2B, participants again have access to side observations of the platform values. However, unlike in Study 2A, these side observations are generated by intentional, goal-directed, social actors. Thus, these side observations *do* constitute social information. Five Exemplar Players were chosen from each Condition in Study 1. Participants in Study 2B have the option to view the pitches submitted (and points earned) by each of the Exemplar Players in the corresponding Condition starting on Trial 2 of each Phase. There is no cost to view Exemplar Players' pitches (aside from time and cognitive load). Participants can view each Exemplar Player's pitch as many times as they wish, but they can only view one Exemplar Player's pitch at a time.

I will compare participants' decisions to view social side observations in Study 2B with participants' decisions to view random side observations in Study 2A. This allows me to identify differences in participants' appetite for social versus non-social information. Achievement (points earned) varies across the five Exemplar Players selected from each Condition in Study 1. This feature of the experimental design allows me to identify effects of success/payoff bias on participants' decisions (not) to view the pitches made by each Exemplar Player.

5.2.1 Participants

159 people participated in Study 2B (Female = 83[16]; Average Age: 40, SD = 12). All participants were recruited through Amazon Mechanical Turk (MTurk). Participants were paid a $6.00 base fee upon completion of the focal procedure, and earned a variable performance-based bonus (Average Bonus: $6.80, SD = $0.40). Participants also earned an Active Participation Bonus of $4.00 if they consistently submitted their responses before the time limits (described in *3.1.1 Recruitment and Compensation*).

Participants were randomly assigned to one of three experimental Conditions: Control (N = 55), Abundance (N = 52), Scarcity (N = 52). Control, Scarcity, and Abundance carry the same meaning as before, and refer to the trends in platform values described in *3.1.3 Procedure* (Control = constant; Abundance = increasing; Scarcity = decreasing).

[16] One MTurk participant did not identify as either male or female, and selected "Other" as their gender.

5.2.2 Procedure

The focal experimental procedure is identical to that described in *3.1.3 Procedure* with the addition of one critical element. In Study 2B, participants have the option to view the pitches made (and points earned) by 5 Exemplar Players starting on Trial 2 of each Phase.

Five participants were selected from each Condition of Study 1 according to the following criteria. For each Condition in Study 1, I separated participants' Cumulative Standardized Achievement Scores (the sum of the Standardized Within-Trial Achievement Scores across Trials 1–15 in a given Phase) into quintiles. I then selected one participant from each achievement quintile: 80-100th, 60-79th, 40-59th, 20-39th, and 0-19th. This produced a *different* list of 5 Exemplar Players from *each* Condition in Study 1 (5 Exemplar Players from the Abundance Condition, 5 from the Control Condition, and 5 from the Scarcity Condition).

Starting on Trial 2 of each Phase, participants in Study 2B have the option to view the pitches made by the Exemplar Players on the immediately preceding Trial, as well as the points the Exemplar Players earned for each platform they included their pitches. No deception is used. Participants in Study 2B are told that they've been matched with 5 participants who played the game as solo players several weeks prior, and that these participants had no access to information about other players' pitches while they were playing the game. Participants are not given any information about how the 5 Exemplar Players were selected. In the instructions, the Exemplar Players are described to the participants as follows:

> In the real world, companies usually employ more than one salesperson, and salespeople can share information about their past experience with customers to help each other decide what to pitch to customers in the future. In The Sales Game, you will be matched up with 5 other players. Each of these people participated in the game as solo players a few weeks ago. They did not have access to information about other players' pitches while they were playing the game. Starting on the second round of each Phase, you will be able to look at the pitches each of the other 5 players submitted on the previous round. You will also see the points these players earned for each platform in their pitch.

In each Phase, you will work for the same company that the other 5 players worked for when they played the game. Each of the other players faced different customers while they were playing the game, so the points each player earned for a given platform may be slightly different than what another player earned for that same platform. You can use the information about each players' results to learn about the average value of each platform.

Each Exemplar Player is represented by a button on the pitch selection screen (Figure 5.11). The Exemplar Players are assigned to the Player buttons as follows: Top-Left Button = 40-59th percentile; Top-Center = 0-19th percentile; Top-Right = 80-100th percentile; 60-79th = Bottom-Left; 20-39th = Bottom-Right. These assignments are consistent across participants.

When participants click a Player button, the platforms selected (and points earned) by the corresponding Exemplar Player are displayed. Only one Exemplar Player's pitch can be viewed at a time. Participants can view each Exemplar Player's pitch as many times as they wish. There is no cost to view this information other than time and cognitive load. Participants have 60 seconds to submit their pitch. After 60 seconds, the screen automatically advances to the results screen. If the participant fails to enter his pitch before time runs out, an empty pitch is recorded, and no points are earned for the current Trial.

After completing the focal procedure, participants in Study 2B complete the Debrief Questionnaire described in *Section 3.1.3 Procedure.* Participants are also asked to rate the extent to which each of the Exemplar Players helped or harmed their performance during the focal procedure on a scale of 0 (Very Harmful) to 100 (Very Helpful).[17]

[17] "Do you feel like the other players you were matched with helped you perform better in The Sales Game? Use the sliding scales below to indicate how much you feel each of the other players helped or harmed your performance in The Sales Game. Select "Very Helpful" if you feel like the player had a big positive impact on your performance, or select "Very Harmful" if you feel like the player had a big negative impact on your performance."

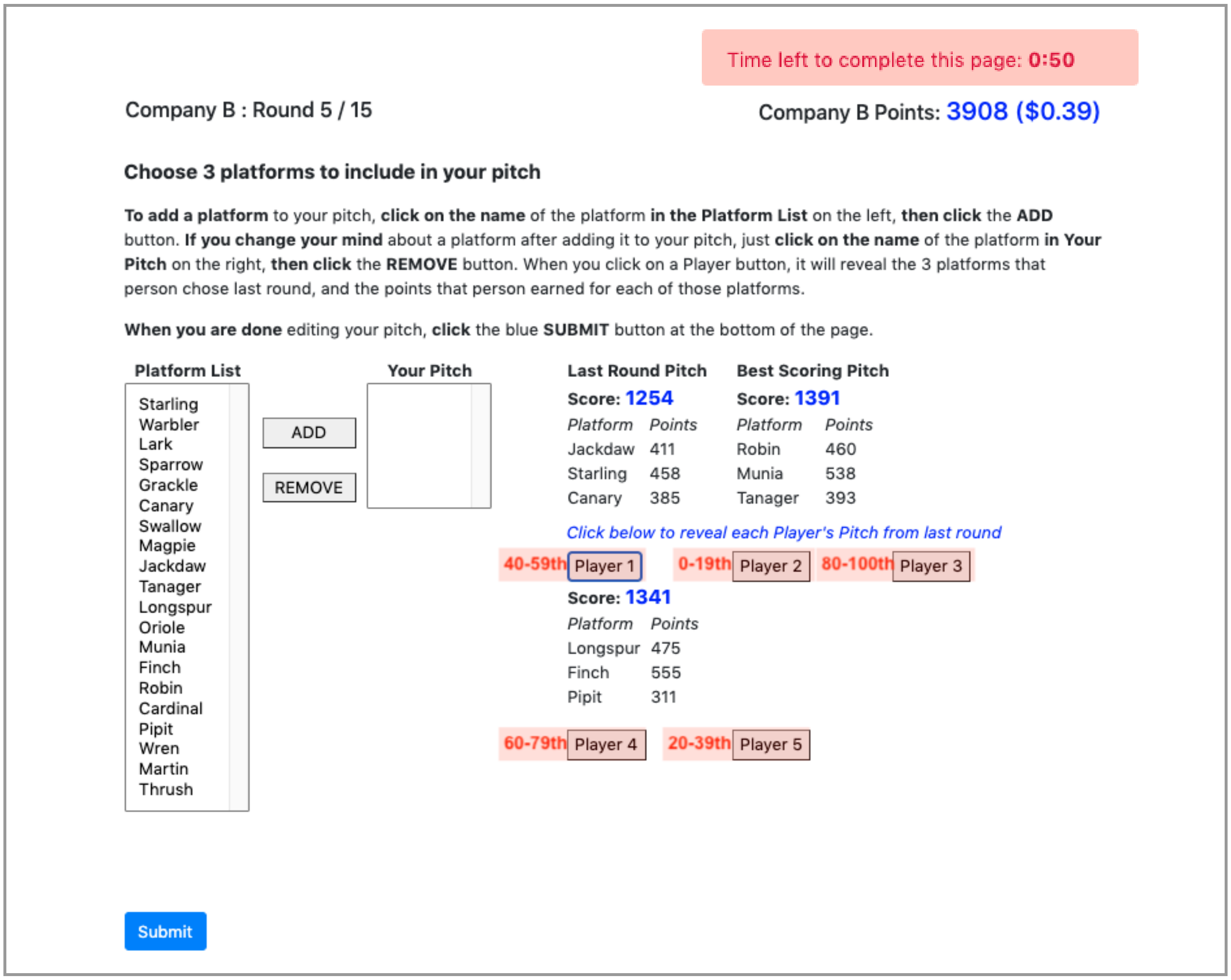


***Figure 5.11*. Screenshot of Pitch Selection Screen on Trials 2-15 of each Phase in Study 2B.** Taken from the perspective of a participant in the Control Condition on Trial 5 of Phase 1. Starting on the second Trial of each Phase, participants can choose to view the platforms selected (and points earned) by each Exemplar Player on the preceding Trial. Each Exemplar Player is represented by a Player button on the pitch selection screen. The red transparent boxes in the above image indicate the performance quintile from which each Exemplar Player was selected. These transparent red boxes are added here for clarity. They were not visible to participants. Only one Exemplar Player can be viewed at a time. Participants can view each Exemplar Player as many times as they wish.

5.2.3 Results

I exclude participants who were marked as dropouts after repeatedly failing to submit their responses before the time limits. One participant in the Scarcity Condition met this criterion. I also exclude Trials on which participants failed to submit their response before the time limit expired (timeouts).

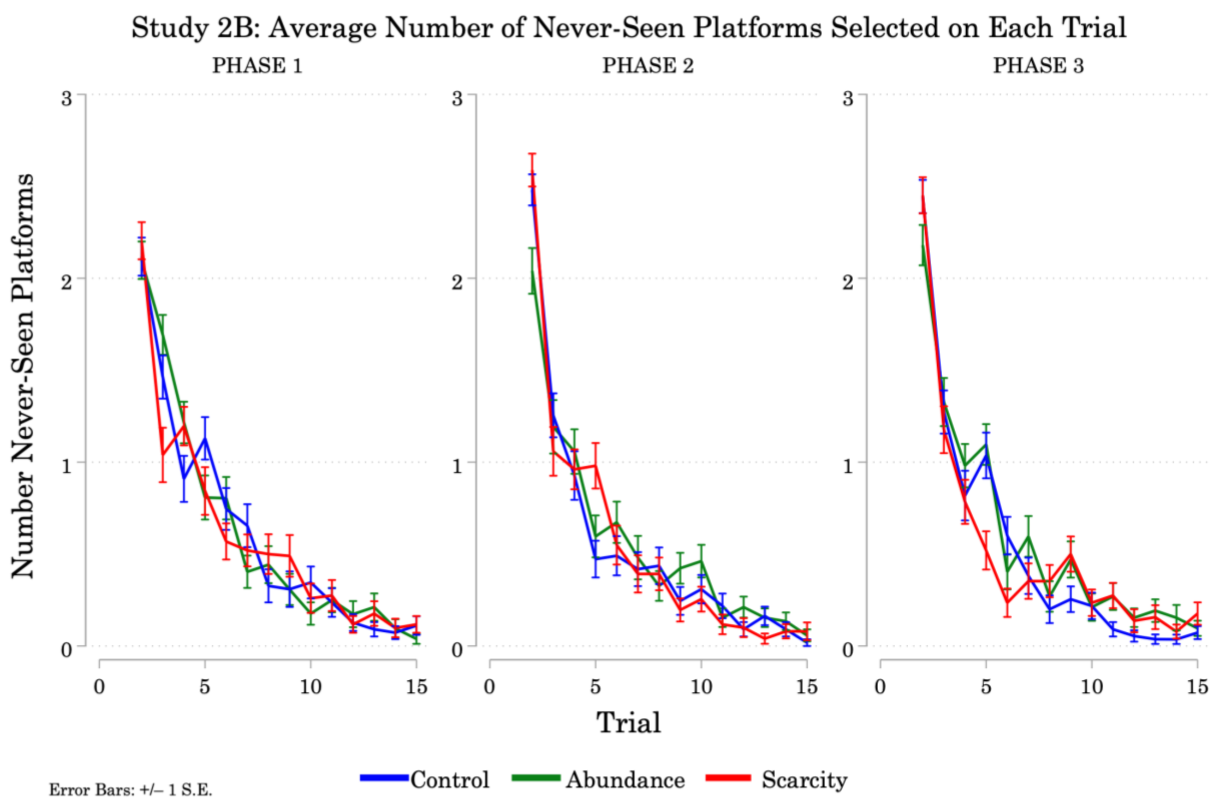


Figure 5.12. Study 2B: Exploration. Average number of Never-Seen platforms selected on each Trial, by Phase and Condition. Error bars = +/– 1 S.E. N = 158. Green = Abundance (N = 52); Blue = Control (N = 55); Red = Scarcity (N = 51). Note that the curves begin on Trial 2, the first opportunity to observe differences (the number of Never-Seen platforms on Trial 1 is always 3 for every participant). There are no significant differences between Conditions in Phase 1. On the second Trial of Phase 2, Scarcity and Control participants select a higher number of Never-Seen platforms than participants in the Abundance Condition. There are no significant differences between Conditions across the later Trials in Phase 2. In Phase 3, there are no significant differences between Conditions.

5.2.3.1 Exploration

Figure 5.12 presents the average number of Never-Seen platforms participants selected on each Trial, in each Phase of Study 2B. There are no significant differences between Conditions in Phase 1. On the second Trial of Phase 2, Scarcity and Control participants select a higher number of Never-Seen platforms than they did on the second Trial of Phase 1. There was no difference in the number of Never-Seen platforms selected by Abundance participants on the second Trial of Phases 1 and 2. There are no consistent differences between Conditions across the later Trials in Phase 2. In Phase 3, there are no significant differences between Conditions.

Table 5.7 presents the parameter estimates and fit statistics from three different Two-Level Random Coefficient models for the total number of unique platforms participants explored across Trials 1–15 in each Phase of Study 2B. Model 1 is the baseline model, and includes an intercept and piecewise linear slopes for Phases 2 and 3). The random part of Model 1 includes a random intercept and a random linear slope for Phase at the Participant level (Level 2). Model 2 includes the main effect of Condition, and Model 3 introduces interactions among elements of the experimental design (Condition, Phase). Model 3 did not provide a significant improvement over Model 2 [$LR\ \chi^2(4) = 2.59$, $p = 0.629$], nor did Model 2 provide a significant improvement over Model 1 [$LR\ \chi^2(2) = 0.54$, $p = 0.764$]. There is no evidence for a main effect of Condition, nor for any interactions between Condition and Phase, so I will focus on the estimates from Model 1.

Table 5.7. Study 2B: Exploration. Maximum likelihood estimates of Two-Level Random-Coefficient models for the total number of unique platforms explored across Trials 1–15 of each Phase. Model 1: Intercept-Slope; Model 2: Main Effects; Model 3: Design Interactions. N = 158.

	Model 1		Model 2		Model 3	
	Est	(SE)	Est	(SE)	Est	(SE)
Fixed Effects						
Intercept β_0	11.40***	0.32	11.22***	0.51	11.33***	0.54
Phase 2 β_1	–0.69***	0.20	–0.69***	0.20	–0.85**	0.34
Phase 3 β_2	–0.00	0.20	–0.00	0.20	0.00	0.34
Abundance β_3			0.48	0.70	0.25	0.77
Scarcity β_4			0.07	0.71	–0.03	0.77
Abundance × Phase 2 β_5					0.16	0.49
Scarcity × Phase 2 β_6					0.34	0.49
Abundance × Phase 3 β_7					0.37	0.49
Scarcity × Phase 3 β_8					–0.37	0.49
Random Effects						
L2 Random Intercept Var $\psi_{11}^{(2)}$	13.27	1.77	13.28	1.77	13.28	1.77
L2 Random Slope Var $\psi_{22}^{(2)}$	0.96	0.30	0.96	0.30	0.96	0.30
L1 (Residual) Error Var θ	2.72	0.31	2.72	0.54	2.70	0.30
Log likelihood	–1164		–1164		–1162	
AIC | *BIC*	2342 | 2371		2345 | 2383		2351 | 2405	

* $p \leq 0.05$; ** $p \leq 0.01$; *** $p \leq 0.001$

From the Model 1 estimates, we see that participants explored about 11.40 (z = 35.83, p < 0.000) platforms by the end of Phase 1. By the end of Phase 2, participants explored significantly fewer platforms than they did by the end of Phase 1 (β_1 = –0.69, z = –3.42, p = 0.001). There was no significant difference between the number of platforms explored by the end of Phase 3 and the number explored by the end of Phase 2 (β_2 = –0.00, z = –0.00, p = 1.000).

5.2.3.2 Exploitation

Figure 5.13 presents the average number of Personal-Best platforms participants selected on each Trial in each Phase of Study 2B (the number of platforms in the current pitch that have one of the three highest empirical averages based on what the participant has seen so far in the current Phase).

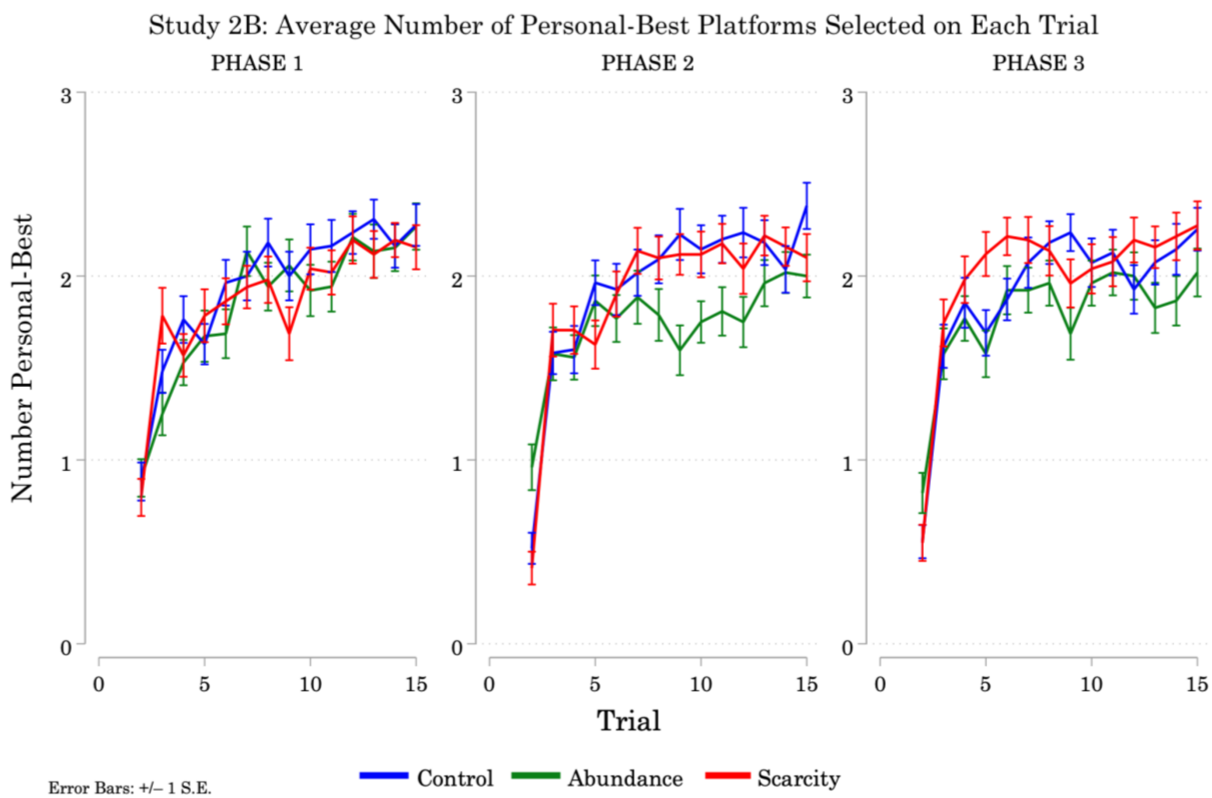


Figure 5.13. Study 2B: Exploitation. Average number of Personal-Best platforms selected on each Trial, by Phase and Condition. Error bars = +/– 1 S.E. N = 158. Green = Abundance (N = 52); Blue = Control (N = 55); Red = Scarcity (N = 51). Note that the curves begin on Trial 2. On Trial 1, all of the platforms selected have no empirical history. Participants in all three Conditions exploited a similar number of Personal-Best platforms across Trials in Phase 1. On Trial 2 of Phase 2, Abundance participants exploited significantly more Personal-Best platforms than Control and Scarcity participants. Abundance participants exploited fewer platforms than Scarcity and Control participants between Trials 9–12 of Phase 2. There were no consistent patterns in Phase 3, participants exploited a similar number of platforms across Trials, on average.

Participants in all three Conditions exploited a similar number of Personal-Best platforms across Trials in Phase 1. On Trial 2 of Phase 2, Control and Scarcity participants exploited significantly fewer Personal-Best platforms than they did on Trial 2 of Phase 1. Abundance participants exploited a similar number of Personal-Best platforms on Trial 2 of Phase 2. Abundance participants exploited fewer platforms than Scarcity and Control participants between Trials 9–12 of Phase 2. There were no consistent patterns in Phase 3.

As before, we will look at the cumulative number of times participants exploited their top-three Personal-Best Platforms across Trials 2–15 of each Phase. Table 5.8 presents the parameter estimates and fit statistics from three different Two-Level Random Coefficient models for the cumulative number of times participants selected their Personal-Best platforms across Trials 2–15 in a given Phase.

Model 1 is the baseline model. The fixed part of Model 1 includes an intercept and piecewise linear slopes for Phases 2 and 3. The random part of Model 1 includes a random intercept and a random linear slope for Phase at the Participant level (Level 2). Model 2 includes Condition as a fixed effect. Model 3 introduces two-way interactions between elements of the experimental design (Condition, Phase). Model 3 did not provide a significant improvement over Model 2 [$LR\ \chi^2(4) = 5.94$, $p = 0.204$], nor did Model 2 provide a significant improvement over Model 1 [$LR\ \chi^2(2) = 1.64$, $p = 0.440$]. Again we find no main effect of Condition, nor do we find a significant interaction between Condition and Phase, so we'll focus on the Model 1 estimates.

Table 5.8. Study 2B: Exploitation. Maximum likelihood estimates of Two-Level Random-Coefficient models for the number of times participants selected any of their top-three Personal-Best platforms across Trials 2–15 of each Phase. Model 1: Intercept-Slope; Model 2: Main Effects; Model 3: Design Interactions. N = 158.

	Model 1		Model 2		Model 3	
	Est	(SE)	Est	(SE)	Est	(SE)
Fixed Effects						
Intercept β_0	26.25***	0.73	26.98***	1.16	27.04***	1.23
Phase 2 β_1	–0.37	0.47	–0.37	0.47	–0.04	0.77
Phase 3 β_2	0.54	0.47	0.54	0.47	–0.36	0.79
Abundance β_3			–1.94	1.62	–1.34	1.76
Scarcity β_4			–0.26	1.63	–1.06	1.77
Abundance × Phase 2 β_5					–1.41	1.13
Scarcity × Phase 2 β_6					0.41	1.13
Abundance × Phase 3 β_7					0.98	1.13
Scarcity × Phase 3 β_8					1.80	1.13
Random Effects						
L2 Random Intercept Var $\psi_{11}^{(2)}$	69.04	9.38	68.77	9.25	68.62	9.19
L2 Random Slope Var $\psi_{22}^{(2)}$	5.07	1.64	5.07	1.63	4.83	1.59
L1 (Residual) Error Var θ	14.74	2.85	14.74	1.66	14.58	1.64
Log likelihood	–1563		–1562		–1559	
AIC | *BIC*	3139 | 3168		3141 | 3179		3144 | 3198	

* $p \leq 0.05$; ** $p \leq 0.01$; *** $p \leq 0.001$; SE = standard error of the mean

In Phase 1, participants exploited their personal-best platforms 26.25 (z = 36.05, p < 0.000) times on average. In Phase 2, participants exploited their personal-best platforms about the same number of times as they did in Phase 1 (β_1 = –0.37, z = –0.79, p = 0.432). In Phase 3, participants exploited their personal-best platforms about the same number of times as they did in Phase 2 (β_2 = 0.54, z = 1.15, p = 0.250).

5.2.3.3 Mental Models

Recall that participants in Study 2 were asked to estimate the average value of each platform after the 8th and 15th Trials of each Phase.

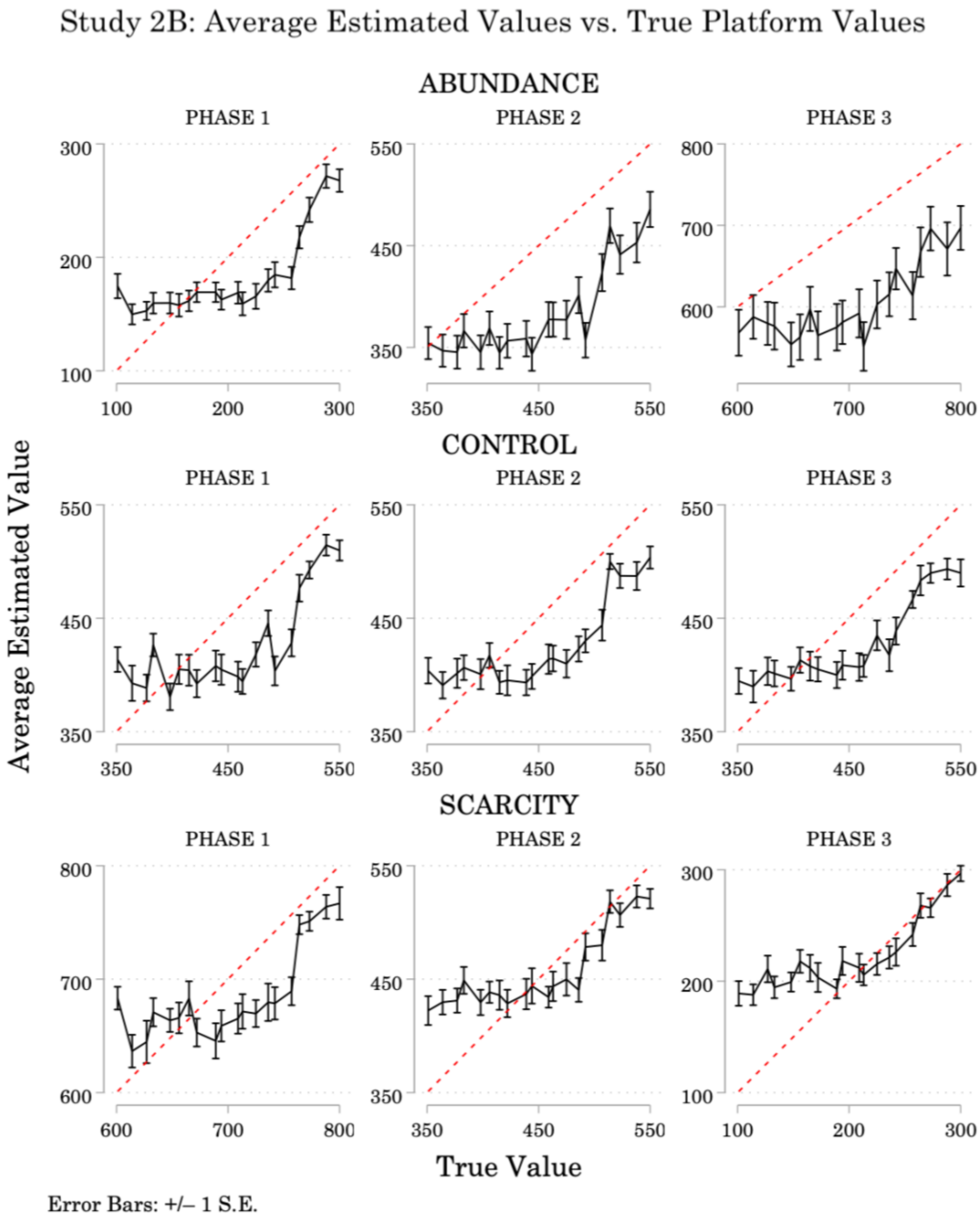


Figure 5.14. Study 2B: Mental Models. Average estimated values submitted by participants following Trial 15 of each Phase versus the true average values of each platform, by Phase and Condition. Error bars = +/– 1 S.E. N = 157.[18] Top Row: Abundance (52 participants). Middle Row: Control (54 participants). Bottom Row: Scarcity (51 participants). Average participant estimates on y-axes. True platform values on the x-axes. Red dotted 45-degree lines mark "perfect agreement" between participants' average estimates of each platform's value and each platform's true value. Scarcity participants' estimates become more accurate across Phases 1-3. Control and Abundance participants' estimates are less accurate in Phase 2 than in Phase 1.

[18] One participant in the Control Condition was dropped because they failed to submit their estimates before time expired on Trial 15 of all three Phases.

Here we will focus on the estimates participants made following Trial 15. Figure 5.14 plots the average estimated value of each platform against that platform's true value. The red, dotted 45-degree lines indicate what the shape of each curve would look like if there was perfect agreement between the average estimated values reported by participants and the true values of each platform. One way to think about the accuracy of participants' estimates is to consider the proximity of the estimates curve to the 45-degree line.

There are only small, non-significant differences between Scarcity and Control participants each Phase. Abundance participants' error is significantly higher than Controls in Phases 2 and 3. Abundance participants' estimates become *less accurate* across Phases 1–3. Control and Scarcity participants' accuracy is similar across Phases 1–3.

Table 5.9 presents the parameter estimates and fit statistics from three different Two-Level Random Coefficient models for the Mean Absolute Difference between participants' estimates of each platform's average value and the true average value of that platform. Model 1 is the baseline model, and includes an intercept and piecewise linear slopes for Phases 2 and 3. The random part of Model 1 includes a random intercept and random linear slope for Phase at the Participant level (Level 2). Model 2 includes the main effect of Condition. Model 3 introduces interactions among elements of the experimental design (Condition, Phase). Model 3 provides a significantly better fit than Model 2 $LR\ \chi^2(4) = 29.22$, $p < 0.000$] and Model 1 [$LR\ \chi^2(6) = 31.51$, $p < 0.000$], so I will focus on the predictions from Model 3.

Table 5.9. Study 2B: Mental Models. Maximum likelihood estimates of Two-Level Random-Coefficient models for Mean Absolute Difference between Estimated Values and True Average Values on Trial 15 of each Phase. Model 1: Intercept-Slope; Model 2: Main Effects; Model 3: Design Interactions. N =157.

	Model 1		Model 2		Model 3	
	Est	(SE)	Est	(SE)	Est	(SE)
Fixed Effects						
Intercept β_0	64.41***	3.45	68.32***	5.74	66.02***	5.86
Phase 2 β_1	8.20*	4.22	8.19*	4.22	–1.60	6.72
Phase 3 β_2	11.03**	4.23	11.03**	4.23	–3.06	6.77
Abundance β_3			–11.70	8.10	–5.81	8.37
Scarcity β_4			–0.03	8.12	1.24	8.40
Abundance × Phase 2 β_5					35.79***	9.65
Scarcity × Phase 2 β_6					–6.01	9.66
Abundance × Phase 3 β_7					39.93***	9.71
Scarcity × Phase 3 β_8					3.28	9.67
Random Effects						
L2 Rand Intercept Var $\psi_{11}^{(2)}$	1305.16	207.92	1300.85	208.35	1295.18	206.37
L2 Rand Slope Var $\psi_{22}^{(2)}$	1671.14	224.34	1672.53	224.38	1347.51	187.52
Level-1 Error Var θ	537.09	61.61	536.99	61.59	534.71	61.34
Log likelihood	–2432		–2431		–2416	
AIC | *BIC*	4878 | 4907		4879 | 4917		4858 | 4912	

* $p \leq 0.05$; ** $p \leq 0.01$; *** $p \leq 0.001$

In Phase 1, Control participants' average error was 66.02 (z = 5.86, p < 0.000). Abundance and Scarcity participants' errors were similar to Controls (β_3 = –5.81, z = –0.69, p = 0.487; β_4 = 1.24, z = 0.15, p = 0.883).

In Phase 2, Control participants' average error was about 64.42, which is similar to their error in Phase 1 (β_1 = –1.60, z = –0.24, p = 0.812). Abundance participants' error was significantly larger than Controls (Abundance Phase 2 – Control Phase 2 = 29.98, z = 2.37, p = 0.018), and significantly larger than their error in Phase 1 (Abundance Phase 2 – Abundance Phase 1 = 34.19, z = 4.94, p < 0.000). Scarcity participants' error was similar to Controls

(Scarcity Phase 2 – Control Phase 2 = –4.77, z = –0.38, p = 0.706), and similar to their error in Phase 1 (Phase 2 – Phase 1 = –7.61, z = –1.10, p = 0.272).

In Phase 3, Control participants' average error was similar to Phase 2 (β_2 = –3.06, z = –0.45, p = 0.652). Abundance participants' error in Phase 3 was significantly larger than Controls (Abundance Phase 3 – Control Phase 3 = 69.91, z = 3.72, p < 0.000), and significantly larger than their error in Phase 2 (Abundance Phase 3 – Abundance Phase 2 = 36.87, z = 5.29, p < 0.000). Scarcity participants' error in Phase 3 was similar to Controls (Scarcity Phase 3 – Control Phase 3 = –1.49, z = –0.08, p = 0.937), and similar to their error in Phase 2 (Scarcity Phase 3 – Scarcity Phase 2 = 0.22, z = 0.03, p = 0.974).

Figure 5.15 presents the adjusted marginal predictions for the Mean Absolute Difference between participants' estimates and the true average value of each platform. Notice there is no significant difference between Abundance and Scarcity participants' average error in Phase 1 (Abundance Phase 1 – Scarcity Phase 1 = –7.05, z = –0.83, p = 0.406). This is somewhat surprising, because Abundance participants' average error in Phase 1 was significantly lower than Scarcity participants' in both Study 1 and Study 2A.

Recall the cautionary discussion we had regarding the potential effects of range magnitude (e.g. High range of platform values versus Low range of platform values) on participants' ability to learn the true average platform values. In Studies 1 and 2A, we found no difference between Abundance and Scarcity participants' average errors when they faced the *same* distributions of platform values. In the present study, we *do* find significant differences between Abundance and Scarcity participants' average errors when they face the same distributions of platform values.

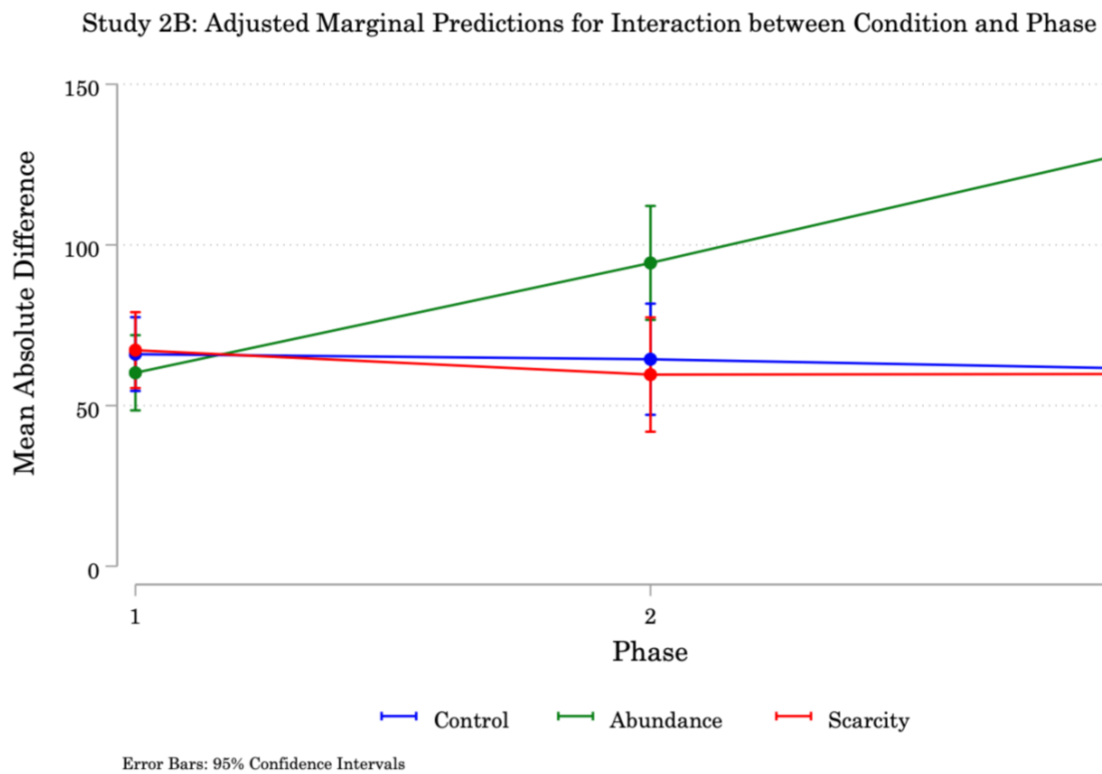


Figure 5.15. Study 2B: Mental Models Interaction. Adjusted marginal predictions for the interaction between Condition and Phase. Error bars = 95% Confidence Interval. N = 157. Green = Abundance (N = 58); Blue = Control (N = 49); Red = Scarcity (N = 47). In Phase 1, there is no difference between Conditions. In Phases 2 and 3, Abundance participants have significantly higher error than Scarcity and Control participants. Abundance participants' error increases significantly in Phase 2, and again in Phase 3. Scarcity and Control participants' error is similar across Phases 1–3.

When Abundance and Scarcity participants both face the Medium distribution in Phase 2, Abundance participants' error is significantly higher than Scarcity participants' (Abundance Phase 2 – Scarcity Phase 2 = 34.75, $z = -2.71$, $p = 0.007$). Scarcity participants' error when they face the Low distribution in Phase 3 is slightly lower than Abundance participants' error when they face the Low distribution in Phase 1, but this difference is not significant (Scarcity Phase 3 – Abundance Phase 1 = –18.76, $z = -1.78$, $p = 0.075$). Scarcity participants' error when they face the High distribution in Phase 1 is significantly lower than Abundance participants' error when they face the High distribution in Phase 3 (Scarcity Phase 1 – Abundance Phase 3 = –45.76, $z = -3.15$, $p = 0.002$).

5.2.3.4 Rewards

Figure 5.16 presents participants' Standardized Achievement Scores on each Trial in each Phase of Study 2B.

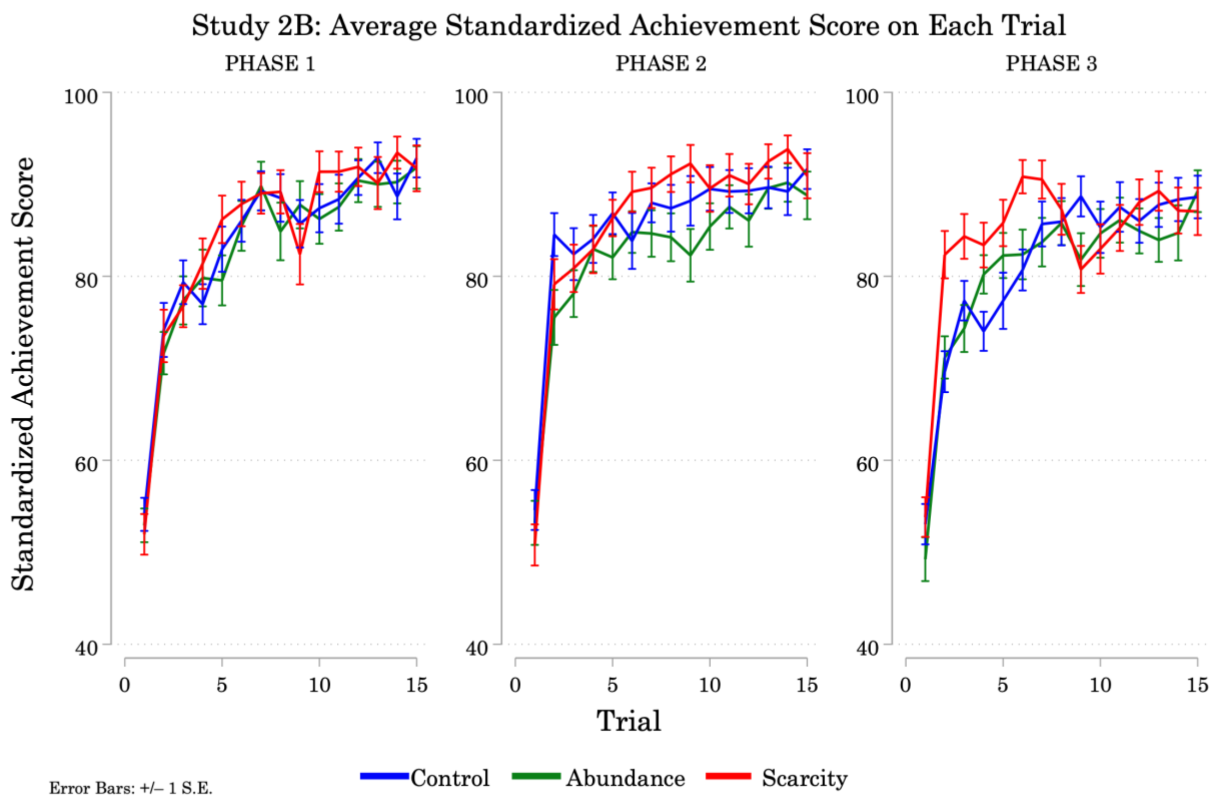


Figure 5.16. Study 2B: Rewards. Average Standardized Achievement Scores on each Trial, by Phase and Condition. N = 158. Green = Abundance (N = 52); Blue = Control (N = 55); Red = Scarcity (N = 51). There are no significant differences between Conditions in Phase 1. In Phases 2 and 3, Scarcity participants occasionally earn higher scores than Abundance and Control participants, but these patterns are not consistent across Trials. Participants' scores increase dramatically between Trials 1 and 2 (participants are able to sample Exemplar Players starting on Trial 2). Participants achieve similar scores toward the end of Phase 2 as they did by the end of Phase 1. Participants' scores at the end of Phase 3 are significantly lower than those they achieved by the end of Phase 2.

There are no significant differences between Conditions in Phase 1. In Phases 2 and 3, Scarcity participants occasionally earn higher scores than Abundance and Control participants, but these patterns are not consistent across Trials. Participants' scores increase dramatically between Trials 1 and 2 (participants are able to sample Exemplar Players starting on Trial 2). Participants achieve similar scores toward the end of Phase 2 as they did by the end of Phase 1. Participants' scores at the end of Phase 3 are significantly lower than those they achieved by the end of Phase 2.

Table 5.10 presents the parameter estimates and fit statistics from three different Two-Level Random Coefficient models for the participants' Cumulative Standardized Achievement Scores on Trial 15 of each Phase in Study 2B. Model 1 is the baseline model, and includes two pairwise linear spline functions representing Phase 2 and Phase 3. The random part of Model 1 includes a random intercept and a random linear slope for Phase at the Participant level (Level 2). Model 2 includes Condition as a fixed effect. Model 3 includes interactions among elements of the experimental design (Condition, Phase). Model 3 does not provide a significantly better fit than Model 2 [$LR\ \chi^2(4) = 4.33$, $p = 0.363$] and Model 2 does not provide a significantly better fit than Model 1 [$LR\ \chi^2(2) = 1.35$, $p = 0.509$]. There's no evidence for a main effect of Condition, nor for any interactions between Condition and Phase, so I will focus on the estimates from Model 1.

Table 5.10. Study 2B: Rewards. Maximum likelihood estimates of Two-Level Random-Coefficient models for participants' Cumulative Standardized Achievement Scores at the end of each Phase. Model 1: Intercept-Slope; Model 2: Main Effects; Model 3: Design Interactions. N = 158.

	Model 1		Model 2		Model 3	
	Est	(SE)	Est	(SE)	Est	(SE)
Fixed Effects						
Intercept β_0	1248***	16	1247***	26	1246***	27
Phase 2 β_1	14	9	14	9	25	15
Phase 3 β_2	–40***	9	–40***	9	–57***	15
Abundance β_3			–20	36	–8	39
Scarcity β_4			23	36	14	39
Abundance × Phase 2 β_5					–30	22
Scarcity × Phase 2 β_6					–2	22
Abundance × Phase 3 β_7					24	22
Scarcity × Phase 3 β_8					30	22
Random Effects						
L2 Random Intercept Var $\psi_{11}^{(2)}$	35182	4472	35127.13	4471	35142	4459
L2 Random Slope Var $\psi_{22}^{(2)}$	2518	645	2518.15	645	2505	638
Level-1 Error Var θ	5140	584	5193.91	584	5109	575
Log likelihood	–2990		–2990		–2988	
AIC | *BIC*	5995 | 6024		5998 | 6035		6001 | 6055	

* $p \leq 0.05$; ** $p \leq 0.01$; *** $p \leq 0.001$

In Phase 1, participants accumulated standardized scores of about 1248.02 (z = 15.99, p < 0.000). In Phase 2, participants accumulated slightly higher scores than they did by the end of Phase 1, but this difference was not significant (β_1 = 14.01, z = 1.55, p = 0.121). In Phase 3, participants accumulated significantly lower scores than they did in Phase 2 (β_2 = –39.73, z = –4.40, p < 0.000).

5.2.3.5 Discovery

Figure 5.17 presents the average number of True Top Three platforms selected by participants on each Trial in each Phase of Study 2B (the number of platforms in the current pitch that have one of the three highest true average values).

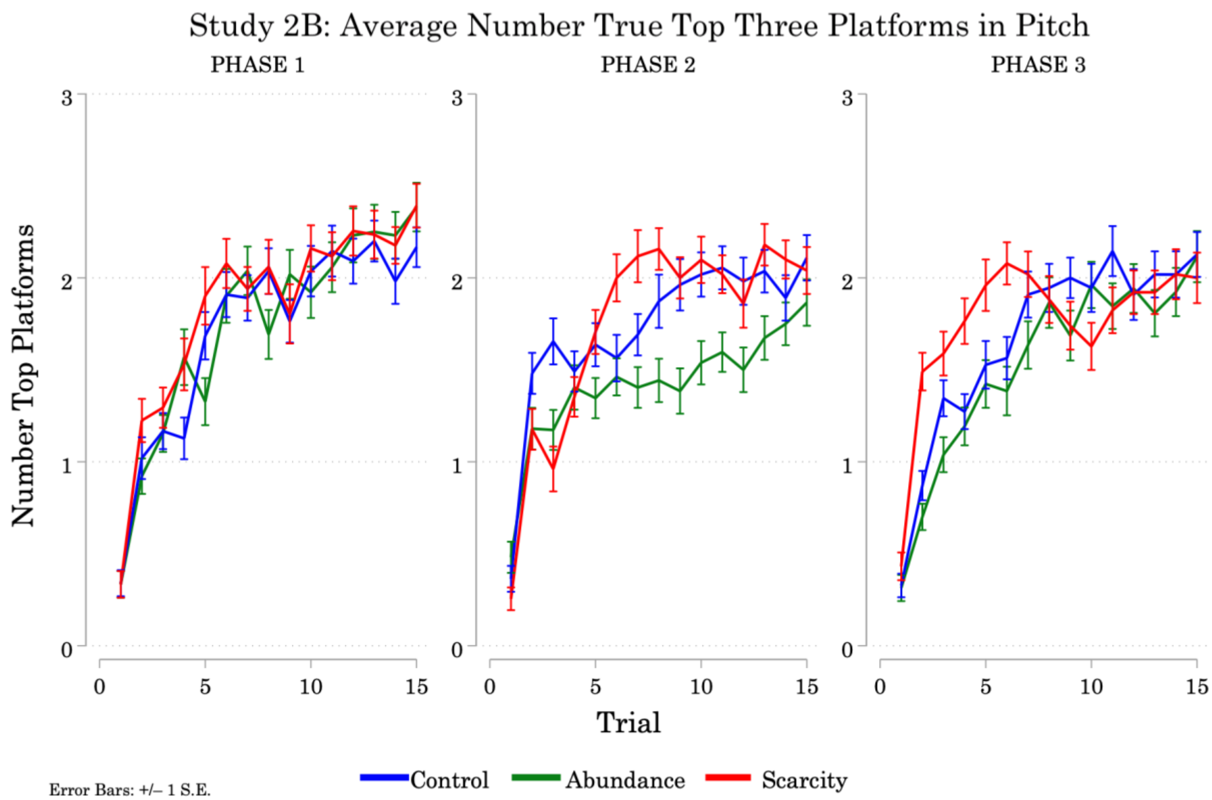


Figure 5.17. Study 2B: Discovery. Average number of True Top Three highest-valued platforms selected on each Trial, by Phase and Condition. Error bars = +/– 1 S.E. N = 158. Green = Abundance (N = 52); Blue = Control (N = 55); Red = Scarcity (N = 51). There are no significant differences Between Conditions in Phase 1. In Phase 2, Abundance participants select True Top Three platforms less often than Scarcity and Control participants across Trials 5–13. Across Trials 2–6 in Phase 3, Scarcity participants select True Top Three platforms more often than Control and Abundance participants. Participants' discovery rates do not consistently improve across Phases.

There are no significant differences Between Conditions in Phase 1. In Phase 2, Abundance participants select True Top Three platforms less often than Scarcity and Control participants across Trials 5–13. Across Trials 2–6 in Phase 3, Scarcity participants select True Top Three platforms more often than Control and Abundance participants. Participants' discovery rates do not improve across Phases.

Table 5.11. Study 2B: Discovery. Maximum likelihood estimates of Two-Level Random-Coefficient models for the number of times participants selected any of the True Top-Three highest-valued platforms across Trials 1–15 of each Phase. Model 1: Intercept-Slope; Model 2: Main Effects; Model 3: Design Interactions. N = 158.

	Model 1		Model 2		Model 3	
	Est	(SE)	Est	(SE)	Est	(SE)
Fixed Effects						
Intercept β_0	26.18***	0.79	26.47***	1.24	25.38***	1.33
Phase 2 β_1	–1.94***	0.55	–1.94***	0.55	0.27	0.90
Phase 3 β_2	0.37	0.55	0.37	0.55	–0.78	0.90
Abundance β_3			–2.01	1.71	0.52	1.90
Scarcity β_4			1.17	1.72	1.95	1.91
Abundance × Phase 2 β_5					–5.02***	1.30
Scarcity × Phase 2 β_6					–1.74	1.30
Abundance × Phase 3 β_7					2.40	1.30
Scarcity × Phase 3 β_8					1.12	1.30
Random Effects						
L2 Random Intercept Var $\psi_{11}^{(2)}$	76.87	10.81	76.36	10.79	77.37	10.70
L2 Random Slope Var $\psi_{22}^{(2)}$	5.37	2.15	5.37	2.15	5.85	2.08
L1 (Residual) Error Var θ	21.15	2.38	21.15	2.38	19.57	2.20
Log likelihood	–1620		–1619		–1611	
AIC | *BIC*	3255 | 3284		3255 | 3293		3248 | 3302	

* $p \leq 0.05$; ** $p \leq 0.01$; *** $p \leq 0.001$; SE = standard error of the mean

As before, we will look at the cumulative number of times participants selected one of the True Top Three Platforms across Trials 1–15 of each Phase. Table 5.11 presents the parameter estimates and fit statistics from three different Two-Level Random Coefficient models of the Number of True Top Three Platforms Selected (Cumulative) across Trials 1–15 in a given Phase. Model 1 is the baseline model. The fixed part of Model 1 includes an intercept and piecewise linear slopes for Phases 2 and 3. The random part of Model 1 includes a random intercept and a random linear slope for Phase at the Participant level (Level 2). Model 2 includes Condition as a fixed effect. Model 3 introduces two-way interactions between elements of the experimental design (Condition, Phase). Model 3 provides a better fit than Model 2 [$LR\ \chi^2(4) = 15.36$, $p = 0.004$] and Model 1 [$LR\ \chi^2(6) = 18.66$, $p = 0.005$], so I will focus on the predictions from Model 3.

In Phase 1, Control participants selected top-three platforms 25.38 ($z = 19.12$, $p < 0.000$) times on average. Abundance and Scarcity participants selected top-three platforms about the same number of times as did Controls ($\beta_3 = 0.52$, $z = 0.27$, $p = 0.784$; $\beta_4 = 1.95$, $z = 1.02$, $p = 0.308$).

In Phase 2, Control participants selected top-three platforms about 25.65 times on average, which is about the same as they did in Phase 1 ($\beta_2 = 0.27$, $z = 0.30$, $p = 0.763$). Abundance participants selected top-three platforms significantly less often than did Controls (Abundance Phase 2 – Control Phase 2 = –4.50, $z = -2.43$, $p = 0.015$), and significantly less often than they did in Phase 1 (Abundance Phase 2 – Abundance Phase 1 = –4.75, $z = -5.11$, $p < 0.000$). Scarcity participants selected top-three platforms with similar frequency to Controls (Scarcity Phase 2 – Control Phase 2 = 0.21, $z = 0.11$, $p = 0.911$), and with similar frequency to what they did in Phase 1 (Scarcity Phase 2 – Scarcity Phase 1 = –1.47, $z = -1.57$, $p = 0.117$).

In Phase 3, Control participants selected top-three platforms about 24.87 times on average, which is about the same as the number of times they selected top-three platforms in Phase 1 ($\beta_3 = -0.78$, $z = -0.86$, $p = 0.387$). Abundance and Scarcity participants selected top-three with similar frequency to Controls (Abundance Phase 3 – Control Phase 3 = –2.10, $z = -1.10$, $p = 0.272$; Scarcity Phase 3 – Control Phase 3 = 1.32, $z = 0.69$, $p = 0.492$), and about the same number of times they each did in Phase 2 (Abundance Phase 3 – Abundance Phase 2 = 1.62, z = 1.74, p = 0.082; Scarcity Phase 3 – Scarcity Phase 2 = 0.33, z = 0.35, p = 0.723).

5.2.3.6 Side Observations: Exemplar Players

Recall that on Trials 2–15 of each Phase, participants in Study 2B had the option to view the pitches made by Study 1 participants on the immediately preceding Trial. Five Exemplar Players were selected from each Condition of Study 1, based on their Cumulative Standardized Achievement Scores in each Phase of the experiment. Each of the 5 Exemplar Players was selected from a different achievement quintile (80-100th, 60-79th, 40-59th, 20-39th, and 0-19th).

Figure 5.18 presents the Average Number of Exemplar Players participants chose to view on each Trial. There are no consistent differences between Conditions in any Phase of the experiment. In each Phase, Participants gradually decreased the number of Exemplar Players they viewed across Trials. Participants viewed Exemplar Players with similar frequency across Phases 1–3.

To investigate differences in participants' overall appetite for side observations of Exemplar Player pitches across Conditions, we'll look at the cumulative number of times participants looked at any Exemplar Player's pitch across Trials 2–15 of a given Phase.

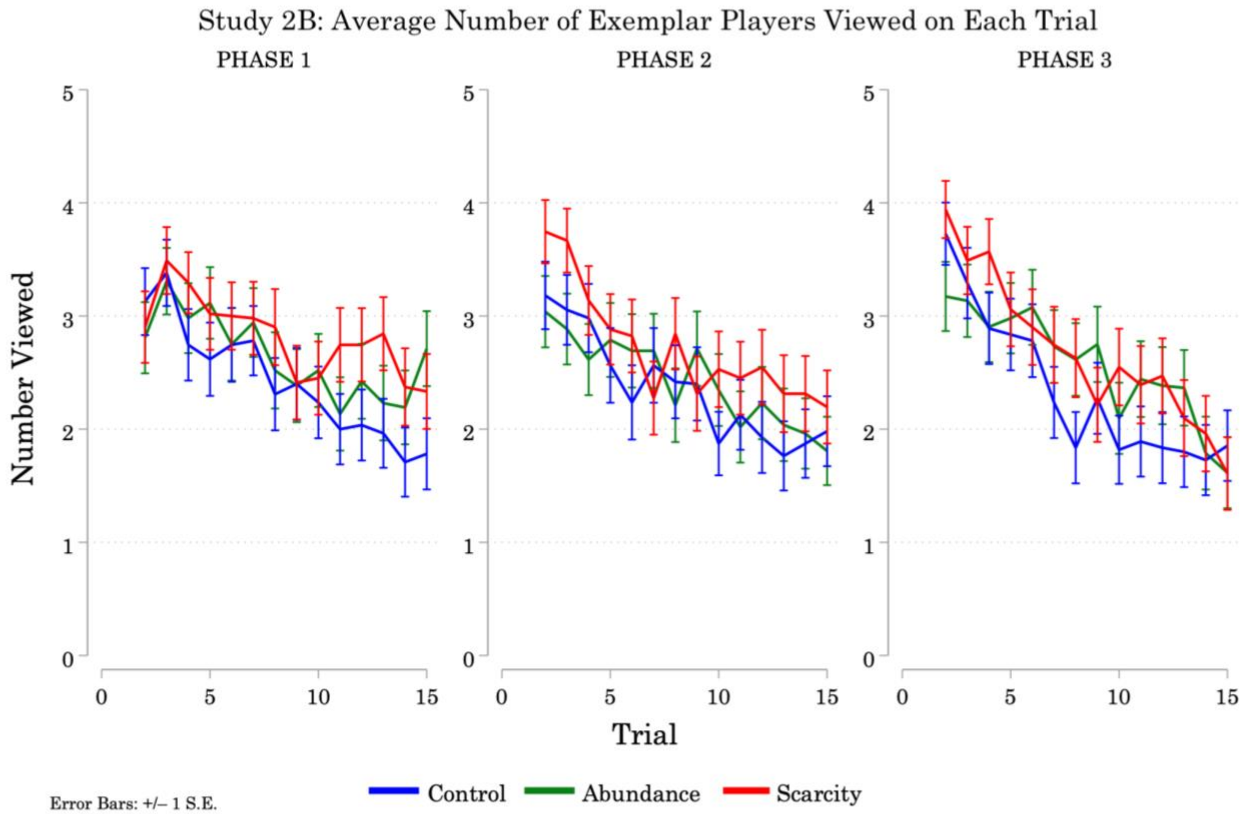


Figure 5.18. Study 2B: Sampling Side Observations. Average number of Exemplar Players viewed on each Trial, by Phase and Condition. Error bars = +/– 1 S.E. N = 158. Green = Abundance (N = 52); Blue = Control (N = 55); Red = Scarcity (N = 51). There are no significant differences between Conditions in any Phase of the experiment. In each Phase, Participants gradually decreased the number of Exemplar Players they viewed across Trials. Participants viewed Exemplar Players with similar frequency across Phases 1–3.

Table 5.12 presents the parameter estimates and fit statistics from three different Two-Level Random Coefficient models for the cumulative number of times participants viewed Exemplar Players in a given Phase. Model 1 is the baseline model. The fixed part of Model 1 includes an intercept and piecewise linear slopes for Phases 2 and 3. The random part of Model 1 includes a random intercept and random linear slope for Phase at the Participant level (Level 2). Model 2 includes Condition as a fixed effect. Model 3 introduces interactions among elements of the experimental design (Condition, Phase).

Model 3 does not provide a significantly better fit than Model 2 [*LR* $\chi^2(4) = 2.54$, p = 0.638] and Model 2 does not provide a significantly better fit than Model 1 [*LR* $\chi^2(2) = 1.42$, p = 0.491]. There's no evidence for a main effect of Condition, nor for any interactions between Condition and Phase, so I will focus on the Model 1 estimates.

In Phase 1, participants viewed Exemplar Players 36.71 times on average ($z = 19.40$, $p <$ 0.000) on average. In Phase 2, participants viewed Exemplar Players significantly less often they did in Phase 1 ($\beta_1 = –1.76$, $z = –2.09$, $p = 0.037$). In Phase 3, participants viewed Exemplar Players with similar frequency as they did in Phase 2 ($\beta_2 = 0.48$, $z = 0.57$, $p = 0.568$).

Table 5.12. Study 2B: Sampling Side Observations. Maximum likelihood estimates of Two-Level Random-Coefficient models for cumulative number of times participants viewed Exemplar Players on Trials 2–15 of each Phase. Model 1: Intercept-Slope; Model 2: Main Effects; Model 3: Design Interactions. N = 158.

	Model 1		Model 2		Model 3	
	Est	(SE)	Est	(SE)	Est	(SE)
Fixed Effects						
Intercept β_0	36.71***	1.89	34.14***	3.16	33.84***	3.19
Phase 2 β_1	–1.76*	0.84	–1.76*	0.84	–0.89	1.42
Phase 3 β_2	0.48	0.84	0.48	0.84	0.15	1.42
Abundance β_3			2.49	4.51	3.18	4.56
Scarcity β_4			5.42	4.53	5.65	4.60
Abundance × Phase 2 β_5					–2.09	2.04
Scarcity × Phase 2 β_6					–0.56	2.05
Abundance × Phase 3 β_7					2.16	2.04
Scarcity × Phase 3 β_8					–0.27	2.05
Random Effects						
L2 Random Intercept Var $\psi_{11}^{(2)}$	524.41	63.00	519.15	62.41	519.66	62.40
L2 Random Slope Var $\psi_{33}^{(2)}$	29.56	6.11	29.56	6.11	29.83	6.09
L1 (Residual) Error Var θ	41.34	4.65	41.34	4.65	40.72	4.58
Log likelihood	–1916		–1915		–1914	
AIC | *BIC*	3846 | 3875		3848 | 3886		3854 | 3908	

* $p \leq 0.05$; ** $p \leq 0.01$; *** $p \leq 0.001$; SE = standard error of the mean

As before, we'd also like to know whether participants' choices to view each Exemplar Player exhibit a bias toward any particular Position on participants' screen. The Exemplar Players were presented as a series of 5 buttons, numbered from one to five. The position of each Exemplar Player was determined by that player's achievement quintile. Figure 5.19 presents the visual display of the Exemplar Player buttons. Each Exemplar Player's achievement quintile is annotated in red to the left of that player's button.

Figure 5.19. Position of Exemplar Players in the On-Screen Button Tray. In the top row, buttons are numbered from one to three, starting with the leftmost button. In the second row, the leftmost button is numbered 4, and the center button is numbered 5. Each Exemplar Player's achievement quintile is annotated in red to the left of that player's button.

The Exemplar Player in the upper-left position (Player 1) earned a Cumulative Standardized Pitch Score that fell in the 40-59th achievement quintile in each Phase of Study 1. In other words, Exemplar Player 1 is the "average" Player. The highest-performing Exemplar Player is located in the upper-right position (Player 3), and the lowest-performing Exemplar Player is located in the upper-middle position (Player 2). If participants choose to view Exemplar Player 1 more often than Exemplar Player 3, this indicates that the position effect (preference for the upper-left position) dominates any performance effect (preference for highest-performing Exemplar Player), because Exemplar Player 1's performance is lower than Exemplar Player 3's performance in every Phase of the experiment.

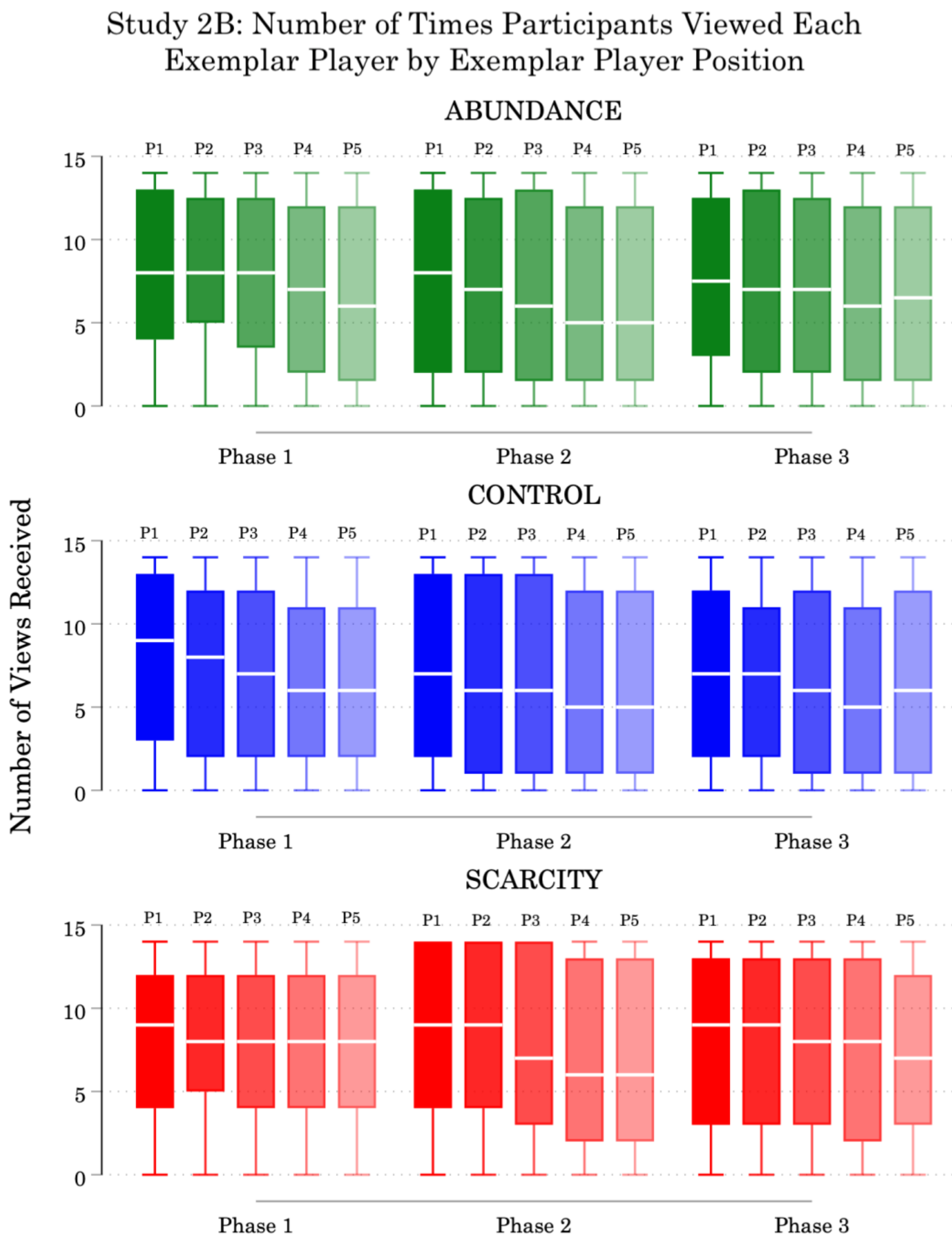


Figure 5.20. Study 2B: Sampling by Position. Number of times participants viewed each Exemplar Player by Exemplar Player Position (the location of the Exemplar Player in the button tray), by Phase and Condition. N = 158. Green = Abundance (N = 52); Blue = Control (N = 55); Red = Scarcity (N = 51). P1 = Top-Left Position, P2 = Top-Middle Position, P3 = Top-Right Position, P4 = Bottom-Left Position, P5 = Bottom-Right Position. Participants in all three Conditions chose to view Exemplar Player 1 (average achievement) significantly more often than Exemplar Player 3 (highest achievement). Participants viewed Exemplar Players in the top row of the button tray (Exemplar Players 1, 2, and 3) more often than Exemplar Players in the bottom row of the button tray (Exemplar Players 4 and 5).

Figure 5.20 presents the number of times participants chose to view each Exemplar Player based on each Player's on-screen Position. As in Study 2A, participants viewed the Exemplar Player in the top-left Position (Exemplar Player 1) more often than any other Player. Participants chose to view Exemplar Players in the top row (1, 2, and 3) significantly more often than they chose to view Exemplar Players in the button row (4, 5).

This position-based bias is consistent with what we observed in Study 2A. But, in Study 2A there were no differences in the expected average value of the platforms in each Random Pitch. In Study 2B, there *are* significant differences between the average value of each Exemplar Player's pitch.

Participants chose to view Exemplar Player 1 significantly more often than Exemplar Player 3 (EP 3 – EP 1 = –0.42, $z = -3.65$, $p < 0.000$). In other words, participants chose to view the *highest*-achievement Player (Exemplar Player 3) significantly *less* often than they chose to view the *average*-achievement Player (Exemplar Player 1). There was no significant difference between the number of times participants chose to view the *lowest*-achievement Player (Exemplar Player 2) and the number of times participants chose to view the *average*-achievement or *highest*-achievement Player (Exemplar Players 1 and 3, respectively). Participants viewed Players in the top row of the button tray (Exemplar Players 1–3) significantly more often than they viewed Players in the bottom row of the button tray (Exemplar Players 4 and 5).[19]

The fact that participants in Study 2B exhibit the same position-based preferences as participants in Study 2A suggests that participants decisions to view Exemplar Players was not

[19] EP 4 – EP 1 = –0.85, $z = -7.47$, $p < 0.000$; EP 4 – EP 2 = –0.64, $z = -5.64$, $p < 0.000$; EP 4 – EP 3 = –0.43, $z = -3.82$, $p < 0.000$; EP 5 – EP 1 = –0.95, $z = -8.36$, $p < 0.000$; EP 5 – EP 2 = –0.74, $z = -6.53$, $p < 0.000$; EP 5 – EP 3 = –0.54, $z = -4.71$, $p < 0.000$.

influenced by each Player's achievement (or, at least, that the effect of on-screen Position exerted more influence over participants' decisions to view Exemplar Players than Players' achievement levels).

5.2.4 Discussion

In Study 2B, participants could learn about the platform values in two ways: 1) through Exploration (sampling platform values by including platforms in their pitch on each Trial), and 2) through side observations (sampling platform values by looking at the pitches made by the Exemplar Players sampled from Study 1). Exploration requires a tradeoff between exploring previously unsampled platforms and exploiting the best platforms encountered on previous Trials. Taking side observations of the platform values by viewing the pitches made by Exemplar Players does not require a tradeoff. Participants are truthfully informed that each Exemplar Player was selected from among the participants in Study 1. Unlike the Random Pitches in Study 2A, the average value of the platforms in each Exemplar Player's pitch increases across Trials.

The purpose of Study 2B was to understand participants' appetite for samples of the resource distribution that are generated by the actions of intentional, goal-directed actors. I will focus on the comparison between behavior in Phase 1, before any resource shock occurs, and behavior in Phase 2, after Abundance and Scarcity participants experience the first resource shock. I find no significant effects of *negative* resource shocks on any of the focal dependent variables in Phase 2. *Positive* resource shocks have a significant effect on average error and Discovery. For each of the focal dependent variables, I will note any differences between Study 2B and Study 2A.

As a reminder, Control participants experience *no change* in platform values between Phases 1 and 2 (they face the Medium range in every Phase of the experiment). Abundance participants experience a *positive* resource shock in Phase 2 (the Medium range platform values are *higher* than the Low range platform values they faced in Phase 1). Scarcity participants experience a *negative* resource shock in Phase 2 (the Medium range platform values are *lower* than the High range platform values they faced in Phase 1).

5.2.4.1 Exploration

Exploration is defined as the total number of unique platforms participants explored across Trials 1–15 of a given Phase. In other words, Exploration is the number of platforms (out of 20) that the participant included in her pitch on at least one Trial. There are no significant differences between Conditions. Participants in all three Conditions explored significantly fewer platforms in Phase 2 than they did in Phase 1.

No change in platform values produced a *decrease* in Exploration. A *decrease* in Exploration was also observed following an *increase* in platform values and following a *decrease* in platform values.

Both *no change* in platform values and a *decrease* in platform values produced a temporary *increase* in Exploration on Trial 2, followed by a global *decrease* in Exploration across the remaining Trials. An *increase* in platform produced a *decrease* in Exploration.

In every Phase of the experiment, participants in each Condition of Study 2B explored a similar number of platforms to participants in the corresponding Condition of Study 2A.[20]

[20] CONTROL: Study 2B Control Phase 1 – Study 2A Control Phase 1 = –1.44, z = –1.79, p = 0.074; Study 2B Control Phase 2 – Study 2A Control Phase 2 = –1.15, z = –1.46, p = 0.144; Study 2B Control Phase 3 – Study 2A Control Phase 3 = –0.92, z = –1.17, p = 0.241. ABUNDANCE: Study 2B Abundance Phase 1 – Study 2A

5.2.4.2 Exploitation

Exploitation is defined as the total number of times that a participant selected one of the platforms with the top three highest empirical averages across Trials 2–15 of a given Phase. A platform's "empirical average" is the average of the *realized* values that the participant has observed for that platform over all preceding Trials. There were no significant differences between Conditions. Participants in all three Conditions exploited their Personal-Best platforms with similar frequency across all three Phases of the experiment.

Both *no change* in platform values and a *decrease* in platform values produced a temporary *decrease* in Exploitation on Trial 2, followed by a global *increase* in Exploitation across the remaining Trials. *No change* in Exploitation was observed following an *increase* in platform values.

In Phase 1 of the experiment, Control participants in Study 2B exploited their Personal-Best platforms significantly more often than Control participants in Study 2A. In Phases 2 and 3 there were no differences between Control participants in Study 2A versus Study 2B.[21]

Abundance Phase 1 = –0.65, z = –0.83, p = 0.409; Study 2B Abundance Phase 2 – Study 2A Abundance Phase 2 = –0.12, z = –0.15, p = 0.882; Study 2B Abundance Phase 3 – Study 2A Abundance Phase 3 = 0.59, z = 0.73, p = 0.465. SCARCITY: Study 2B Scarcity Phase 1 – Study 2A Scarcity Phase 1 = –1.44, z = –1.73, p = 0.083; Study 2B Scarcity Phase 2 – Study 2A Scarcity Phase 2 = –0.61, z = –0.75, p = 0.454; Study 2B Scarcity Phase 3 – Study 2A Scarcity Phase 3 = –1.00, z = –1.17, p = 0.241.

[21] CONTROL: Study 2B Control Phase 1 – Study 2A Control Phase 1 = 3.70, *z* = 2.02, p = 0.043; Study 2B Control Phase 2 – Study 2A Control Phase 2 = 1.43, *z* = 0.79, p = 0.429; Study 2B Control Phase 3 – Study 2A Control Phase 3 = 1.01, *z* = 0.53, p = 0.595.

There were no significant differences between Abundance participants in Study 2A versus Study 2B in any Phase of the experiment.[22] There were no differences between Scarcity participants in Study 2A versus Study 2B in any Phase of the experiment.[23]

5.2.4.3 Mental Models

Mean Absolute Difference is defined as the average absolute value of the difference between participants' estimates of the platform values at the end of each Phase and the true average values of each platform. We'll refer to the Mean Absolute Difference as "average error." Control participants' average error was slightly lower in Phase 2 than in Phase 1, but this difference was not significant. Abundance participants' average error in Phase 2 was significantly higher than in Phase 1. Scarcity participants' average error in Phase 2 was lower than in Phase 1, but this difference was not significant. Scarcity participants' average error was significantly lower than Abundance participants' in Phase 2.

No change in platform values produced *no change* in average error. An *increase* in platform values produced an *increase* in average error. A *decrease* in platform values produced a *no change* in average error.

Control and Scarcity participants in Study 2B had similar average error to participants in Study 2A in every Phase of the experiment.[24] Abundance participants in Study 2B had

[22] ABUNDANCE: Study 2B Abundance Phase 1 – Study 2A Abundance Phase 1 = 2.05, $z = 1.14$, p = 0.254; Study 2B Abundance Phase 2 – Study 2A Abundance Phase 2 = –1.30, $z = –0.73$, p = 0.464; Study 2B Abundance Phase 3 – Study 2A Abundance Phase 3 = –1.34, $z = –0.73$, p = 0.466.

[23] SCARCITY: Study 2B Scarcity Phase 1 – Study 2A Scarcity Phase 1 = 2.81, $z = 1.48$, p = 0.138; Study 2B Scarcity Phase 2 – Study 2A Scarcity Phase 2 = 1.96, $z = 1.04$, p = 0.296; Study 2B Scarcity Phase 3 – Study 2A Scarcity Phase 3 = 1.76, $z = 0.90$, p = 0.369.

[24] CONTROL: Study 2B Control Phase 1 – Study 2A Control Phase 1 = –16.34, z = –1.55, p = 0.122; Study 2B Control Phase 2 – Study 2A Control Phase 2 = –7.75, z = –0.63, p = 0.527; Study 2B Control Phase 3 – Study 2A Control Phase 3 = –13.69, z = –0.81, p = 0.418. SCARCITY: Study 2B Scarcity Phase 1 – Study 2A Scarcity Phase

significantly higher average error than Abundance participants in Study 2A in Phase 3.[25]

5.2.4.4 Rewards

Cumulative Standardized Achievement is the sum of the Standardized Achievement Scores a participant earns across Trials 1–15 of a given Phase. There were no significant differences between Conditions. Participants in all three Conditions earned similar scores in Phase 2 to what they did in Phase 1.

No change in platform values produced *no change* in Cumulative Standardized Achievement scores. *No change* in Cumulative Standardized Achievement was observed following an *increase* in platform values and following a *decrease* in platform values.

In every Phase of the experiment, Abundance and Scarcity participants in Study 2B earned similar scores to Abundance and Scarcity participants in Study 2A.[26] In Phase 1, Control participants in Study 2B earned significantly higher scores than Control participants in Study 2A. In Phases 2 and 3, there was no significant difference between Control participants in Study 2B and Control participants in Study 2A.[27]

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1 = –8.19, z = –0.76, p = 0.449; Study 2B Scarcity Phase 2 – Study 2A Scarcity Phase 2 = –8.05, z = –0.64, p = 0.521; Study 2B Scarcity Phase 3 – Study 2A Scarcity Phase 3 = 1.91, z = 0.11, p = 0.913.

[25] ABUNDANCE: Study 2B Abundance Phase 1 – Study 2A Abundance Phase 1 = 19.06, z = 1.86, p = 0.063; Study 2B Abundance Phase 2 – Study 2A Abundance Phase 2 = 12.90, z = 1.08, p = 0.278; Study 2B Abundance Phase 3 – Study 2A Abundance Phase 3 = 36.50, z = 2.22, p = 0.027.

[26] ABUNDANCE: Study 2B Abundance Phase 1 – Study 2A Abundance Phase 1 = 37.35, z = 0.97, p = 0.333; Study 2B Abundance Phase 2 – Study 2A Abundance Phase 2 = 12.87, z = 0.34, p = 0.734; Study 2B Abundance Phase 3 – Study 2A Abundance Phase 3 = 17.55, z = 0.45, p = 0.655. SCARCITY: Study 2B Scarcity Phase 1 – Study 2A Scarcity Phase 1 = 75.06, z = 1.85, p = 0.065; Study 2B Scarcity Phase 2 – Study 2A Scarcity Phase 2 = 37.31, z = 0.94, p = 0.349; Study 2B Scarcity Phase 3 – Study 2A Scarcity Phase 3 = 54.45, z = 1.31, p = 0.189.

[27] CONTROL: Study 2B Control Phase 1 – Study 2A Control Phase 1 = 77.92, z = 1.98, p = 0.047; Study 2B Control Phase 2 – Study 2A Control Phase 2 = 26.36, z = 0.68, p = 0.494; Study 2B Control Phase 3 – Study 2A Control Phase 3 = 39.51, z = 0.99, p = 0.324.

5.2.4.5 Discovery

Discovery is defined as the number of times a participant selected any of the True Top-Three highest-valued platforms across Trials 1–15 of a given Phase. Control and Scarcity participants selected True Top Three platforms with similar frequency in Phase 2 to what they did in Phase 1. Abundance participants selected True Top-Three platforms significantly less often in Phase 2 than they did in Phase 1.

No change in platform values produced *no change* in Discovery. A *decrease* in platform values produced *no change* in Discovery. An *increase* in platform values produced a *decrease* in Discovery.

In every Phase of the experiment, Abundance participants in Study 2B selected True Top-Three platforms with similar frequency to Abundance participants in Study 2A.[28] In Phase 1, Control and Scarcity participants in Study 2B selected the True Top-Three platforms significantly more often than Control and Scarcity participants in Study 2A. In Phases 2 and 3, Control and Scarcity participants in Study 2B selected True Top-Three platforms with similar frequency to Control and Scarcity participants in Study 2A.[29]

5.2.4.6 Side Observations: Exemplar Players

Sampling Frequency. Starting on Trial 2 of each Phase, participants had the opportunity to view the pitches made by five Exemplar Players on the previous Trial. Therefore, participants had a

[28] ABUNDANCE: Study 2B Abundance Phase 1 – Study 2A Abundance Phase 1 = 3.52, $z = 1.84$, $p = 0.066$; Study 2B Abundance Phase 2 – Study 2A Abundance Phase 2 = –0.66, $z = -0.35$, $p = 0.728$; Study 2B Abundance Phase 3 – Study 2A Abundance Phase 3 = –0.78, $z = -0.40$, $p = 0.691$.

[29] CONTROL: Study 2B Control Phase 1 – Study 2A Control Phase 1 = 4.51, $z = 2.31$, $p = 0.021$; Study 2B Control Phase 2 – Study 2A Control Phase 2 = 2.11, $z = 1.10$, $p = 0.273$; Study 2B Control Phase 3 – Study 2A Control Phase 3 = 2.19, $z = 1.09$, $p = 0.276$. SCARCITY: Study 2B Scarcity Phase 1 – Study 2A Scarcity Phase 1 = 5.48, $z = 2.72$, $p = 0.007$; Study 2B Scarcity Phase 2 – Study 2A Scarcity Phase 2 = 2.76, $z = 1.39$, $p = 0.165$; Study 2B Scarcity Phase 3 – Study 2A Scarcity Phase 3 = 1.32, $z = 0.88$, $p = 0.380$.

total of 70 opportunities to sample side observations of the platform values by viewing Exemplar Players (70 opportunities = 5 Exemplar Players × 14 Trials). There were no differences between Conditions in any Phase of the experiment. Participants in all three Conditions chose to view Exemplar Players with similar frequency across Phases 1 and 2.

No change in platform values produced *no change* in the frequency of viewing Exemplar Players. *No change* in the frequency of viewing Exemplar Players was observed following an *increase* in platform values, or following a *decrease* in platform values.

The frequency with which Study 2B participants chose to view Exemplar Players was similar to the frequency with which Study 2A participants chose to view Random Pitches in every Condition and Phase of the experiment.[30] We don't find evidence that participants' appetite for side observations differs when those side observations are generated by a random sampling process (Random Pitches) versus the actions of an intentional, goal-directed actor (Exemplar Players).

Sampling Bias. Each of the 5 Exemplar Players was represented by a button on the participants' screen. Three Exemplar Players appeared in the top row of the button tray (in order from left to right: Exemplar Player 1, Exemplar Player 2, Exemplar Payer 3). Two Exemplar Players appeared in the bottom row of the button tray (in order from left to right: Exemplar Player 4, Exemplar Player 5). Participants in all three Conditions viewed Exemplar Players in

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[30] CONTROL: Study 2B Control Phase 1 – Study 2A Control Phase 1 = 0.51, $z = 0.11$, $p = 0.915$; Study 2B Control Phase 2 – Study 2A Control Phase 2 =0.28, $z = 0.06$, $p = 0.953$; Study 2B Control Phase 3 – Study 2A Control Phase 3 = 0.31, $z = 0.06$, $p = 0.951$. ABUNDANCE: Study 2B Abundance Phase 1 – Study 2A Abundance Phase 1 = 5.23, $z = 1.11$, $p = 0.267$; Study 2B Abundance Phase 2 – Study 2A Abundance Phase 2 = 5.19, $z = 1.11$, $p = 0.269$; Study 2B Abundance Phase 3 – Study 2A Abundance Phase 3 = 6.20, $z = 1.25$, $p = 0.212$. SCARCITY: Study 2B Scarcity Phase 1 – Study 2A Scarcity Phase 1 = 4.97, $z = 1.11$, $p = 0.267$; Study 2B Scarcity Phase 2 – Study 2A Scarcity Phase 2 = 3.54, $z = 0.72$, $p = 0.474$; Study 2B Scarcity Phase 3 – Study 2A Scarcity Phase 3 = 3.67, $z = 0.70$, $p = 0.482$.

the top row of the button tray more often than Exemplar Players in the bottom row of the button tray.

Exemplar Player 1, who was located in the top-left corner of the button tray and had average achievement, received significantly more views than Exemplar Player 3, who was located in the top-right corner of the button tray and had the highest achievement. Exemplar Player 2, who was located in the top-middle position of the button tray and had the lowest achievement, received significantly more views than Exemplar Player 4, who had the second-highest achievement and was located in the bottom-left position in the button tray. Exemplar Player achievement seems to have no effect on the number of times participants choose to view each Player.

5.2.4.7 Take-Aways from Study 2B

The central hypothesis of the present research program is that *negative* resource shocks reduce a person's appetite for social information. I proposed social information appetite as the underlying mechanism driving the contraction observed in "real world" communication networks following a negative shock (e.g. among coastal fisherfolk in Ramirez-Sanchez & Pinkerton, 2009; among hedge fund employees in Romero, Uzzi, & Kleinberg, 2016). The biggest take-away from Study 2B is that we observe *no effect* of resource shocks on participants' appetite for social information – participants choose to view Random Pitches with the same frequency following *no change* in platform values (Control), an *increase* in platform values (Abundance), or a *decrease* in platform values (Scarcity).

Study 2B is not a perfect test of the hypothesis that resource shocks affect appetite for social information. It is possible that participants were not convinced that the Exemplar Player pitches were actually sampled from real participants in Study 1. It is also possible that participants did believe the Exemplar Player pitches were sampled from Study 1, but that these pitches would not contain very useful information because Study 1 participants were isolated and had no access to side observations of the platform values. However, as a first approximation, Study 2B does cast doubt over my hypothesis that negative resource shocks reduce a person's appetite for social information.

To my knowledge, Studies 2A and 2B are the first to contrast participants' appetite for random samples with samples taken by intentional actors within the same experimental paradigm. So, I did not have strong priors over potential differences in participants' attitude toward these two sources of information. It is possible that people perceive both types of information as equally informative. And, it might depend on task incentive structure. But, in the present context, it seems reasonable to expect *some* difference in participants' valuation of the two information types. The reason is that the expected value of randomly sampled pitches does not increase across Trials, but the average value of past participants' pitches *does* increase across Trials. Intuitively, participants should be more interested in viewing pitches if those pitches are more likely to contain higher-valued platforms. This is especially true on later Trials, when participants are less likely to engage in independent exploration.

Study 2B also raises concerns over the current experimental design. Participants' decisions to access social information in Study 2B are not consistent with behavioral patterns observed in related social learning experiments that offer participants the opportunity to learn about the distribution of rewards in their environment by sampling information about their peers. In related experiments, participants exhibited a strong preference for viewing their highest-achieving peers (McElreath et al., 2008; Mesoudi, 2011; Mesoudi & O'Brien, 2008; Morgan et al., 2012) even when this sampling heuristic was not optimal (Offerman & Schotter, 2009).

Study 2B participants *did not* view higher-achieving Exemplar Players more often than lower-achieving Exemplar Players. Instead, participants' preference to view one Exemplar Player over another was influenced by the Position of each Exemplar Player in the button tray. Exemplar Players whose Player buttons were located closer to the top-left corner of the button tray were viewed more often. (This may signal that participants were not convinced by the *true* cover story that Exemplar Players were sampled from the Study 1 participant pool.)

Participants in related experiments also viewed their peers more often following a "failure" or a decline in realized rewards (Atkisson, O'Brien, & Mesoudi, 2012; Morgan et al., 2012). In Study 2B, participants who experience a decline in rewards (Scarcity) do not view Exemplar Players more often than participants who experience stable rewards (Control) or participants who experience an increase in rewards (Abundance).

One obvious explanation for differences between the behavior of Study 2B participants and the behavior of participants in related experiments is that the design of the present experiments is too complicated. Perhaps participants were unable to discriminate among Exemplar Players' achievement levels because they were overwhelmed by the task and were unable to respond strategically.

However, the present experimental task is actually *less* complicated than the tasks used in many of the related experiments. For example, in Mesoudi's Arrowhead Task (Atkisson, Mesoudi, & O'Brien, 2012; Mesoudi, 2008; Mesoudi, 2011; Mesoudi & O'Brien, 2008), participants design an arrowhead by manipulating levels of five distinct features. The optimal design is not a linear combination of these features, but a function that forms a multi-peaked landscape (NK-landscape). This is arguably more complicated than the present experimental task, in which participants need only discover the three highest-valued platforms in order to maximize their payoffs.

We also observe substantial learning across Trials within each Phase of the experiment. And, in Study 1, participants' response to a decrease in resource levels (increased Exploration, decreased Exploitation) was consistent with the response of participants in similar solo explore-exploit tasks with shifting resource distributions.

We'll return to a discussion of the limitations of the present experimental design in our final discussion. For now, it is just important to keep in mind that the primary mechanism expected to drive contraction in communication network size (decreased appetite for social information following a decrease in resource values) is not observed in Study 2B.

6 STUDIES 3A & 3B: INTERACTIVE PARTICIPANT GROUPS

6.1 Study 3A: Groups (No Competition)

In Study 2B, we *did not* find that a decrease in resource values reduced participants' appetite for social information. Study 3A moves above the individual level to test whether the effect of resource shocks on the structure of communication networks is moderated by a dynamic process of interaction between peers. In the context of a sales organization like the one modeled in the present experiments, it is difficult for salespeople to directly observe their peers' decisions, or the outcomes of those decisions. Information about the environment can't be collected through passive observation, it must be *exchanged*. In Study 3A, I make access to peer results contingent on participants' willingness to exchange information with one another. This allows me to test whether resource shocks affect the structure of communication networks by altering people's willingness to engage in information exchange.

Studies of knowledge sharing in firms, professional associations, and online communities have identified reciprocity (the expectation that information will be received in return for information shared) as one of the primary factors that determine whether an individual chooses to engage in information exchange (Ackerman, 1998; Bock et al., 2005; Chiu, Hsu, and Wang, 2006; Lin, 2007; Mirc & Park, 2019; cf. Wasko and Faraj, 2005; Watson & Hewett, 2006). People are more likely to share information with peers when they believe those peers will also share information in return. When the expectation of reciprocity decreases, so does information sharing.

When resources are scarce, expectations of reciprocity are likely to decrease. Sirola and Pitesa (2017) found that employees were more likely to report holding a zero-sum construal of success during economic downturns, which resulted in decreased helping behavior among coworkers. Antisocial behaviors (including knowledge hoarding) increase when resources are scarce (Roux, Goldsmith, and Bonezzi, 2015), even when such behaviors come at a personal cost to the perpetrator (Prediger, Vollan, and Herrmann, 2014). If participants reason egocentrically about their peers' behavior, they will expect their peers to behave selfishly and withhold information about their results.

Participants in Study 3A are matched into groups of 6 at the start of the game. At the end of each Trial, participants must choose whether or not to *share* their results with the other people in their group. If two participants *both* choose to share their results with each other, then they *both* have the option to view each other's results while making their pitch selection on the next Trial. If *either* participant chooses *not* to share with the other, then *neither* participant can see the other's results. I will refer to this rule as the "sharing contingency.

Not that there is no competition among participants in Study 3A, and no strategic reason to withhold information from peers in this context. Participants are compensated based on individual performance, and have no expectation that their performance will be contrasted with their peers.

6.1.1 Participants

534 people participated in Study 3A. All participants were recruited online. 162 participants (Female = 112[1]; Average Age = 28, SD = 6) were recruited through the Center for Decision Research (CDR) at the University of Chicago Booth School of Business. 372 participants

[1] Demographic information was not collected from 1 participant in the Control Condition recruited through the CDR due to a software platform error. This participant is excluded from subsequent figures and analyses to maintain consistent cases across models. Five CDR participants selected "Other" as their gender.

(Female = 170; Average Age: 39, SD = 12) were recruited through Amazon Mechanical Turk (MTurk).

CDR participants were paid a $10.00 base fee upon completion of the focal procedure, and earned a variable performance-based bonus (Average Bonus: $6.80, SD = $0.27). MTurk participants were paid a $6.00 base fee upon completion of the focal procedure, and earned a variable performance-based bonus (Average Bonus: $6.79, SD = $0.43). MTurk participants also earned an Active Participation Bonus of $4.00 if they consistently submitted their responses before the time limits (described in *3.1.1 Recruitment and Compensation*).

Table 6.1. Study 3A: Distribution of Participants by Recruiting Source. Count of groups (and participants) in each experimental Condition, by recruiting platform (CDR vs. MTurk).

			CDR		MTurk	
Condition	N (Groups)	N (Ps)	N (Groups)	N (Ps)	N (Groups)	N (Ps)
Abundance	30	180	8	48	22	132
Control	30	180	11	66	19	114
Scarcity	29	174	8	48	21	126
Total	89	534	27	162	62	372

Participants completed the focal procedure in groups of size 6.[2] All participants in a given group were assigned to the same Condition.[3] Groups were assigned to one of six experimental Conditions (Table 6.1): Abundance (180 participants, 30 groups); Control (180

[2] After successfully completing the Comprehension Check, participants enter a virtual waiting room. As soon as 6 participants are present in the waiting room, these 6 participants advance to the focal procedure as a group.
[3] Conditions were assigned to each experimental group quasi-randomly. After completing the Enrollment Questionnaire, participants were allowed to participate in any of the pre-scheduled experimental sessions. The number of days between completing the Enrollment Questionnaire and participating in an experimental session varied across participants. Information and recruitment materials were identical for each experimental session. All groups in a given experimental session were assigned to the same Condition, to maximize the probability of group matching and minimize participant wait times between passing the Comprehension Check and being assigned to their experimental group.

participants, 30 groups); or Scarcity (174 participants, 29 groups).   Control, Scarcity, and Abundance carry the same meaning as before, and refer to the trends in platform values described in *Section 3 Common Design Elements* (Abundance = increasing; Control = constant; Scarcity = decreasing).

6.1.2 Procedure

The focal experimental procedure is identical to that described in *3.1.3 Procedure* with the addition of two critical elements. Participants in Study 3A have the option to share their results with their peers, and to view their peers' results. As before, participants are taken to a results screen at the end of each Trial where they are shown the points the customer assigned to each platform in their pitch. On the results screen, participants in Study 3A are given the option to share their results with each of their peers (see Figure 6.1).

Participants are instructed that they will only be able to view each peer's results if *both* the participant *and* the participant's peer choose to share their results with each other. If *either* the participant *or* the peer choose *not* to share their results, then *neither* the participant *nor* the peer are able to view the other's results. There is no cost to share results with peers other than time and cognitive load. Participants have 60 seconds to review their results and enter their sharing decisions. After 60 seconds, the procedure automatically advances to the next screen. If the participant fails to enter his sharing decisions before time runs out, all decisions are set to "NO, DON'T SHARE."

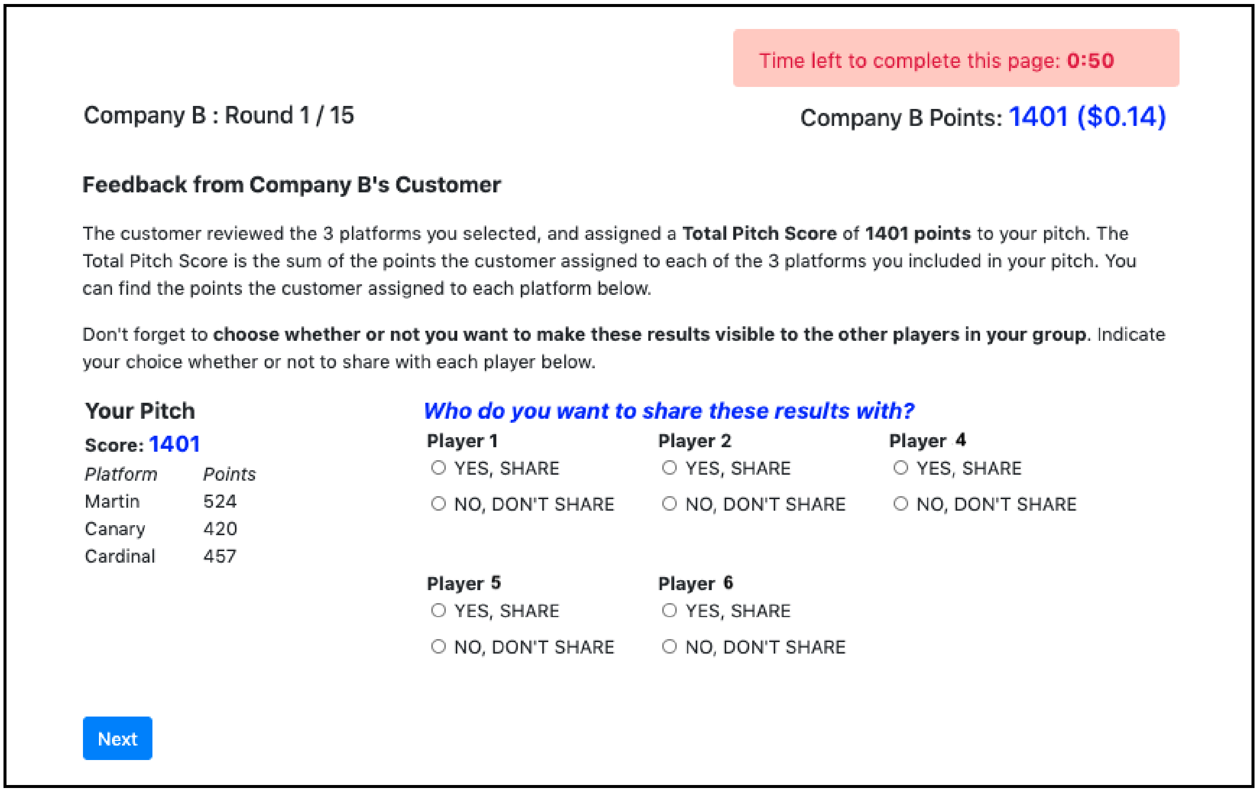

Figure 6.1. Screenshot of Results Screen in Study 3A. Taken from the perspective of a Control participant in Position 3 on Trial 1 of Phase 1. Following Trials 1–14 of each Phase, participants choose whether or not to share their results with their peers by selecting “YES, SHARE” or “NO, DON’T SHARE” beneath each peer’s label. Participants have 60 seconds to review their results and enter their sharing decisions. Sharing decisions are not elicited on Trial 15 of each Phase because participants move on to a different Company, and a different list of platforms, after completing Trial 15.

After making their sharing decisions, participants advance to the next Trial. Starting with the second Trial of each Phase, participants can choose whether or not view each of their peers’ results while selecting their pitch. Each peer is represented by a button on the pitch selection screen (see Figure 6.2).

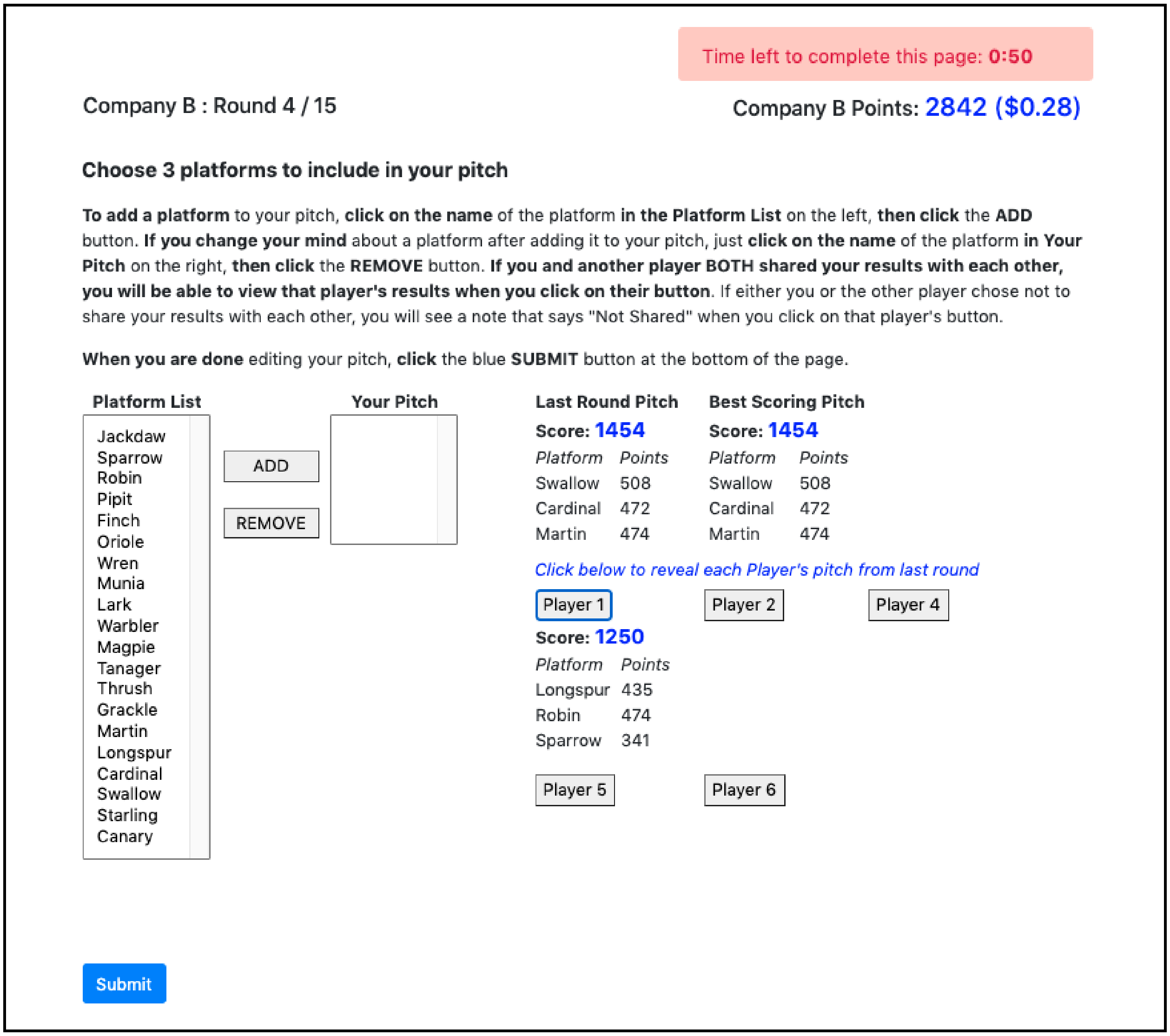

Figure 6.2. Screenshot of Pitch Selection Screen on Trials 2-15 of Each Phase. Taken from the perspective of Player 3 in Phase 1 of the Control Condition in Study 3A. Starting on the second Trial of each Phase, participants can choose to view their peers' results from the last Trial while selecting their pitch. Peer results are only shown if *both* the participant *and* the peer chose to share their results with each other at the end of the preceding Trial. Each peer is represented by a Player button on the pitch selection screen. Participants click a peer's button to view that peer's results from the preceding Trial. Only one peer's results can be viewed at a time. Participants can view each peer's results as many times as they wish.

Participants in each group are randomly assigned a Position in their Group, designated by a number between 1 and 6. The participant's Position determines the location of his Player button on the screens of each of his peers. From the perspective of each participant, peers'

Player buttons are ordered from lowest Position to highest Position in the button tray, starting with the top-left position and ending with the bottom-center position. Refer to Figure 6.3 to see the layout of the peer Player buttons on the Pitch Selection screen for Trials 2–15, from the perspective of the participant in each Position.

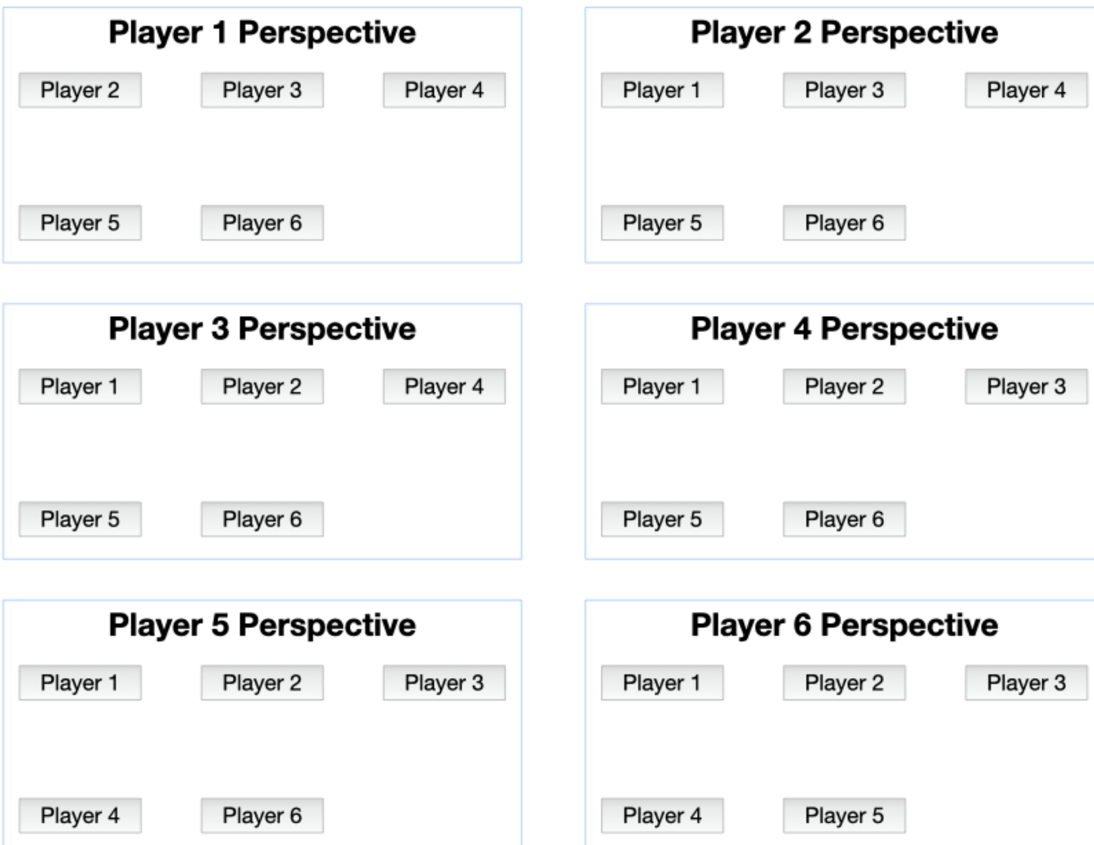

Figure 6.3. Order of Peer Player Buttons. Order of peer Player buttons in the button trays on the Pitch Selection and Results screens, from the perspective of each participant Position (1,...,6). Note that the relative ordering of the Player Positions is the same from each perspective. The only difference is that the Player button for the participant's own Position is excluded from his perspective. The layout of the Results screen on Trials 1–14 – on which participants choose whether or not to share their results with each peer – is analogous.

Note that the *relative* ordering of the Player buttons is the same from each perspective. The only difference is that the Player button for the participant's own Position is excluded from his perspective. (The layout of the Results screen on Trials 1–14 – on which participants choose whether or not to share their results with each peer – is analogous.)

When participants click a peer's button, that peer's results from the preceding Trial are displayed. Only one peer's results can be viewed at a time. (If the peer's results are not shared – either because the participant did not choose to share with the peer, the peer did not choose to share with the participant, or both – then the participant sees the message "*Not shared*" when she clicks on the peer's button.) Participants can view each peer's results as many times as they wish. There is no cost to view this information other than time and cognitive load. Participants have 60 seconds to submit their pitch. After 60 seconds, the procedure automatically advances to the results screen. If the participant fails to enter his pitch before time runs out, an empty pitch is recorded and no points are earned for the current Trial.

After completing the focal procedure, participants in Study 3A complete the Debrief Questionnaire described in *3.1.3 Procedure*. Participants are also asked to rate the extent to which each of their peers helped or harmed their performance during the focal procedure on a scale of 0 (Very Harmful) to 100 (Very Helpful).[4]

6.1.3 Participant-Level Results

I exclude participants who were marked as dropouts after repeatedly failing to submit their responses before the time limits. 21 participants across 18 groups met this exclusion criteria: Abundance = 11 participants, 9 groups; Control = 6 participants, 6 groups; Scarcity = 4

[4] "Do you feel like the other players in your group helped you perform better in The Sales Game? Use the sliding scales below to indicate how much you feel each of the other players helped or harmed your performance in The Sales Game. Select "Very Helpful" if you feel like the player had a big positive impact on your performance, or select "Very Harmful" if you feel like the player had a big negative impact on your performance."

participants, 3 groups). I also exclude Trials on which participants failed to submit their response before the time limit expired (timeouts).

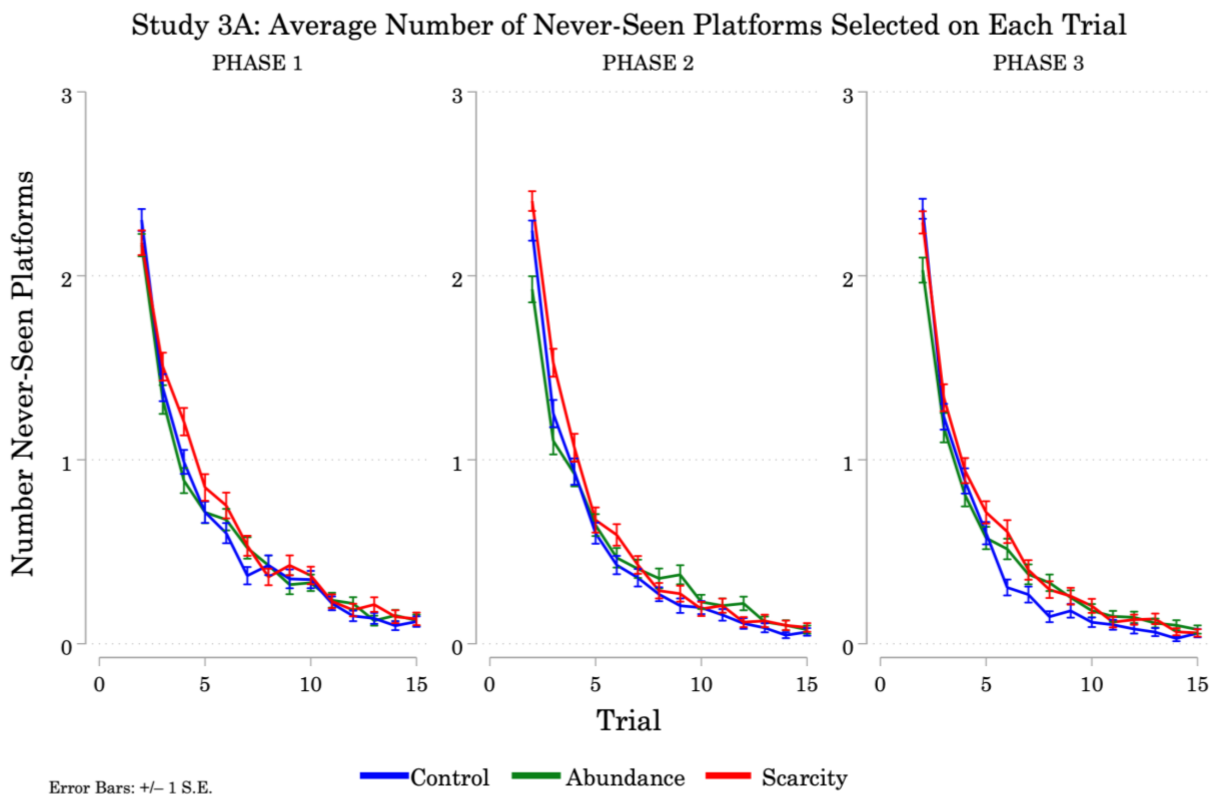

Figure 6.4. Study 3A: Exploration. Average number of Never-Seen platforms selected on each Trial, by Phase and Condition. Error bars = +/– 1 S.E. N = 513. Green = Abundance (169 participants, 30 groups); Blue = Control (174 participants, 30 groups); Red = Scarcity (170 participants, 29 groups). Note that the curves begin on Trial 2, the first opportunity to observe differences (the number of Never-Seen platforms on Trial 1 is always 3 for every participant). In Phase 1, there are no consistent differences between Conditions. In Phase 2, Scarcity participants explore a higher number of platforms than Control and Abundance participants on Trials 2 and 3, and then exploration rates converge across the three Conditions. In Phase 3, Scarcity and Control participants explore more platforms than Abundance participants on Trial 2, and then exploration rates converge (except for a slight increase in exploration among Scarcity participants around Trials 6 and 7).

6.1.3.1 Exploration

Figure 6.4 presents the average number of Never-Seen platforms participants selected on each Trial, in each Phase of Study 3A. In Phase 1, there are no consistent differences between

Conditions (Scarcity participants explore slightly more platforms than Control participants on Trials 4 and 6). In Phase 2, Scarcity participants explore a higher number of platforms than Control participants, and Control participants explore a higher number of platforms than Abundance participants, across Trials 2–3. By Trial 4, exploration rates across the three Conditions converge. In Phase 3, Scarcity and Control participants explore more platforms than Abundance participants on Trial 2. (Scarcity participants also explore slightly more platforms than Controls on Trials 6 and 7, but otherwise the exploration rates across the three Conditions appear to converge around Trial 3.)

Table 6.2 presents the parameter estimates and fit statistics from three different Three-Level Random Coefficient models for the number of unique platforms participants explored across Trials 1–15 of each Phase in Study 3A. Model 1 is the baseline model, and includes an intercept and piecewise linear slopes for Phases 2 and 3 (in the form of two linear spline functions for the change between Phases 1 and 2, and between Phases 2 and 3). The random part of Model 1 includes a random intercept at the Group level (Level 3) and a random intercept and random linear slope for Phase at the Participant level (Level 2).[5,6] Model 2 includes the main effect of Condition, and Model 3 introduces interactions among elements of the experimental design (Condition, Phase). The interaction between Condition and Phase was not significant, and Model 3 does not provide a significant improvement over Model 2 [$LR\ \chi^2(4) = 1.05$, $p = 0.903$]. However, the main effect of Condition was significant, and Model 2 does provide a

[5] Including a single linear slope in the random part of the model is more computationally efficient than estimating two separate slopes for each of the linear spline functions, and produces similar estimates.

[6] An alternative baseline model was fit with a random linear slope for Phase at the Group level (Level 3), but calculation of standard errors failed when main effects and interactions were added in Models 2 and 3, indicating that the data do not provide enough information to estimate these relationships. The solution in this case is to simplify the model starting at the highest group level, so the random linear slope for Phase at the Group level was removed in the final version of each model.

significant improvement over Model 1 [$LR\ \chi^2(2) = 9.04$, $p = 0.011$], so I will focus on the predictions from Model 2 .

Table 6.2. Study 3A: Exploration. Maximum likelihood estimates of Three-Level Random-Coefficient models for the number of unique platforms participants explored across Trials 1–15 of each Phase. Model 1: Intercept-Slope; Model 2: Main Effects; Model 3: Design Interactions. N = 513.

	Model 1		Model 2		Model 3	
	Est	(SE)	Est	(SE)	Est	(SE)
Fixed Effects						
Intercept β_0	11.18***	0.17	10.79***	0.26	10.89***	0.28
Phase 2 β_1	–0.93***	0.13	–0.93***	0.13	–1.08***	0.22
Phase 3 β_2	–0.44***	0.13	–0.44***	0.13	–0.43	0.22
Abundance β_3			0.18	0.35	0.01	0.39
Scarcity β_4			0.99**	0.35	0.87*	0.39
Abundance × Phase 2 β_5					0.23	0.32
Scarcity × Phase 2 β_6					0.23	0.32
Abundance × Phase 3 β_7					0.06	0.32
Scarcity × Phase 3 β_8					–0.10	0.32
Random Effects						
L3 Random Intercept Var $\psi_{11}^{(3)}$	0.10	0.31	0.00	0.00	0.00	0.00
L2 Random Intercept Var$\psi_{11}^{(2)}$	9.63	0.86	9.54	0.85	9.54	0.82
L2 Random Slope Var $\psi_{22}^{(2)}$	1.02	0.22	1.02	0.22	1.02	0.22
L1 (Residual) Error Variance θ	3.79	0.24	3.79	0.24	3.79	0.24
Log likelihood	–3864		–3859		–3859	
AIC | *BIC*	7743 | 7786		7738 | 7792		7745 | 7820	

* $p \le 0.05$; ** $p \le 0.01$; *** $p \le 0.001$

In Phase 1, Control participants explored 10.79 ($z = 42.25$, $p < 0.000$) platforms on average. Abundance participants explored a similar number of platforms to Controls ($\beta_3 = 0.18$ $z = 0.50$, $p = 0.614$). Scarcity participants explored a significantly higher number of platforms than Controls ($\beta_4 = 0.99$, $z = 2.85$, $p = 0.004$).

In Phase 2, Control participants explored significantly fewer platforms than they did in Phase 1 (β_1 = –0.93, z = –7.15, p < 0.000). In Phase 3, Control participants explored significantly fewer platforms than they did by the end of Phase 2 (β_2 = –0.44, z = –3.39, p = 0.001). As the interaction between Phase and Condition was not significant, the relationships between Conditions are the same in Phases 2 and 3 as in Phase 1: Abundance participants explored a similar number of platforms to Controls, and Scarcity participants explored significantly more platforms than Controls. Abundance and Scarcity participants decrease their exploration rates across Phases to a similar extent as Controls.

6.1.3.2 Exploitation

Figure 6.5 presents the average number of Personal-Best platforms selected by participants on each Trial of each Phase in Study 3A (the number of platforms in the current pitch that have one of the three highest empirical averages based on what the participant has seen so far in the current Phase). There are no consistent differences between Conditions in Phase 1. In Phase 2, Scarcity participants exploit their Personal-Best platforms slightly less often than Controls on a majority of Trials. In Phase 3, Scarcity and Abundance participants exploit their Personal-Best platforms significantly less often than Controls on a majority of Trials.

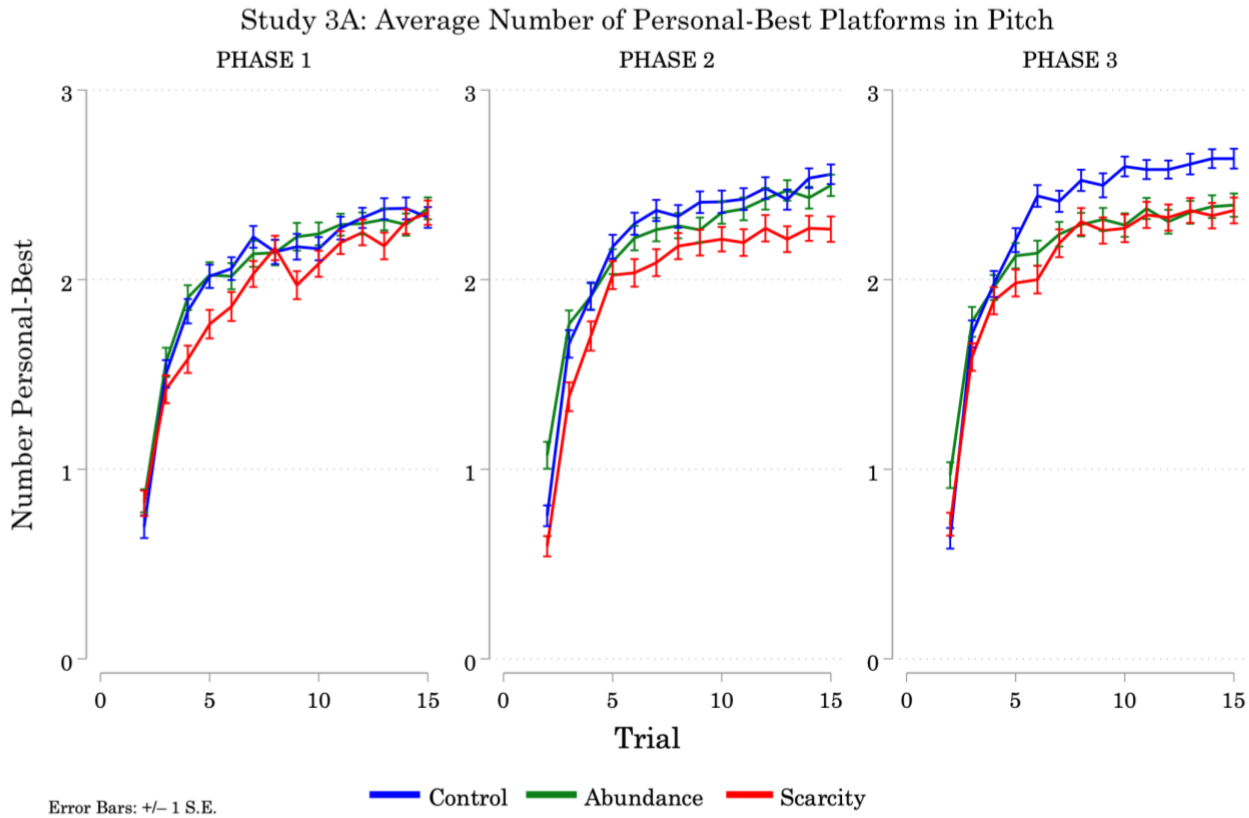

Figure 6.5. Study 3A: Exploitation. Average number of Personal-Best platforms selected on each Trial, by Phase, Condition. Error bars = +/– 1 S.E. N = 513. Green = Abundance (169 participants, 30 groups); Blue = Control (174 participants, 30 groups); Red = Scarcity (170 participants, 29 groups). Note that the curves begin on Trial 2. On Trial 1, all of the platforms selected have no empirical history. There are no consistent differences between Conditions in Phase 1. In Phase 2, Scarcity participants exploit their Personal-Best platforms slightly less often than Controls on a majority of Trials. In Phase 3, Scarcity and Abundance participants exploit their Personal-Best platforms significantly less often than Controls on a majority of Trials.

As before, we will look at the cumulative number of times participants exploited their top-three Personal-Best Platforms across Trials 2–15 of each Phase. Table 6.3 presents the parameter estimates and fit statistics from three different Three-Level Random Coefficient models for the cumulative number of times participants selected their Personal-Best platforms across Trials 2–15 in a given Phase.

Model 1 is the baseline model. The fixed part of Model 1 includes an intercept and piecewise linear slopes for Phases 2 and 3. The random part of Model 1 includes a random intercept and a random linear slope for Phase at the Participant level (Level 2) and at the Group level (Level 3). Model 2 includes Condition as a fixed effect. Model 3 introduces two-way interactions between elements of the experimental design (Condition, Phase). Model 3 provides a significant improvement over Model 2 [*LR* $\chi^2(4) = 14.29$, $p = 0.006$], and over Model 1 [*LR* $\chi^2(6) = 22.61$, $p = 0.001$], so I will focus on the Model 3 estimates.

Table 6.3. Study 3A: Exploitation. Maximum likelihood estimates of Three-Level Random-Coefficient models for the number of times participants selected their Personal-Best platforms across Trials 2–15 of each Phase. Model 1: Intercept-Slope; Model 2: Main Effects; Model 3: Design Interactions. N = 513.

	Model 1		Model 2		Model 3	
	Est	(SE)	Est	(SE)	Est	(SE)
Fixed Effects						
Intercept β_0	27.76***	0.38	28.62***	0.60	28.22***	0.64
Phase 2 β_1	1.60***	0.30	1.60***	0.30	2.15***	0.51
Phase 3 β_2	0.72*	0.30	0.72*	0.30	1.45**	0.51
Abundance β_3			–0.32	0.83	0.16	0.90
Scarcity β_4			–2.27**	0.83	–1.53	0.91
Abundance × Phase 2 β_5					–0.24	0.73
Scarcity × Phase 2 β_6					–1.44*	0.73
Abundance × Phase 3 β_7					–2.09**	0.73
Scarcity × Phase 3 β_8					–0.11	0.73
Random Effects						
L3 Random Intercept Var $\psi_{11}^{(3)}$	3.35	1.95	2.59	1.86	2.49	1.83
L3 Random Slope Var $\psi_{22}^{(3)}$	1.49	0.53	1.49	0.53	1.26	0.49
L2 Random Intercept Var $\psi_{11}^{(2)}$	37.78	3.75	37.75	3.74	37.97	3.74
L2 Random Slope Var $\psi_{22}^{(2)}$	1.88	0.96	2.07	0.95	2.21	0.95
L1 (Residual) Error Var θ	18.16	1.13	18.16	1.13	17.88	1.12
Log likelihood	–5025		–5021		–5014	
AIC | *BIC*	10070 | 10123		10066 | 10130		10059 | 10145	

* $p \leq 0.05$; ** $p \leq 0.01$; *** $p \leq 0.001$; SE = standard error of the mean

In Phase 1, Control participants exploited their personal-best platforms 28.22 ($z = 44.36$, $p < 0.000$) times on average. Abundance and Scarcity participants exploited their personal-best platforms about the same number of times as did Controls (β_3 = 0.16, z = 0.17, p = 0.864; β_4 = –1.53, z = –1.69, p = 0.091).

In Phase 2, Control participants exploited their personal-best platforms about 30.37 times on average, which is a significant increase over the number of times they exploited their personal-best platforms in Phase 1 (β_2 = 2.15, z = 4.22, p < 0.000). Abundance participants exploited their personal-best platforms about the same number of times as did Controls (Abundance Phase 2 – Control Phase 2 = –0.08, z = –0.09, p = 0.929), which was a significant increase over the number of times they exploited their personal-best platforms in Phase 1 (Abundance Phase 2 – Abundance Phase 1 = 1.92, z = 3.71, p < 0.000). Scarcity participants exploited their personal-best platforms significantly less often than did Controls (Scarcity Phase 2 – Control Phase 2 = –2.97, z = –3.22, p = 0.001), which was similar to the number of times they exploited their personal-best platforms in Phase 1 (Scarcity Phase 2 – Scarcity Phase 1 = 0.72, z = 1.39, p = 0.164).

In Phase 3, Control participants exploited their personal-best platforms about 31.82 times on average, which is a significant increase over the number of times they exploited their personal-best platforms in Phase 1 (β_3 = 1.44, z = 2.84, p = 0.005). Abundance participants exploited their personal-best platforms significantly less often than did Controls (Abundance Phase 3 – Control Phase 3 = –2.17, z = –2.07, p = 0.038), which was similar to the number of times they exploited their personal-best platforms in Phase 2 (Abundance Phase 3 – Abundance Phase 2 = –0.64, z = –1.24, p = 0.216). Scarcity participants exploited their personal-best platforms significantly less often than did Controls (Scarcity Phase 3 – Control Phase 3 = –3.08, z = –2.93, p = 0.003), and significantly more often than the number of times they exploited their personal-best platforms in Phase 2 (Scarcity Phase 3 – Scarcity Phase 2 = 1.34, $z = 2.59$, $p = 0.010$).

6.1.3.3 Mental Models

Participants were asked to estimate the average value of each platform after the 8th and 15th Trials of each Phase. Here we will focus on participants' second estimates, following Trial 15. Figure 6.6 plots the average estimated value of each platform against that platform's true average value. The red, dotted 45-degree lines indicate what the shape of each curve would look like if there was perfect agreement between the average estimated values reported by participants and the true values of each platform. One way to think about the accuracy of participants' estimates is to consider the proximity of the estimates curve to the 45-degree line.

Control participants' average error was similar across Phases 1–3. Abundance participants' average error increased significantly across Phases, and was significantly higher than Controls in Phases 2 and 3. Scarcity participants' average error decreased significantly in Phase 2 and in Phase 3. Scarcity participants' average error was significantly higher than Controls in Phase 1, and similar to Controls in Phases 2 and 3.

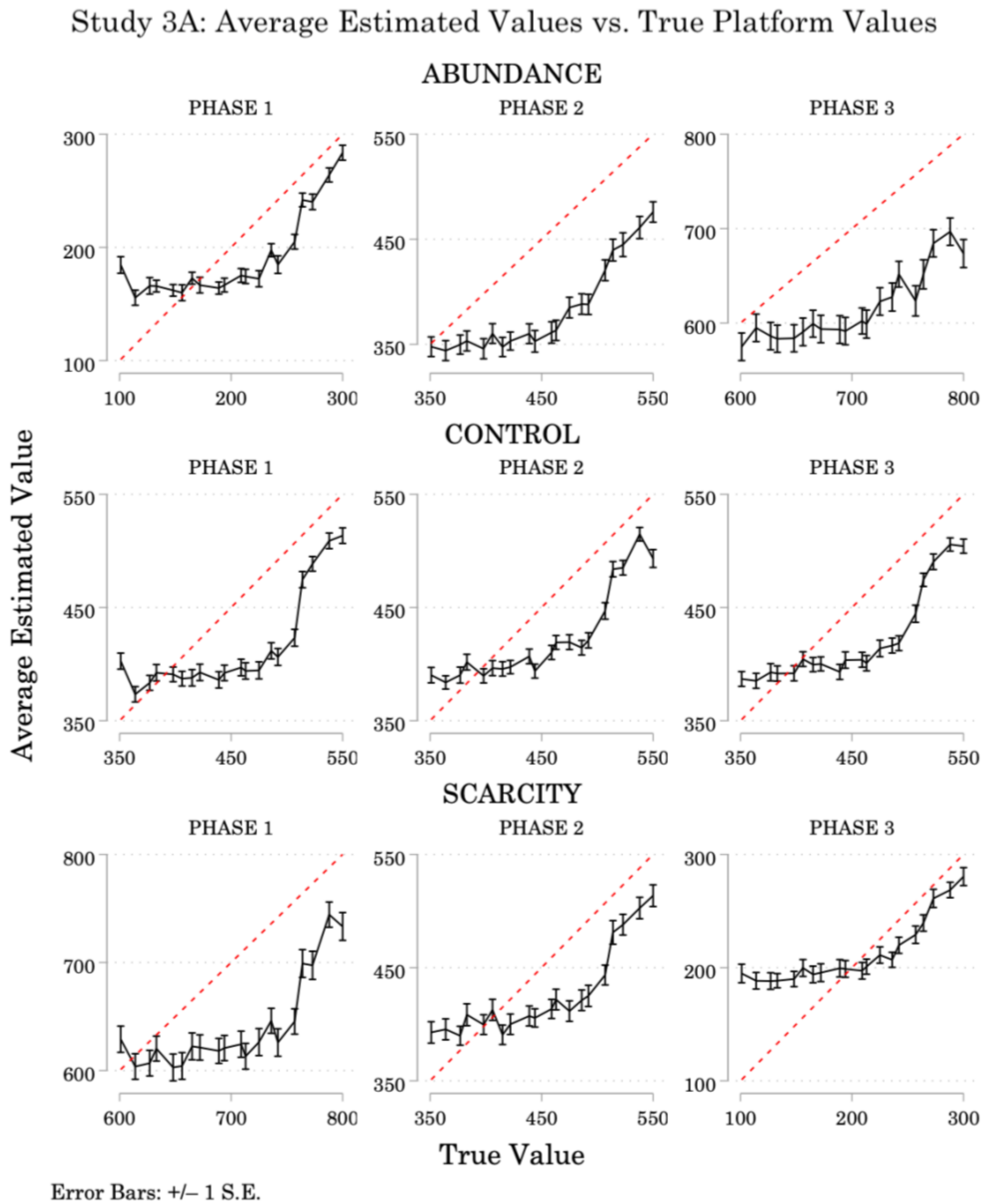

Figure 6.6. Study 3A: Mental Models. Average estimated values versus true average values of each platform, by Phase and Condition. Error bars = +/– 1 S.E. N = 501.[7] Top Row: Abundance (164 participants, 30 groups). Middle Row: Control (172 participants, 30 groups). Bottom Row: Scarcity (165 participants, 29 groups). Results for second estimate made by participants in each Phase (following Trial 15). Average estimated values on y-axes. True average platform values on the x-axes. Red dotted 45-degree lines mark "perfect agreement" between average values estimated by participants and each platform's true average value.

[7] 9 participants were dropped because they shirked the task (Abundance = 5; Control = 2; Scarcity = 3). Shirking behavior includes entering zeros or alternating single digit numbers (e.g. 1-0-1-0) for at least half of their estimates in at least one Phase of the experiment. 3 Scarcity participants were dropped because at least four of their estimates were extreme outliers (Extreme outliers are defined as estimates that fall more than two times the size of the interquartile range above the 75th percentile, or more than two times the size of the interquartile range below the 35th percentile.)

Table 6.4 presents the parameter estimates and fit statistics from three different Three-Level Random Coefficient models for the Mean Absolute Difference between participants' estimates of each platform's average value on Trial 15 of each Phase, and the true average value of each platform. Model 1 is the baseline model, and includes an intercept and piecewise linear slopes for Phases 2 and 3. The random part of Model 1 includes a random intercept and random linear slope for Phase at the Group level (Level 3) and at the Participant level (Level 2). Model 2 includes Condition as a fixed effect. Model 3 introduced interactions among elements of the experimental design (Condition, Phase). Model 3 provides a significantly better fit than Model 2 $LR\ \chi^2(4) = 53.06$, $p < 0.000$] and Model 1 [$LR\ \chi^2(6) = 59.59$, $p < 0.000$], so I will focus on the predictions from Model 3.

In Phase 1, Control participants' average error was about 67.56 ($z = 10.70$, $p < 0.000$). Abundance participants' average error was similar to Controls ($\beta_3 = –9.89$, $z = –1.10$, $p = 0.271$). Scarcity participants' average error was significantly larger than Controls ($\beta_4 = 27.86$, $z = 3.09$, $p = 0.002$).

In Phase 2, Control participants' average error was 62.27, which was slightly lower than in Phase 1, but this decrease was not significant ($\beta_1 = –5.29$, $z = –0.99$, $p = 0.323$). Abundance participants' error was significantly higher than Controls (Abundance Phase 2 – Control Phase 2 = 33.78, $z = 3.64$, $p < 0.000$), and significantly higher than their error in Phase 1 (Abundance Phase 2 – Abundance Phase 1 = 37.79, $z = 6.95$, $p < 0.000$). Scarcity participants' error was similar Controls (Scarcity Phase 2 – Control Phase 2 = 13.48, $z = 1.47$, $p = 0.142$), but significantly lower than their error in Phase 1 (Scarcity Phase 2 – Scarcity Phase 1 = –19.68, $z = –3.58$, $p < 0.000$).

Table 6.4. Study 3A: Mental Models. Maximum likelihood estimates of Three-Level Random-Coefficient models for Mean Absolute Difference between Estimated Values and True Average Values on Trial 15 of each Phase. Model 1: Intercept-Slope; Model 2: Main Effects; Model 3: Design Interactions. N =501.

	Model 1		Model 2		Model 3	
	Est	(SE)	Est	(SE)	Est	(SE)
Fixed Effects						
Intercept β_0	73.33***	3.91	62.75***	5.91	67.56***	6.31
Phase 2 β_1	4.43	3.79	4.44	3.79	–5.29	5.35
Phase 3 β_2	7.82*	3.79	7.85*	3.79	0.79	5.35
Abundance β_3			11.01	8.01	–9.89	8.98
Scarcity β_4			21.08**	8.05	27.86**	9.03
Abundance × Phase 2 β_5					43.08***	7.62
Scarcity × Phase 2 β_6					–14.39	7.67
Abundance × Phase 3 β_7					28.92***	7.61
Scarcity × Phase 3 β_8					–8.04	7.66
Random Effects						
L3 Rand Intcpt Var $\psi_{11}^{(3)}$	154.15	223.75	45.26	225.13	18.39	52.71
L3 Rand Slope Var $\psi_{22}^{(3)}$	542.15	152.24	541.74	152.19	141.69	85.27
L2 Rand Intcpt Var $\psi_{11}^{(2)}$	5632.22	463.68	5632.95	463.33	5559.21	415.70
L2 Rand Slope Var $\psi_{22}^{(2)}$	1859.87	172.92	1859.52	172.90	1858.38	168.78
Level-1 Error Var θ	1092.52	70.06	1092.53	70.06	1080.56	69.29
Log likelihood	–8329		–8325		–8299	
AIC | *BIC*	16677 | 16730		16675 | 16738		16630 | 16715	

* $p \leq 0.05$; ** $p \leq 0.01$; *** $p \leq 0.001$

In Phase 3, Control participants' error was about 63.06, which was similar to their error in Phase 2 (β_2 = 0.79, z = 0.15, p = 0.882). Abundance participants' error was significantly higher than Controls (Abundance Phase 3 – Control Phase 3 = 62.10, z = 5.08, p < 0.000), and significantly higher than in Phase 2 (Abundance Phase 3 – Abundance Phase 2 = 37.79, z = 6.95, p < 0.000). Scarcity participants' error was similar to Controls (Scarcity Phase 3 – Control Phase 3 = 5.43, z = 0.44, p = 0.659), and similar to their own error in Phase 2 (Scarcity Phase 3 – Scarcity Phase 2

= –7.25, z = –1.32, p = 0.186).

Figure 6.7 presents the adjusted marginal predictions for the Mean Absolute Difference between participants' estimates and the true average value of each platform. Notice that Scarcity participants' average error is significantly higher than Abundance participants' average error in Phase 1 (Scarcity Phase 1 – Abundance Phase 1 = 39.42, z = 4.19, p < 0.000).

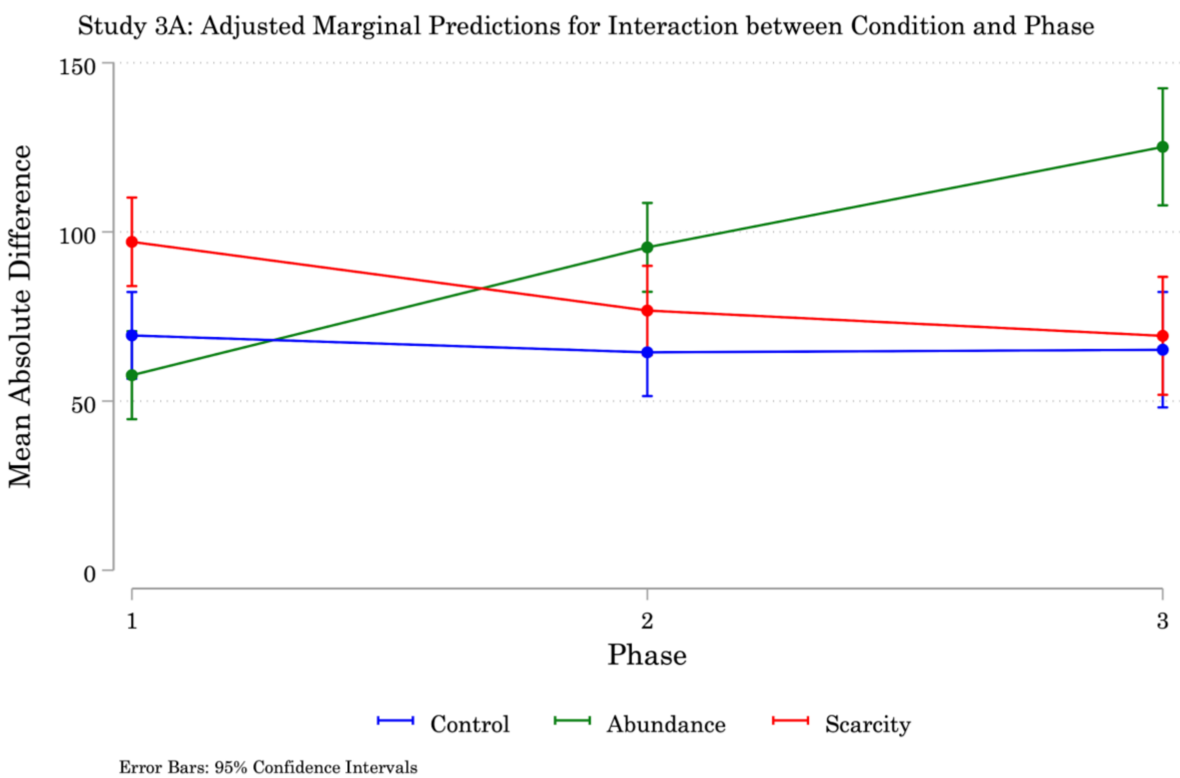

Figure 6.7. Study 3A: Mental Models Interaction. Adjusted marginal predictions for the interaction between Condition and Phase. Error bars = 95% Confidence Interval. N = 501. Green = Abundance (164 participants, 30 groups); Blue = Control (172 participants, 30 groups); Red = Scarcity (165 participants, 29 groups). In Phase 1, Scarcity participants' average error is significantly higher than Abundance and Control participants. In Phases 2 and 3, Abundance participants have significantly higher error than Scarcity and Control participants. Abundance participants' error increases significantly in Phase 2, and again in Phase 3. Scarcity participants' error decreases significantly in Phase 2. Control participants' error is similar across Phases 1–3.

When Abundance and Scarcity participants both face the Medium distribution in Phase 2, Abundance participants' error is significantly higher than Scarcity participants' (Abundance

Phase 2 – Scarcity Phase 2 = 18.68, $z = 1.97$, $p = 0.049$). Scarcity participants' error when they face the Low distribution in Phase 3 is slightly higher than Abundance participants' error when they face the Low distribution in Phase 1, but this difference is not significant (Scarcity Phase 3 – Abundance Phase 1 = 8.76, $z = 0.93$, $p = 0.355$). Scarcity participants' error when they face the High distribution in Phase 1 is significantly lower than Abundance participants' error when they face the High distribution in Phase 3 (Scarcity Phase 1 – Abundance Phase 3 = –25.01, $z = –2.49$, $p = 0.013$).

6.1.3.4 Rewards

Figure 6.8 presents participants' Standardized Achievement Scores on each Trial in each Phase of Study 3A. In Phase 1, Scarcity participants' scores are significantly lower than Controls across a majority of Trials. In Phase 2, Scarcity and Abundance participants' scores are slightly lower than Controls on a handful of Trials, but there are no consistent differences between Conditions. In Phase 3, Scarcity and Abundance participants' scores are lower than Controls across a majority of Trials.

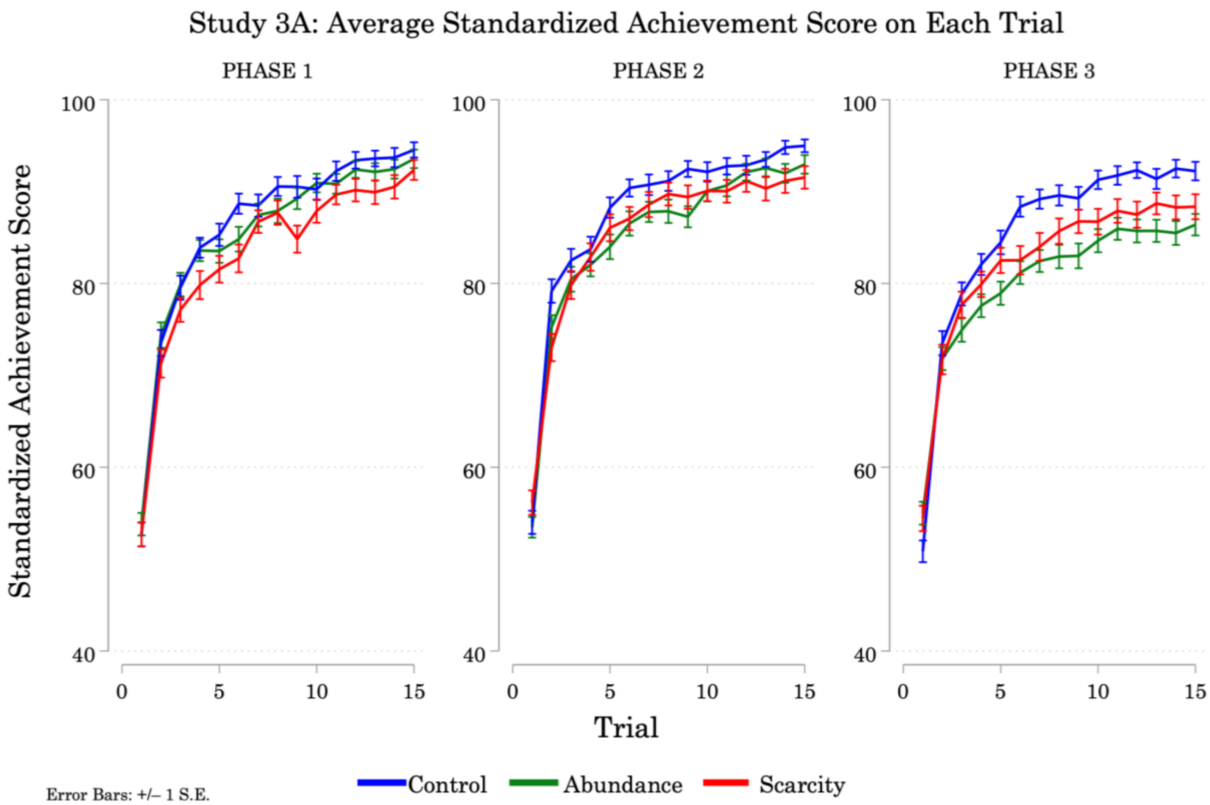

Figure 6.8. Study 3A: Rewards. Average Standardized Achievement Scores on each Trial, by Phase and Condition. N = 513. Green = Abundance (169 participants, 30 groups); Blue = Control (174 participants, 30 groups); Red = Scarcity (170 participants, 29 groups). In Phase 1, Scarcity participants' scores are significantly lower than Controls across a majority of Trials. In Phase 2, Scarcity and Abundance participants' scores are slightly lower than Controls on a handful of Trials, but there are no consistent differences between Conditions. In Phase 3, Scarcity and Abundance participants' scores are lower than Controls across a majority of Trials.

Table 6.5 presents the parameter estimates and fit statistics from three different Three-Level Random Coefficient models for participants' Cumulative Standardized Achievement Scores on Trial 15 of each Phase in Study 3A. Model 1 is the baseline model, and includes two pairwise linear spline functions representing Phase 2 and Phase 3. The random part of Model 1 includes a random intercept and a random linear slope for Phase at the Group level (Level 3), and at the Participant level (Level 2). Model 2 includes Condition as a fixed effect. Model 3 includes interactions among elements of the experimental design (Condition, Phase). Model 3 provides a significantly better fit than Model 2 [*LR* $\chi^2(4) = 10.15$, $p = 0.038$] and Model 1 [*LR* $\chi^2(6) = 15.04$, $p = 0.020$], so I will focus on the predictions from Model 3.

Table 6.5. Study 3A: Rewards. Maximum likelihood estimates of Three-Level Random-Coefficient models for participants' Cumulative Standardized Achievement Scores on Trial 15 of each Phase. Model 1: Intercept-Slope; Model 2: Main Effects; Model 3: Design Interactions. N = 513.

	Model 1		Model 2		Model 3	
	Est	(SE)	Est	(SE)	Est	(SE)
Fixed Effects						
Intercept β_0	1254***	8	1275***	13	1274***	14
Phase 2 β_1	23**	7	23**	7	23	12
Phase 3 β_2	–50***	7	–50***	7	–29*	12
Abundance β_3			–23	18	–14	20
Scarcity β_4			–41*	18	–46*	20
Abundance × Phase 2 β_5					–15	17
Scarcity × Phase 2 β_6					14	17
Abundance × Phase 3 β_7					–49**	17
Scarcity × Phase 3 β_8					–15	17
Random Effects						
L3 Random Intercept Var $\psi_{11}^{(3)}$	2140	921	1886	889	1838.36	875
L3 Random Slope Var $\psi_{22}^{(3)}$	2110	430	2109	430	1873.06	396
L2 Random Intercept Var $\psi_{11}^{(2)}$	15710	1545	15699	1544	15731.06	1543
L2 Random Slope Var $\psi_{22}^{(2)}$	393	361	393	361	415.36	361
Level-1 Error Variance θ	7339	458	7339	458	7300.75	456
Log likelihood	–9655		–9653		–9648	
AIC | *BIC*	19331 | 19384		19330 | 19394		19328 | 19413	

* $p \leq 0.05$; ** $p \leq 0.01$; *** $p \leq 0.001$

In Phase 1, Control participants accumulated standardized scores of about 1273.81 ($z = 91.49$, $p < 0.000$) on average. Abundance participants accumulated similar scores to Controls ($\beta_3 = –14.05$, $z = –0.71$, $p = 0.478$). Scarcity participants' scores were significantly lower than Controls ($\beta_4 = –45.92$, $z = –2.32$, $p = 0.021$).

In Phase 2, Control participants' accumulated standardized scores of about 1296.80, which is similar to the scores they earned in Phase 1 (β_1 = 22.99, z = 1.88, p = 0.059). Abundance and Scarcity participants' scores were similar to Controls (Abundance Phase 2 – Control Phase 2 = –28.55, z = –1.35, p = 0.177; Scarcity Phase 2 – Control Phase 2 = –31.92, z = –1.51, p = 0.132). Abundance participants' scores were similar to what they accumulated by the end of Phase 1 (Abundance Phase 2 – Abundance Phase 1 = 8.50, z = 0.69, p = 0.490). Scarcity participants' scores were significantly higher than what they accumulated by the end of Phase 1 (Scarcity Phase 2 – Scarcity Phase 1 = 36.99, z = 2.99, p = 0.003).

In Phase 3, Control participants accumulated standardized scores of about 1267.95, which is significantly lower than what they accumulated by the end of Phase 2 (β_2 = –28.85, z = –2.36, p = 0.018). Abundance participants' scores were significantly lower than Controls (Abundance Phase 3 – Control Phase 3 = –77.98, z = –2.82, p = 0.005), and significantly lower than what they accumulated by the end of Phase 2 (Abundance Phase 3 – Abundance Phase 2 = –78.28, z = –6.36, p < 0.000). Scarcity participants' scores were similar to Controls (Scarcity Phase 3 – Control Phase 3 = –46.43, z = –1.67, p = 0.094), but significantly lower than what they accumulated by the end of Phase 2 (Scarcity Phase 3 – Scarcity Phase 2 = –43.35, z = –3.50, p < 0.000).

6.1.3.5 Discovery

Figure 6.9 presents the average number of True Top Three platforms selected by participants on each Trial in each Phase of Study 3A (the number of platforms in the current pitch that have one of the three highest true average values). There are no consistent differences between Conditions in Phase 1. In Phase 2, Abundance participants selected True Top Three platforms slightly less often than Controls across a handful of Trials. In Phase 3, Scarcity participants selected True Top Three platforms significantly less often than Controls across a majority of Trials, and Abundance participants selected True Top Three platforms significantly less often than Scarcity participants across a majority of Trials.

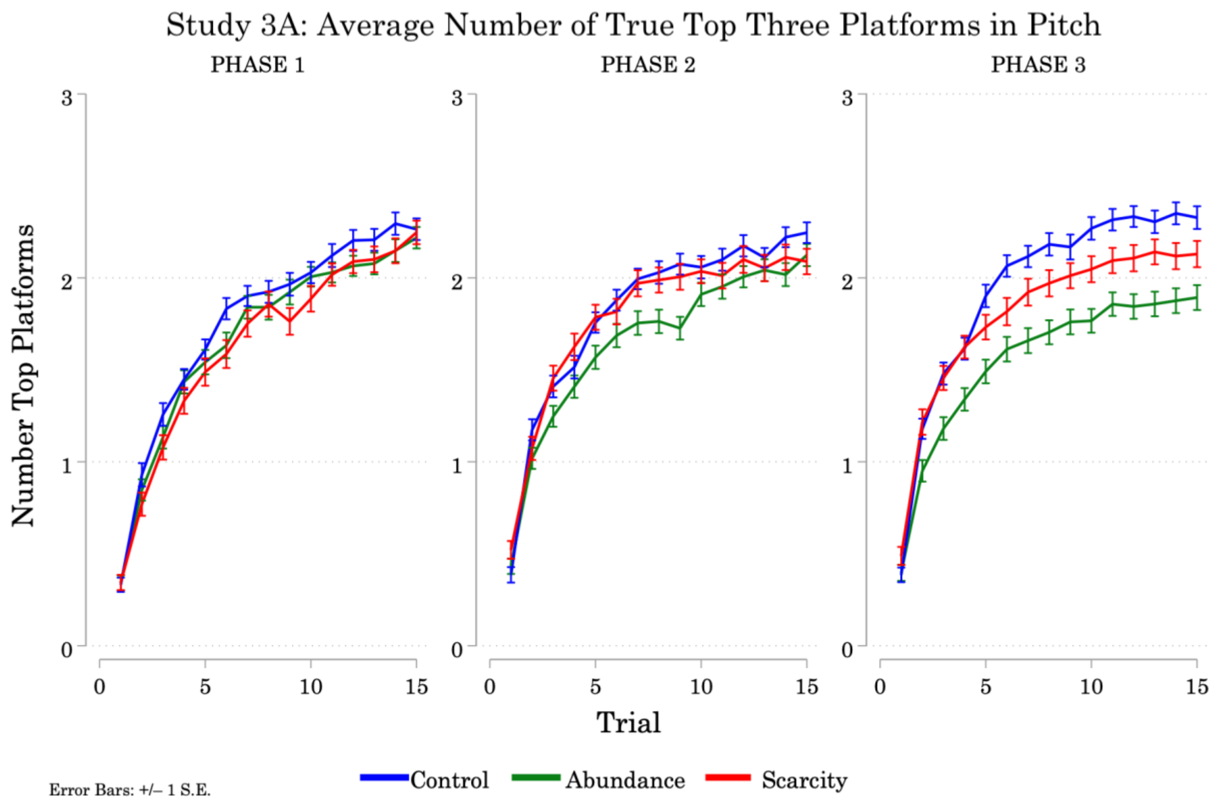

Figure 6.9. Study 3A: Discovery. Average number of True Top Three platforms selected on each Trial, by Phase and Condition. Error bars = +/– 1 S.E. N = 513. Green = Abundance (169 participants, 30 groups); Blue = Control (174 participants, 30 groups); Red = Scarcity (170 participants, 29 groups). There are no consistent differences between Conditions in Phase 1. In Phase 2, Abundance participants selected True Top Three platforms slightly less often than Controls across a handful of Trials. In Phase 3, Scarcity participants selected True Top Three platforms significantly less often than Controls across a majority of Trials, and Abundance participants selected True Top Three platforms significantly less often than Scarcity participants across a majority of Trials.

As before, we will look at the cumulative number of times participants selected any of the True Top Three Platforms across Trials 1–15 of each Phase. Table 22 presents the parameter estimates and fit statistics from three different Three-Level Random Coefficient models of the Number of True Top Three Platforms Selected (Cumulative) across Trials 1–15 in a given Phase. Model 1 is the baseline model. The fixed part of Model 1 includes an intercept and piecewise linear slopes for Phases 2 and 3. The random part of Model 1 includes a random intercept and a random linear slope for Phase at the Participant level (Level 2) and at the Group level (Level 3). Model 2 includes Condition as a fixed effect. Model 3 introduces two-way interactions between elements of the experimental design (Condition, Phase). Model 3 provides a better fit than Model 2 [$LR\ \chi^2(4) = 11.44$, $p = 0.022$] and Model 1 [$LR\ \chi^2(6) = 16.33$, $p = 0.012$], so I will focus on the predictions from Model 3.

In Phase 1, Control participants selected True Top Three platforms 26.04 ($z = 25.90$, $p < 0.000$) times on average. Abundance and Scarcity participants selected True Top Three platforms about the same number of times as did Controls ($\beta_3 = –1.30$, $z = –0.91$, $p = 0.362$; $\beta_4 = –1.86$, $z = –1.30$, $p = 0.193$).

In Phase 2, Control participants selected True Top Three platforms about 26.80 times on average, which is about the same as they did in Phase 1 ($\beta_2 = 0.76$, $z = 0.86$, $p = 0.387$). Abundance and Scarcity participants selected True Top Three platforms with similar frequency to Controls (Abundance Phase 2 – Control Phase 2 = –2.29, $z = –1.80$, $p = 0.072$; Scarcity Phase 2 – Control Phase 2 = 0.43, $z = –0.33$, $p = 0.739$). Abundance participants selected True Top Three platforms with similar frequency to what they did in Phase 1 (Abundance Phase 2 – Abundance Phase 1 = –0.23, $z = –0.27$, $p = 0.790$). Scarcity participants selected True Top

Three platforms significantly more often than they did in Phase 1 (Scarcity Phase 2 – Scarcity Phase 1 = 2.20, z = 2.47, p = 0.013).

Table 6.6. Study 3A: Discovery. Maximum likelihood estimates of Two-Level Random-Coefficient models for the number of times participants selected any of the True Top Three highest-valued platforms across Trials 1–15 of each Phase. Model 1: Intercept-Slope; Model 2: Main Effects; Model 3: Design Interactions. N = 513.

	Model 1		Model 2		Model 3	
	Est	(SE)	Est	(SE)	Est	(SE)
Fixed Effects						
Intercept β_0	25.00***	0.59	26.36***	0.89	26.04***	1.01
Phase 2 β_1	0.89	0.52	0.89	0.52	0.76	0.87
Phase 3 β_2	0.23	0.52	0.23	0.52	1.99*	0.87
Abundance β_3			–2.66*	1.16	–1.30	1.43
Scarcity β_4			–1.46	1.16	–1.86	1.43
Abundance × Phase 2 β_5					–0.99	1.24
Scarcity × Phase 2 β_6					1.44	1.25
Abundance × Phase 3 β_7					–3.52**	1.24
Scarcity × Phase 3 β_8					–1.76	1.25
Random Effects						
L3 Random Intercept Var $\psi_{11}^{(3)}$	21.28	4.49	21.69	4.62	21.03	4.45
L3 Random Slope Var $\psi_{22}^{(3)}$	13.63	2.46	13.63	2.46	12.56	2.30
L2 Random Intercept Var $\psi_{11}^{(2)}$	23.66	3.11	23.64	3.11	23.69	3.11
L2 Random Slope Var $\psi_{22}^{(2)}$	0.21	0.19	0.21	0.19	0.21	0.19
L1 (Residual) Error Variance θ	30.17	1.39	30.17	0.95	30.00	1.39
Log likelihood	–5282		–5280		–5274	
AIC | *BIC*	10584 | 10637		10583 | 10647		10580 | 10665	

* $p \leq 0.05$; ** $p \leq 0.01$; *** $p \leq 0.001$; SE = standard error of the mean

In Phase 3, Control participants selected True Top Three platforms about 28.79 times on average, which is significantly more often than in Phase 2 (β_3 = 1.99, z = 2.28, p = 0.023). Abundance participants selected True Top Three platforms significantly less often than Controls (Abundance Phase 3 – Control Phase 3 = –5.81, z = –3.42, p = 0.001), but with similar frequency to what they did in Phase 2 (Abundance Phase 3 – Abundance Phase 2 = –1.53, z = –1.74, p =

0.082). Scarcity participants selected True Top Three platforms with similar frequency to Controls (Scarcity Phase 3 – Control Phase 3 = –2.19, $z = –1.28$, $p = 0.201$), which was similar to what they did in Phase 2 (Scarcity Phase 3 – Scarcity Phase 2 = 0.23, $z = 0.26$, $p = 0.795$).

6.1.3.6 Side Observations: Peer Results

On Trials 1–14 of each Phase, participants had the option to share their results with each of their peers. On Trials 2–15 of each Phase, participants had the option to view each of their peer's results from the previous Trial. If *both* the participant *and* the peer chose to share their results with one another at the end of the previous Trial, the peer's results appeared if the participant clicked on that peer's Player button. If *either* the participant *or* the peer chose *not* to share their results with the other, then the message "*Not shared*" would appear when the participant clicked on the peer's Player button.

Sharing. Figure 6.10 presents the number of peer shares on each Trial in each Phase of Study 3A (the number of peers with whom participants chose to share results on each Trial). Participants make sharing decisions at the end of Trials 1–14 (sharing decisions are not elicited on Trial 15, because participants move on to a different Company and platform list after that Trial).

Participants in all three Conditions chose to share with 4–5 of their peers on every Trial in every Phase. (Note that the count includes shares made by active participants to peers who dropped out of the experiment. 21 participants across 18 groups were classified as dropouts for repeatedly failing to submit their responses before the time limits: Abundance = 11 participants, 9 groups; Control = 6 participants, 6 groups; Scarcity = 4 participants, 3 groups. No group had more than two dropouts.)

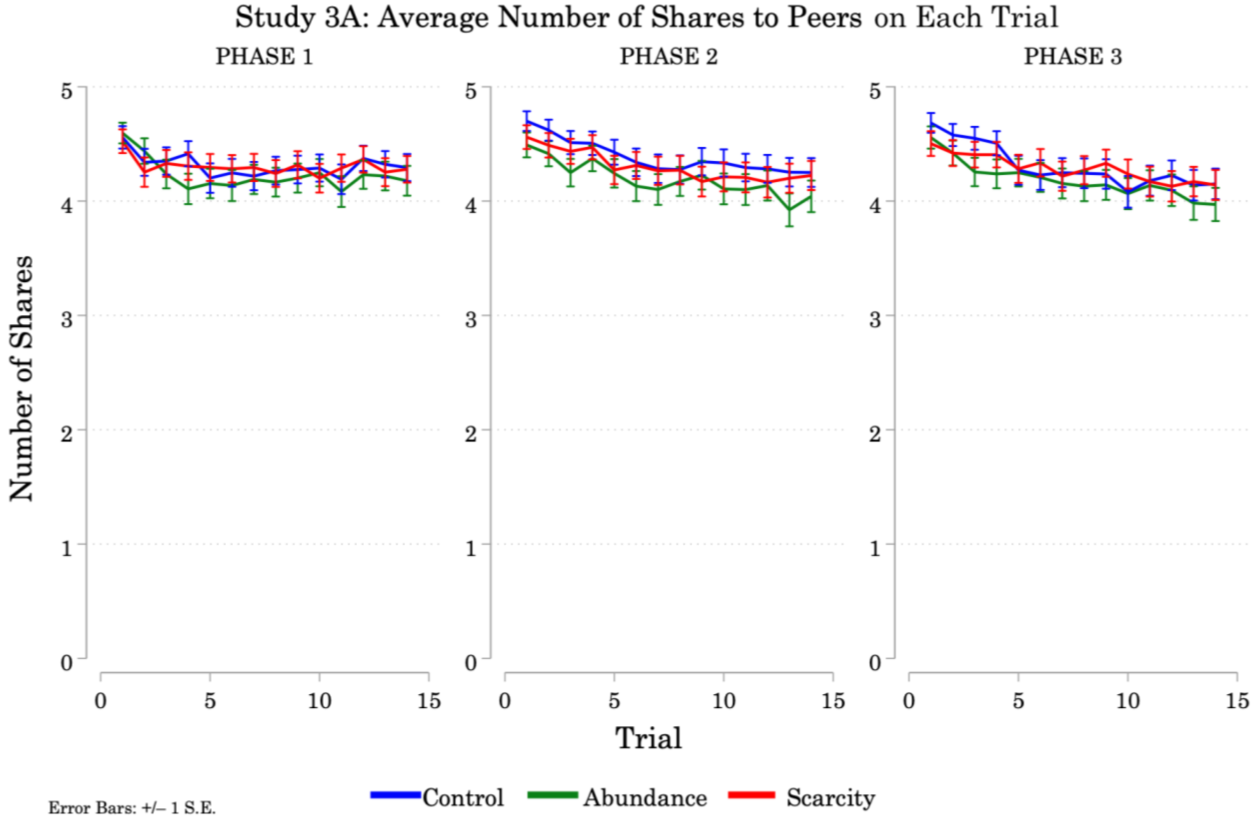

Figure 6.10. Study 3A: Shares to Peers. Average number of shares to peers on each Trial, by Phase and Condition. Error bars = +/– 1 S.E. N = 513. Green = Abundance (169 participants, 30 groups); Blue = Control (174 participants, 30 groups); Red = Scarcity (170 participants, 29 groups). Excludes sharing decisions made by participants who dropped out of the experiment, but includes decisions made by active participants to share with peers who dropped out. Note that participants were not asked to make sharing decisions on the final Trial of each Phase (Trial 15). Participants in all three Conditions choose to share with 4–5 of their peers on every Trial in every Phase.

Table 6.7 presents the parameter estimates and fit statistics from three different Three-Level Random Coefficient models for the *cumulative* number of times participants chose to share results with their peers across Trials 1–14 of each Phase in Study 3A. The cumulative number of shares to peers ranges from zero (the participant did not share with *any* of her peers on *any* Trial in a given Phase) to 70 (the participant chose to share with *all five* of her peers on *every* possible Trial, 1–14, in a given Phase).

Table 6.7. Study 3A: Shares to Peers. Maximum likelihood estimates of Three-Level Random-Coefficient models for the cumulative number of shares to peers across Trials 1–14 of each Phase. Model 1: Intercept-Slope; Model 2: Main Effects; Model 3: Design Interactions. N = 513.

	Model 1		Model 2		Model 3	
	Est	(SE)	Est	(SE)	Est	(SE)
Fixed Effects						
Intercept β_0	59.72***	0.97	60.39***	1.55	60.09***	1.56
Phase 2 β_1	0.14	0.43	0.14	0.43	1.03	0.74
Phase 3 β_2	–0.53	0.43	–0.53	0.43	–1.30	0.74
Dropouts β_3	0.83	1.90	1.08	1.92	1.08	1.92
Abundance β_4			–1.77	2.15	–1.23	2.18
Scarcity β_5			–0.43	2.14	–0.05	2.17
Abundance × Phase 2 β_6					–1.55	1.05
Scarcity × Phase 2 β_7					–1.13	1.05
Abundance × Phase 3 β_8					1.22	1.05
Scarcity × Phase 3 β_9					1.12	1.05
Random Effects						
L3 Random Intercept Var $\psi_{11}^{(3)}$	18.18	10.62	17.54	10.55	17.54	10.55
L2 Random Intercept Var $\psi_{11}^{(2)}$	264.74	20.29	264.80	20.29	265.00	20.29
L2 Random Slope Var $\psi_{22}^{(2)}$	20.68	2.73	20.68	2.73	20.80	2.72
L1 (Residual) Error Var θ	37.53	2.34	37.53	2.34	37.28	2.33
Log likelihood	–5982		–5982		–5980	
AIC | *BIC*	11982 | 12030		11985 | 12044		11990 | 12070	

* $p \leq 0.05$; ** $p \leq 0.01$; *** $p \leq 0.001$; SE = standard error of the mean

Model 1 is the baseline model. The fixed part of Model 1 includes an intercept and piecewise linear slopes for Phases 2 and 3. I also include a fixed effect for the number of dropouts in a participants' group.[8] The random part of Model 1 includes a random intercept at

[8] This effect is included to control for a possible decrease in the cumulative number of shares sent by participants in groups with at least one dropout. When active participants attempt to view the results of a peer who has dropped out

the Group level (Level 3) and a random intercept and a random linear slope for Phase the Participant level (Level 2).[9] Model 2 includes Condition as a fixed effect. Model 3 introduces interactions among elements of the experimental design (Condition, Phase). Model 3 did not provide a better fit than Model 2 [$LR\ \chi^2(4) = 3.40$, $p = 0.493$], nor did Model 2 provide a better fit than Model 1 [$LR\ \chi^2(2) = 0.73$, $p = 0.696$]. There is no evidence for a main effect of Condition, so I will focus on the predictions from Model 1.

In Phase 1, participants in all three Conditions shared with their peers 59.72 times on average ($z = 61.50$, $p < 0.000$). Participants shared with their peers a similar number of times in Phases 2 and 3.

Sampling Frequency. Figure 6.11 presents the average number of peers viewed on each Trial (the number of peers whose Player button participants clicked at least once in an attempt to view that peer's results from the previous Trial). Participants may choose to view their peers' results on Trials 2-15.

There are no significant differences between Conditions in any Phase of the experiment. Participants in all three Conditions choose to view about 4 of their peers at the start of each Phase, and then reduce the number of peers they choose to view across Trials. There is a sharper decrease in the number of peers viewed across Trials in each subsequent Phase of the experiment. (Note that the count of peer views includes attempts to view peers who dropped out of the experiment.)

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of the experiment, they see the same message they would if the peer had chosen not to share with them ("*Not shared"*). After repeatedly observing this message, participants may decide to stop sharing with the dropout, and redirect their focus to the active participants in their group. (The maximum number of dropouts in any experimental group is 2.)

[9] Alternative models were fit with a random linear slope at the Group level, but calculation of standard errors failed for these models, so the slope at Level 3 was removed.

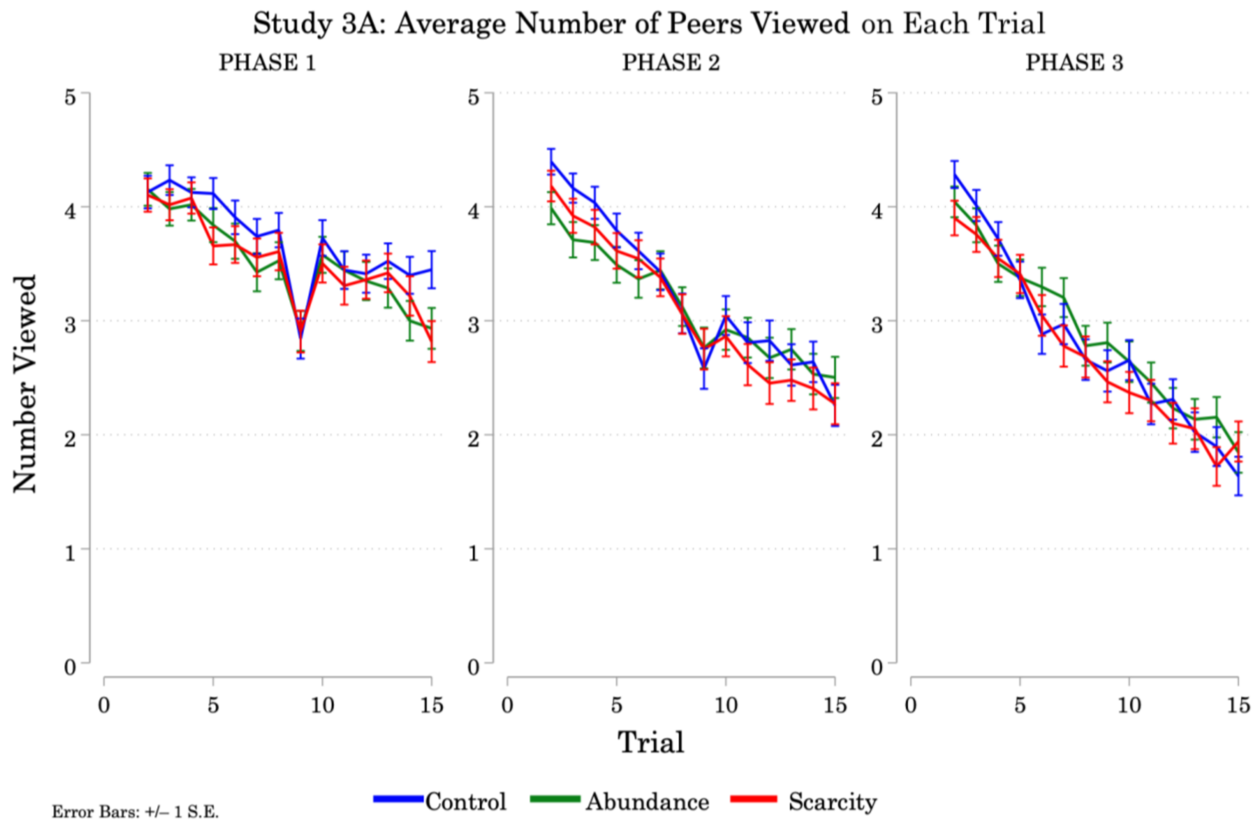


Figure 6.11. Study 3A: Peer Views. Average number of peers viewed across Trials 2–15, by Phase and Condition, Error bars = +/– 1 S.E. N = 513. Green = Abundance (169 participants, 30 groups); Blue = Control (174 participants, 30 groups); Red = Scarcity (170 participants, 29 groups). Excludes viewing decisions made by participants who dropped out of the experiment, but includes decisions made by active participants to view peers who dropped out. Note that participants can only view peer results on Trials 2-15 of each Phase. Participants in all three Conditions choose to view about 4 of their peers at the start of each Phase. Participants reduce the number of peers they choose to view across Trials within a given Phase. There is a sharper decrease in the number of peers viewed across Trials in each subsequent Phase of the experiment.

The most plausible explanation for the sharp drop in peer views on Trial 9 of Phases 1 and 2 is that participants are experiencing heightened anxiety about the time limits after submitting their Platform Value Estimates at the end of Trial 8.[10]

[10] In their open responses at the end of the procedure, many participants noted their frustration with the 2-minute time limit on the Platform Value Estimates pages. Participants are not warned in advance that they will be asked to estimate the value of all 20 platforms at any point in the experiment. They encounter this task for the first time on

Table 6.8 presents the parameter estimates and fit statistics from three different Three-Level Random Coefficient models for the average *cumulative* number of peer views across Trials 2–15 of each Phase in Study 3A. The cumulative number of peer views ranges from zero (the participant did not view *any* of her peers on *any* Trial in a given Phase) to 70 (the participant viewed *all five* of her peers on *every* possible Trial, 2–15, in a given Phase).

Model 1 is the baseline model. The fixed part of Model 1 includes an intercept and piecewise linear slopes for Phases 2 and 3. I also include a fixed effect for the number of dropouts in a participants' group. The random part of Model 1 includes a random intercept and a random linear slope for Phase at the Group level (Level 3) and at the Participant level (Level 2). Model 2 includes Condition as a fixed effect. Model 3 introduces interactions among elements of the experimental design (Condition, Phase). Model 3 did not provide a better fit than Model 2 [$LR\ \chi^2(4) = 3.48$, $p = 0.481$], nor did Model 2 provide a better fit than Model 1 [$LR\ \chi^2(2) = 1.84$, $p = 0.400$]. There is no evidence for a main effect of Condition, so I will focus on the predictions from Model 1.

In Phase 1, participants in all three Conditions viewed their peers 49.19 times on average ($z = 43.50$, $p < 0.000$). Participants viewed their peers significantly less often in Phase 2 than in Phase 1 ($\beta_1 = –5.62$, $z = –9.95$, $p < 0.000$), and significantly less often in Phase 3 than in Phase 2 ($\beta_2 = –4.87$, $z = –8.62$, $p < 0.000$). Interestingly, for each additional dropout in a participant's group, the number of times the participant viewed their peers in a given Phase increased by 5.00 ($z = 2.34$, $p = 0.019$).

Trial 8 of Phase 1, and apparently this first encounter significantly (but briefly) heightens their level of stress about the time limits (they seem to recover by Trial 9, however).

Table 6.8. Study 3A: Peer Views. Maximum likelihood estimates of Three-Level Random-Coefficient models for the cumulative number of peer views across Trials 2–15 of each Phase. Model 1: Intercept-Slope; Model 2: Main Effects; Model 3: Design Interactions. N = 513.

	Model 1		Model 2		Model 3	
	Est	(SE)	Est	(SE)	Est	(SE)
Fixed Effects						
Intercept β_0	48.19***	1.08	49.88***	1.72	50.03***	1.74
Phase 2 β_1	–5.63***	0.58	–5.61***	0.59	–6.42***	1.00
Phase 3 β_2	–4.88***	0.58	–4.86***	0.59	–5.70***	1.00
Dropouts	5.58**	2.13	5.91**	2.16	5.85**	2.16
Abundance β_3			–3.22	2.40	–3.47	2.44
Scarcity β_4			–2.08	2.38	–2.26	2.42
Abundance × Phase 2 β_5					1.55	1.42
Scarcity × Phase 2 β_6					0.84	1.42
Abundance × Phase 3 β_7					1.98	1.42
Scarcity × Phase 3 β_8					0.50	1.42
Random Effects						
L3 Random Intercept Var $\psi_{11}^{(3)}$	14.24	11.23	14.07	10.78	14.79	10.99
L3 Random Slope Var $\psi_{22}^{(3)}$	2.24	1.87	2.54	1.91	2.16	1.76
L2 Random Intercept Var $\psi_{11}^{(2)}$	357.13	27.15	355.17	26.88	354.47	26.87
L2 Random Slope Var $\psi_{22}^{(2)}$	37.44	4.91	37.15	4.89	36.99	4.85
L1 (Residual) Error Var θ	61.95	3.87	61.95	3.87	61.93	3.87
Log likelihood	–6323		–6322		–6321	
AIC | *BIC*	12669 | 12727		12671 | 12740		12675 | 12766	

* $p \leq 0.05$; ** $p \leq 0.01$; *** $p \leq 0.001$; SE = standard error of the mean

All views made by active participants are included in the cumulative number of peer views, including attempts to view the results of peers who dropped out of the experiment. Participants are not alerted when peers drop out of the experiment. If a participant tries to view the results from a dropout peer, they see the message "*Not shared,*" which is the same message they would see if that peer had been active and simply chose not to share their results. So, participants cannot discriminate between dropout peers and peers who choose not to share. We might assume that participants would stop trying to view a dropout peer after repeatedly seeing a message indicating that the peer did not share results. If this was the case, and participants in groups with dropouts continued to view their remaining active peers at the same rate, then the cumulative number of peer views should *decrease* for each additional dropout in a participant's group.

There are a few ways for a participant's cumulative number of peer views to *increase* when that participant is in a group with dropouts. Participants in groups with dropouts may choose to view their remaining active peers more often than they would have if there were no dropouts in the group. Participants in groups with dropouts may choose to view their dropout peers more often than they would have if those peers had remained active. Or, participants in groups with dropouts may choose to view all of their peers (including dropouts) more often than if there were no dropouts in the group. On closer inspection, the latter explanation seems the most likely.

At the individual peer level, the effect of a peer's dropout status on the number of views received from the participant is not significant ($\beta = 0.50$, $z = 0.39$, $p = 0.693$). So, it seems that the presence of at least one dropout in a group raises the number of times active participants choose to view all of their peers (active and dropout). It's not possible to determine the true root cause of this behavior, but perhaps repeatedly observing the message indicating that dropout peers chose not to share their results increases participants' curiosity about peer results in general.

Sampling Bias. Aside from the volume of shares and views to peers in each Phase, we are also interested in whether participants exhibit any position- or achievement-based preferences in their choices to share with or to view their peers. In Studies 2A and 2B, we found position-based preferences in participants' choices to view Random Pitches / Exemplar Players. Participants viewed Random Pitches / Exemplar Players located in the top row of the button tray more often than those located in the bottom row of the button tray. Despite differences in achievement levels between Exemplar Players in Study 2B, we found no achievement-based preferences in participants' choices to view each Exemplar Player.

In Study 3A, each participant is randomly assigned a Position in his Group, designated by a number between 1 and 6. The participant's Position determines the location of his Player button on the screens of each of his peers. (Refer to Figure 6.3 to see the layout of the peer Player buttons on the Pitch Selection screen for Trials 2–15, from the perspective of the participant in each Position. The layout of the Results screen on Trials 1–14 is analogous.)

Due to the random assignment of participants across Positions, the relationship between Position and relative achievement level (Rank) is not constant across experimental groups. In a given experimental group, the highest-performing player (Rank 1) could appear in the upper-left position, the lower-middle position, the upper-right position, etc. To understand whether participants in Study 3A exhibited a preference to view peers in a particular Position (e.g. Position 1, top-left location in button tray) or a particular Rank (e.g. Rank 1, highest achieving peer in the current Phase), we must aggregate the number of views received by each participant in two different ways. (In this and all subsequent analyses, I exclude shares and views sent *from* dropout participants to active peers, and shares and views sent from active participants *to* dropout peers.)

First, we will look at the number of times participants choose to view each peer in a given Phase, based on the peer's randomly assigned Position in the participant's group. This will show us whether participants tend to view peers in certain Positions more often than others. Second, we will look at the number of times participants choose to view each peer based on the peer's relative achievement (Rank) in a given Phase. Participants are assigned a relative achievement

Rank for each Phase based on the total number of points they earned in that Phase. Within each group, in each Phase, the participant who earned the highest total number of points is assigned Rank 1, and the participant who earned the lowest total number of points is assigned Rank 6.[11]

Figure 6.12 presents the number of times participants chose to view each of their peers in each Phase of the experiment, based on each peer's randomly-assigned Positions within their groups. The average number of views ranges from zero (the participant did not view the peer in a given Position on any Trial in a given Phase) to 14 (the participant chose to view the peer in a given Position on every possible Trial, 2–15, in a given Phase). The Abundance Condition (green) is on the top row, the Control Condition (blue) is on the middle row, and the Scarcity Condition (red) is on the bottom row. Each row has three sets of six boxes. Each set of boxes represent one Phase of the experiment (Phase 1 on the far left, Phase 3 on the far right). Each of the six boxes in a given Phase represents a different peer Position, with Position 1 located on the far-left side of each set (darkest color) and Position 6 located on the far-right side of each set (lightest color).

[11] Note that participant Rank is not necessarily constant across Phases, as Ranks are determined by the points earned *within* each Phase.

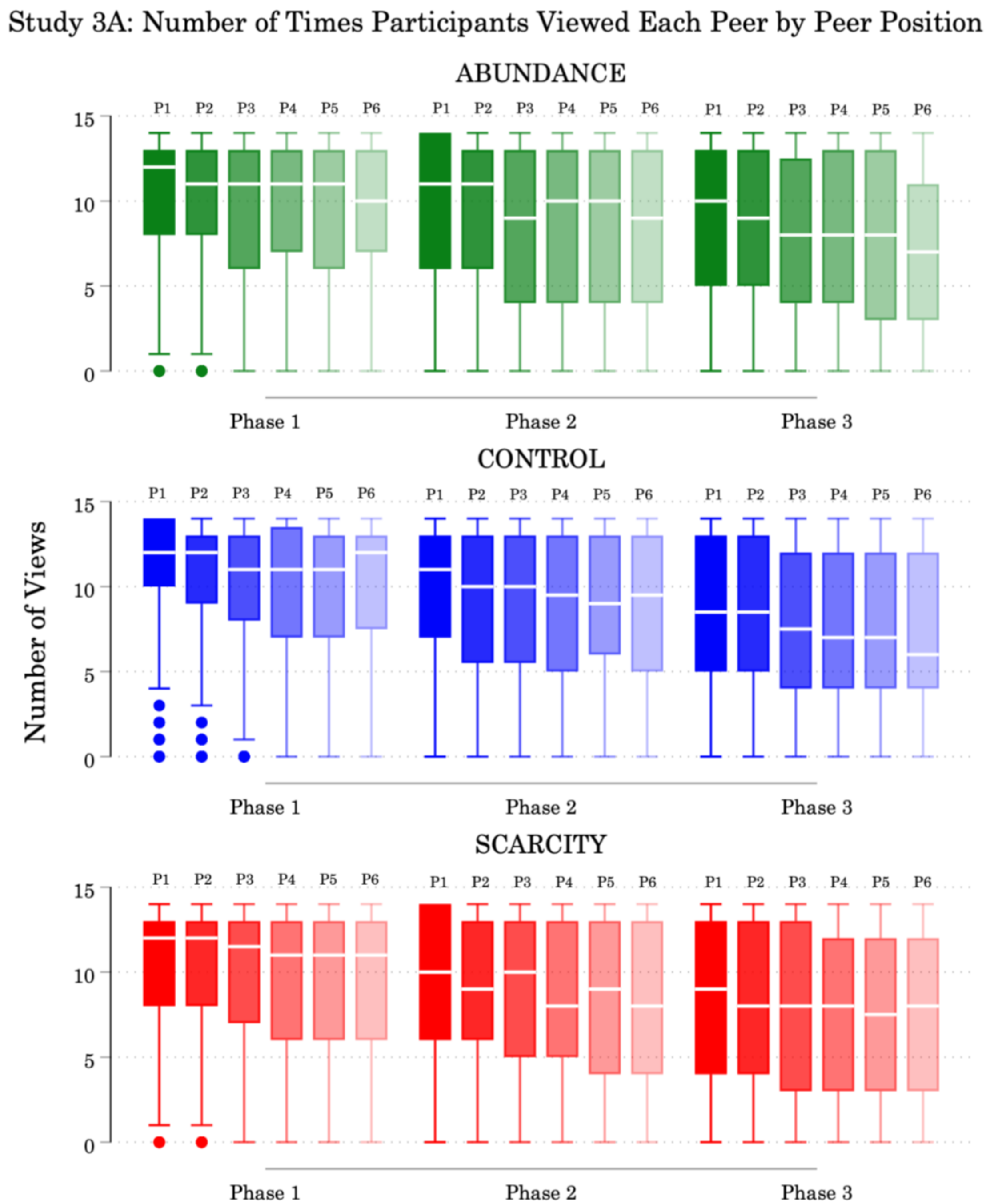


Figure 6.12. Study 3A: Peer Views by Peer Position. Number of times participants viewed each of their peers based on each peer's randomly-assigned Position, by Phase and Condition. N = 513. Top Row = Abundance (169 participants, 30 groups); Middle Row = Control (174 participants, 30 groups); Bottom Row = Scarcity (170 participants, 29 groups). Excludes attempts to view peers who dropped out of the experiment. Boxes ordered by peer Position, from left to right, within each Phase. P1 = Position 1 (darkest color), P2 = Position 2, P3 = Position 3, P4 = Position 4, P5 = Position 5, P6 = Position 6 (lightest color).

Participants choose to view peers slightly more often when the peer's Player button is located closer to the top-left corner of the button tray (Position 1). This position-based preference is consistent with the pattern we observed in Studies 2A and 2B.

There is a subtle detail that is important to note when interpreting the apparent patterns in participants' preferences for viewing peers in a given Position. Each participant in a given group occupies one of six Positions, and the Player button representing the participant's own Position is not displayed in the button tray on his own screen. A participant's *own* results from the preceding Trial are presented *above* the button tray under the heading "Last Round Pitch," and these results are always visible. The participant does not need to click a button to reveal his own results.

For example, Participant X is randomly assigned to Position 3, and his peers are assigned to Positions 1, 2, 4, 5, and 6. There is no "Player 3" button in the participant's button tray, only Player buttons 1, 2, 3, 4, and 6. Participant X's decisions to view his peers contribute to the calculation of the mean number of views received by Positions 1, 2, 4, 5, and 6. But, his decisions *do not affect* the calculation of the mean number of views received by Position 3 (his own position).

When we calculate the mean number of views received by participants in each Position, a given participant's decisions to view his peers only contribute to the mean number of views received by the 5 Positions occupied by his peers. If Participant X is assigned to Position 3, his decisions contribute to the calculation of the interquartile range for Positions 1 and 2 (the first two boxes above each Phase in Figure 6.12), and for Positions 4, 5, and 6 (the last three boxes above each Phase in Figure 6.12), but not to Position 3 (the third box above each Phase in Figure 6.12). (This might not seem like an important distinction right now, but it will become obvious why this is relevant later in this section when we switch perspectives to look at participants' choices to view peers based on peer Rank.)

Recall that participants could only see their peers' results if *both* the participant *and* the peer choose to share with each other. If a participant tries to view the results of a peer who *did not* choose to share with the participant, then the participant sees the message "*Not shared*" when she clicks on the peer's Player button. It is possible that participants in Study 3A chose to view peers located closer to the top-left corner of the button tray because those peers chose to share with the participant more often than peers located further away from the top-left corner of the button tray. Figure 6.13 presents the number of times each peer shared with a participant, based on the peer's randomly-assigned Position. The number of shares ranges from zero (the peer did not share with the participant on any Trial in a given Phase) to 14 (the peer shared with the participant on every possible Trial, 1–14, in a given Phase).

Participants received more shares from peers whose Player buttons were closer to Position 1. The only major difference in the number of shares received from each peer Position appears in the Abundance Condition, where peers assigned to Position 6 shared slightly less often than peers in the other 5 Positions. It's possible that Abundance participants in Position 6 chose to share less often with their peers because their peers chose to share less often with them. But, on closer inspection of the data, we find that this is not the case.

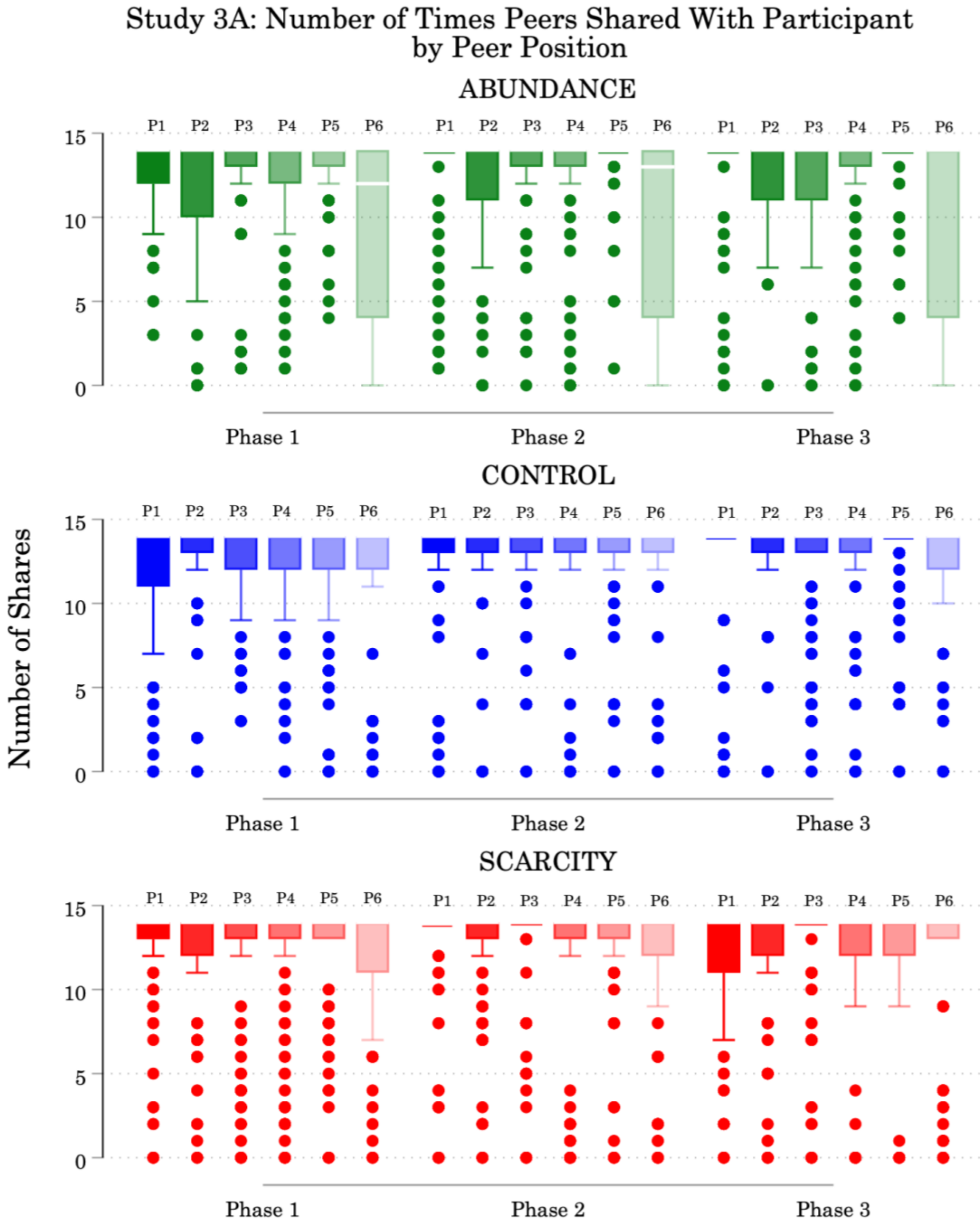


Figure 6.13. Study 3A: Shares from Peers by Peer Position. Number of times peers shared with participants based on peers' randomly-assigned Positions, by Phase and Condition. N = 513. Top Row = Abundance (169 participants, 30 groups); Middle Row = Control (174 participants, 30 groups); Bottom Row = Scarcity (170 participants, 29 groups). Excludes shares received from peers who dropped out of the experiment. Boxes ordered by peer Position, from left to right, within each Phase. P1 = Position 1 (darkest color), P2 = Position 2, P3 = Position 3, P4 = Position 4, P5 = Position 5, P6 = Position 6 (lightest color).

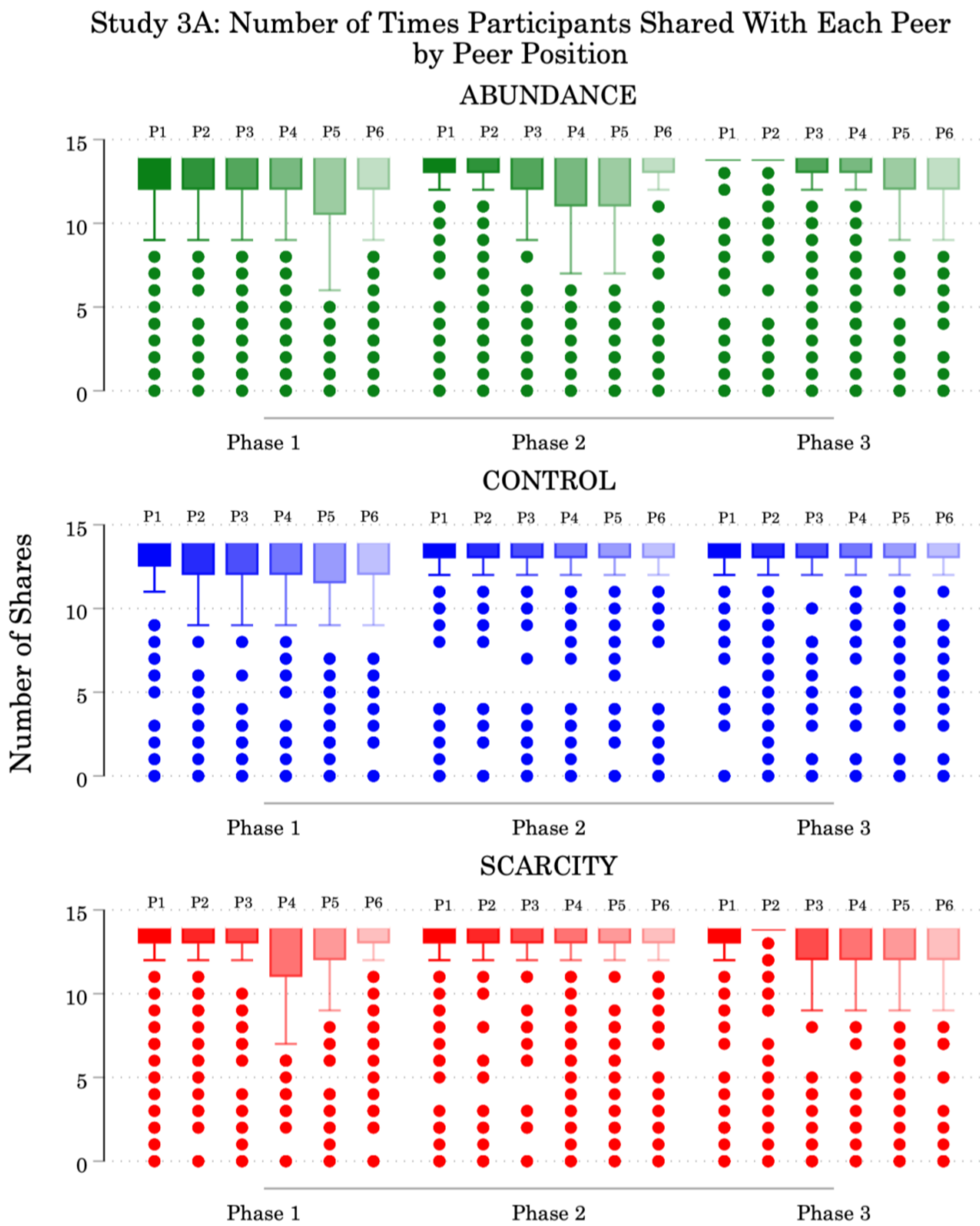


Figure 6.14. Study 3A: Shares to Peers by Peer Position. Number of times participants shared with peers based on peers' randomly-assigned Positions, by Phase and Condition. N = 513. Top Row = Abundance (169 participants, 30 groups); Middle Row = Control (174 participants, 30 groups); Bottom Row = Scarcity (170 participants, 29 groups). Excludes shares sent to peers who dropped out of the experiment. Boxes ordered by peer Position, from left to right, within each Phase. P1 = Position 1 (darkest color), P2 = Position 2, P3 = Position 3, P4 = Position 4, P5 = Position 5, P6 = Position 6 (lightest color).

Figure 6.14 presents sharing decisions from the opposite perspective - the number of times participants chose to share with each of their peers based on their peers' Positions. There don't seem to be any significant differences in the number of times participants chose to share with peers in each Position.

Next, we will look at the number of times participants chose to view each of their peers based on each peer's relative achievement Rank within a given Phase. Figure 6.15 presents the number of times participants chose to view each of their peers based on each peer's achievement Rank in each Phase of Study 3A. The Abundance Condition (green) is on the top row, the Control Condition (blue) is on the middle row, and the Scarcity Condition (red) is on the bottom row. Each row has three sets of six boxes. Each set of boxes represent one Phase of the experiment (Phase 1 on the far left, Phase 3 on the far right). Each of the six boxes in a given Phase represents a different peer Rank, with Rank 1 (highest achievement in group) located on the far-left side of each set (darkest color) and Rank 6 (lowest achievement in group) located on the far-right side of each set (lightest color).

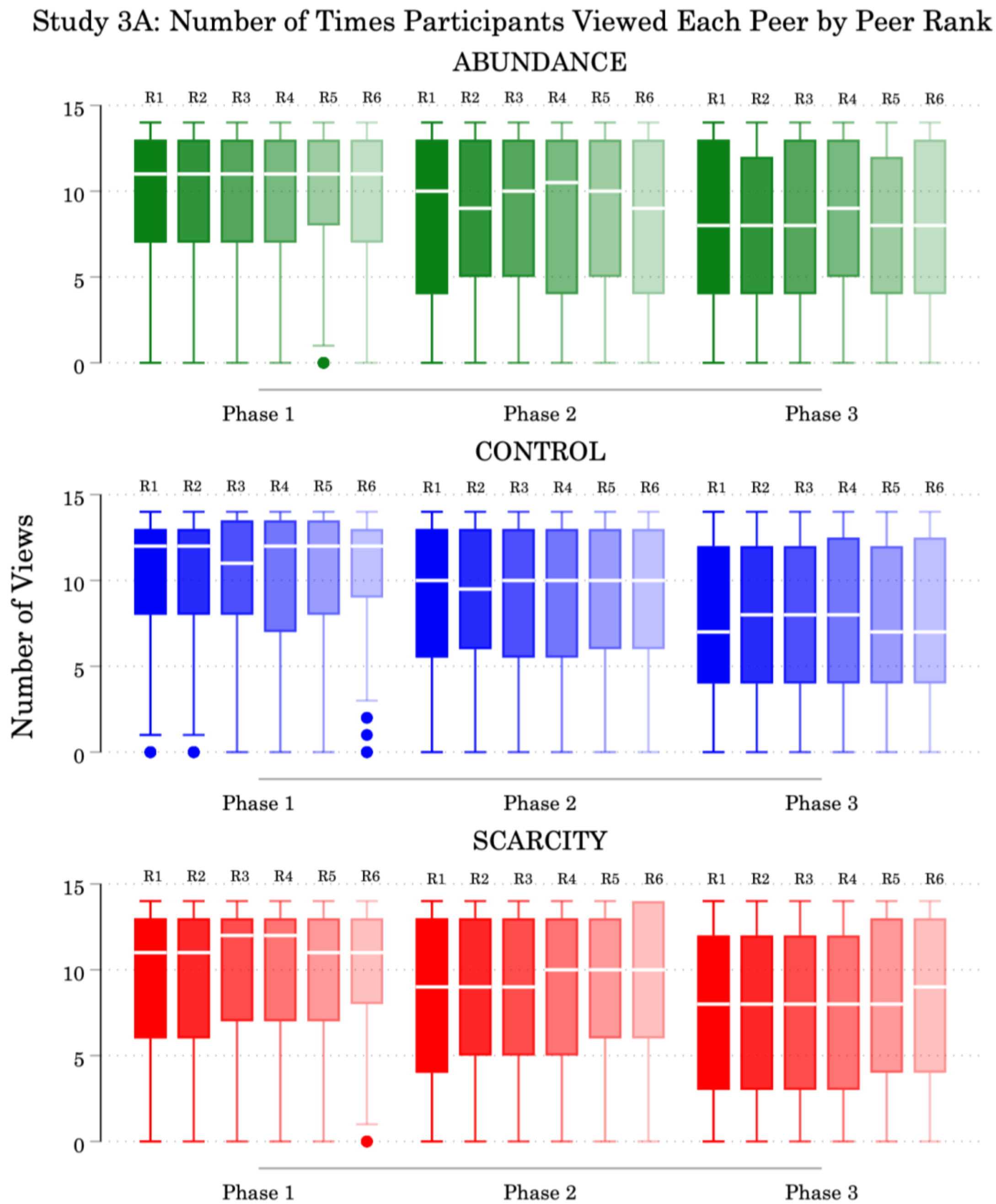


Figure 6.15. Study 3A: Peer Views by Peer Rank. Number of times participants viewed each of their peers based on each peer's achievement Rank, by Phase and Condition. N = 513. Top Row = Abundance (169 participants, 30 groups); Middle Row = Control (174 participants, 30 groups); Bottom Row = Scarcity (170 participants, 29 groups). Excludes attempts to view peers who dropped out of the experiment. Boxes are ordered by peer achievement Rank, from left to right, within each Phase. R1 = Rank 1 (highest achievement), R2 = Rank 2, R3 = Rank 3, R4 = Rank 4, R5 = Rank 5, R6 = Rank 6 (lowest achievement). Note that the on-screen Position of the participant in each Rank varies across groups.

There don't seem to be any consistent patterns in the Abundance or Control Conditions. In the Scarcity Condition, it seems like participants choose to view the *lowest* achieving peer (Rank 6) slightly more often than higher-achieving peers. But, here's where the interpretation gets complicated. Each participant occupies one of the six Ranks, and a participant cannot view himself. So, each participant's decisions to view his peers are only captured by 5 out of the 6 boxes above a given Phase. For example, Scarcity Participant X has the highest score in his group in the first Phase of the experiment, so this participant has Rank 1 in Phase 1. His peers then occupy Ranks 2, 3, 4, 5, and 6. Scarcity Participant X cannot view himself. As a result, no views of "Rank 1" are recorded for Participant X, only views of Ranks 2, 3, 4, 5, and 6.

This means that Participant X's decisions contribute to the calculation of the interquartile range for the last 5 boxes above each Phase (Ranks 2, 3, 4, 5, and 6), but not to the first box above each Phase (Rank 1). If participants in Rank 1 choose to view *all* of their peers (regardless of Rank) much more often than participants in Rank 6 choose to view *any* of their peers, then it would be impossible for Rank 1 participants to accumulate more views, on average, than Rank 6 participants. A concrete example will help clarify.

Suppose the six participants in a given group did the following in Phase 1 of the experiment: the highest- and second-highest performing participants (Ranks 1 and 2) chose to view all five of their peers on every possible Trial, 2–15; the third- and fourth-highest performing participants (Ranks 3 and 4) chose to view each of their peers on 7 of the 14 possible Trials; the fifth- and sixth-highest performing participants (Ranks 5 and 6) never chose to view any of their peers on any Trial. In this case, the highest-performing participant in the group (Rank 1) would receive 14 views from Rank 2 + 7 views from Rank 3 + 7 views from Rank 4 + 0 views from Rank 5 + 0 views from Rank 6 = 28 views total / 5 peers = 5.60 views on average.

The lowest-performing participant in the group (Rank 6) would receive 14 views from Rank 1 + 14 views from Rank 2 + 7 views from Rank 3 + 7 views from Rank 4 + 0 views from Rank 5 = 42 views total / 5 peers = 8.40 views on average.

In the hypothetical case presented above, each participant allocates the exact same number of views to each peer, regardless of the peer's Rank. Despite the fact that each participant sends the exact same number of views to each of her peers, the fact that higher-ranked participants send a higher number of views across all of their peers results in lower-ranked participants receiving a higher number of views, on average, than higher-ranked participants. We can explore whether something like this is happening in Study 3A by looking at the average number of times a participant in a given Rank is viewed by each of his peers, based on each peer's Rank (Figure 6.16).

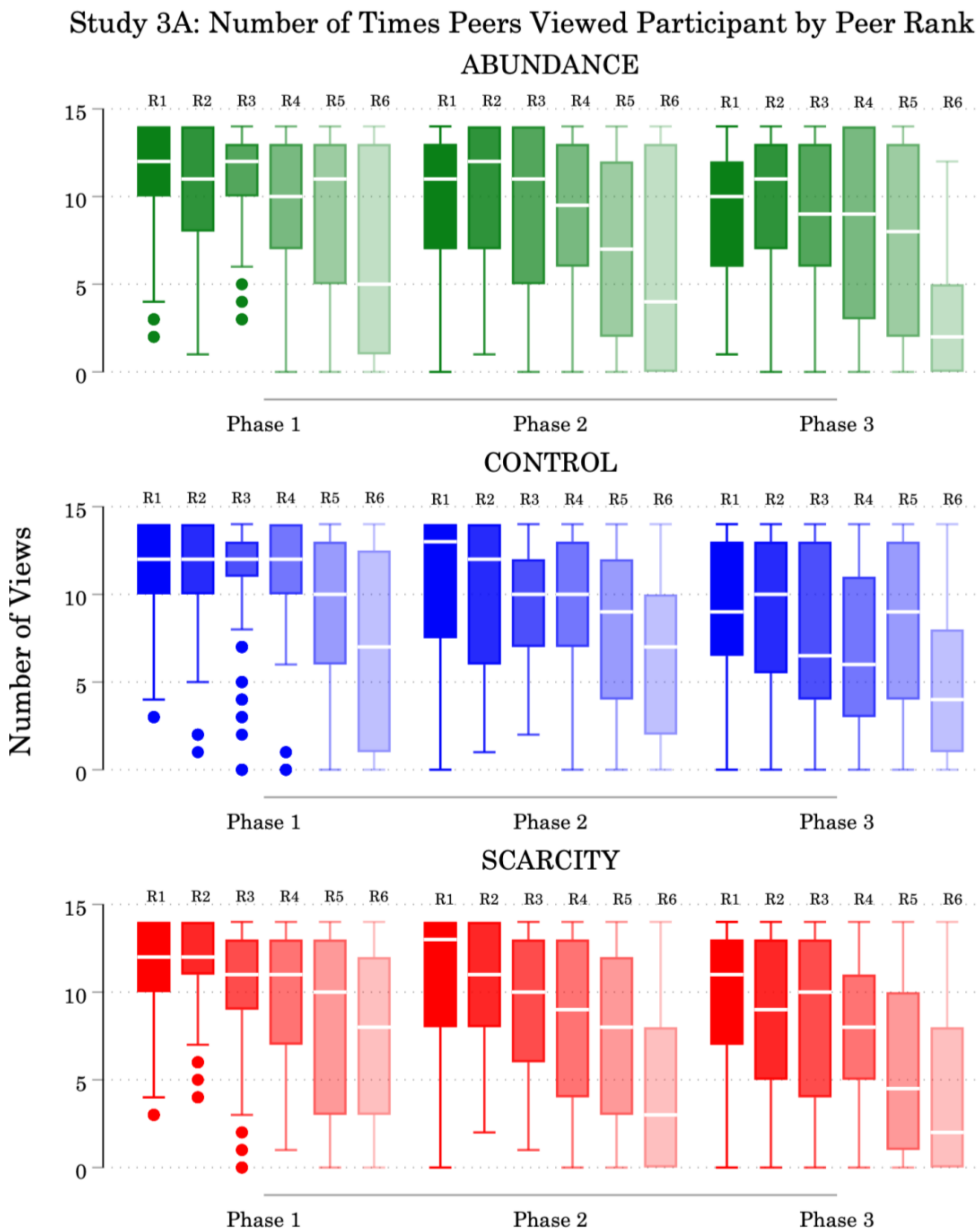


Figure 6.16. Study 3A: Views Received by Peer Rank. Number of times peers viewed participants based on peers' relative achievement Rank, by Phase and Condition. N = 513. Top Row = Abundance (169 participants, 30 groups); Middle Row = Control (174 participants, 30 groups); Bottom Row = Scarcity (170 participants, 29 groups). Excludes views received from peers who dropped out of the experiment. Boxes are ordered by peer achievement Rank, from left to right, within each Phase. R1 = Rank 1 (highest achievement), R2 = Rank 2, R3 = Rank 3, R4 = Rank 4, R5 = Rank 5, R6 = Rank 6 (lowest achievement).

Participants (in any Rank) receive more views from the highest-achieving peers in their group (Ranks 1 & 2) than from the lowest-achieving peers in their group (Ranks 5 & 6). This tells us that the highest-achieving participants in a given group choose to view their peers *of every Rank* more often than the lowest-achieving participants in a given group choose to view their peers *of every Rank*. When we aggregate across participant Ranks (e.g. looking at the number of times a participant *of any Rank* chooses to view a peer *of a specific Rank*) it is difficult to differentiate between patterns driven by peer characteristics (e.g. participants choose to view the lowest-achieving peer, Rank 6, more often) and patterns driven by participant characteristics (e.g. the highest-achieving participant, Rank 1, views all of his peers more often than the lowest-achieving participant, Rank 6, views any of his peers.).

To really understand the factors that drive participants' decisions to view their peers, we need to look at these decisions at the dyad (participant-to-peer) level. This will allow us to take into account both characteristics of the participant, and the peer, and explore the effect of these characteristics on the number of times the participant chooses to view the peer in a given Phase. We have already explored a few factors that may drive these decisions: Peer Position, Peer Shares, and Peer Rank.

Peer Position. Participants seem to view a peer more often the closer that peer's Player button is located to the top-left corner of the button tray. So, we might expect a *negative* effect of Position on the number of times a participant views a given peer (e.g. the higher the peer's Position number, the further the peer's Player button from the top-left corner of the button tray).

Peer Shares. We might also expect participants to view a peer more often if that peer chooses to share her results with the participant more often. Participants can only view a peer's results if *both* the participant *and* the peer choose to share their results with each other. If a given peer never chooses to share her results, the participant will see the message "*Not shared*" each time he tries to view the peer's results. Participants may choose to stop viewing a peer who has not shared in the past because the participant believes that peer is less likely to share in the future. This would lead to a *positive* effect of the number of shares received from a given peer on the number of times a participant chooses to view that peer.

Participant / Peer Rank. When we aggregated over all participant Ranks, it seemed like participants (of any rank) chose to view the lowest-achieving peer in a given group (Rank 6) more often than the highest-achieving peer in a given group (Rank 1). This pattern is surprising as it runs counter to a well-established preference for viewing the *highest*-achieving peers in social explore-exploit tasks (e.g. Mesoudi 2008, 2011). We discussed possible explanations for this counter-intuitive pattern, and found that it may be driven by differences in the absolute volume of views made by higher- versus lower-performing participants. If we base our prior expectations on the results of similar experimental studies of explore-exploit tasks, we would expect a *positive* effect of peer achievement on the number of times a participant chooses to view that peer.

In the present context, peer achievement *decreases* as peer Rank *increases* (the highest-achieving participant in a given group is assigned Rank 1, and the lowest achieving participant is assigned Rank 6). For ease of exposition, I will *reverse code* Peer Rank in the upcoming statistical analysis so that an *increase* in reverse-coded (RC) Peer Rank is associated with an *increase* in performance. This will make it easier to interpret the regression coefficient for RC Peer Rank in the multilevel model. A *positive* coefficient for RC Peer Rank can be interpreted as a *positive* effect of achievement on the number of times a participant chooses to view a given peer (i.e. the number of times a participant chooses to view a peer *increases* with RC Peer Rank, which *increases* with peer achievement).

We also want to account for the fact that higher-achieving participants tend to view all of their peers more often than lower-achieving participants. I will include a coefficient for reverse-coded (RC) Participant Rank to control for these apparent differences in the overall volume of peer views across participant Ranks. If it is the case that higher-achieving participants view all of their peers more often (regardless of Peer Rank), then we should expect a *positive* effect of RC Participant Rank on the number of times a participant chooses to view a given peer (i.e. the number of times a participant chooses to view a peer *increases* with RC Participant Rank, which *increases* with participant achievement).

Differences in the explore-exploit strategies of participants and their peers could also drive differences in the number of times a participant chooses to view a given peer. Participants', and peers', rates of Exploration, Exploitation, and Discovery may affect participants' appetite for information about their peers' results.

Participant / Peer Exploration. We saw that participants in Studies 2A and 2B explored fewer platforms than participants in Study 1. It seems that participants substitute side observations (of Random Pitches, Exemplar Players) for direct sampling (including a larger number of unique platforms in their pitches across Trials). Therefore, we might expect participants who explore *less* to choose to view their peers *more*. In this case, we would observe a *negative* effect of Participant Exploration on the number of times a participant chooses to view a given peer. Conversely, if a peer chooses to explore at a higher rate, viewing that peer's results will expose participants to a larger number of unique platforms across Trials. This might be attractive for participants who are substituting peer results for independent exploration of the platform values. In this case, we would observe a *positive* effect of Peer Exploration on the number of times a participant chooses to view a peer.

Participant / Peer Exploitation. Participants who exploit their personal-best platforms more often may be ambiguity averse – they may prefer to select a platform whose value they have observed at least once to exploring a platform whose value they have never observed. Viewing peer results reduces ambiguity over the platform values, without submitting to the cost of having to select platforms one has explored yet. So, we might expect a *positive* effect of Participant Exploitation on the number of times a participant chooses to view a given peer. Conversely, peers who exploit their personal-best platforms more often have less variety in their pitches across Trials, making them less attractive sources of information about platforms the participant has not explored. As a result, we would expect a *negative* effect of Peer Exploitation on the number of times a participant chooses to view a given peer. (It turns out we won't be able to test the effects of Participant / Peer Exploitation and Participant / Peer Exploration concurrently. Due to the collinearity of Exploitation and Exploration, I had to drop Exploitation from the subsequent analysis.)

Participant / Peer Discovery. There are two possible explanations for participants selecting the true top three highest-valued platforms more often during a given Phase. Participants could have discovered these platforms independently through direct sampling (including them in their pitch), or they could have discovered these platforms by observing their peers' results. If participants discovered the true top three highest-valued platforms independently, then they are likely to observe that they are earning more points on each Trial than their peers (especially if the participant discovered the highest-valued platforms before his peers did). This may decrease participants' interest in viewing peers' results, which would result in a *negative* effect of Participant Discovery on the number of times a participant views a given peer.

However, if participants discovered the highest-valued platforms by looking at his peers' results, we would expect a *positive* relationship between participant Discovery and the number of times the participant chooses to view his peers. In this case the causal direction runs in reverse, observing high-valued platforms in his peers' pitches increases the participant's interest in viewing his peers' results. Similarly, if a participant observes one of his peers repeatedly selecting the highest-valued platforms, the participant may be more interested in continuing to view that peer's results. This would result in a *positive* effect of Peer Discovery on the number of times a participant chooses to view a given peer.

Table 6.9 summarizes the participant- and peer-level explanatory variables described above and the predicted direction of their effects on the number of times a participant views a given peer in a given Phase of Study 3A.

Table 6.9. Study 3A: Participant- and Peer-Level Explanatory Variables. Summary of participant- and peer-level explanatory variables and predicted effects on the number of times a participant chooses to view a given peer in a given Phase of the experiment.

Variable	Description	Predicted Effect (Direction)
Peer Position	Peer's randomly-assigned position in the button tray (Position 1 = top left)	–
Peer Shares to Participant	Number of times peer shared with participant in the current Phase	+
RC Participant Rank	Participant's relative achievement Rank within the current Phase (reverse-coded so that Rank 6 = 0, lowest achievement)	+
RC Peer Rank	Peer's relative achievement Rank within the current Phase (reverse-coded so that Rank 6 = 0, lowest achievement)	+
Participant Exploration	Number of unique platforms participant explored in the current Phase	–
Peer Exploration	Number of unique platforms peer explored in the current Phase	+
Participant Discovery	Number of times participant selected any of the true top three highest-valued platforms in the current Phase	– / +
Peer Discovery	Number of times peer selected any of the true top three highest-valued platforms in the current Phase	+

Table 6.10 presents the parameter estimates and fit statistics from three different Three-Level Random Coefficient models for the number of times participants chose to view a given peer in each Phase of Study 3A. Model 1 is the baseline model. The fixed part of Model 1 includes an intercept, piecewise linear slopes for Phases 2 and 3, and a fixed effect for the number of dropouts in a participant's group. The random part of Model 1 includes a random intercept at the Group level (Level 3) and at the Participant level (Level 2).[12] Model 2 includes

[12] Alternative models were fit with a random linear slope for Phase at the Group and Participant levels, and just at the Participant level, but calculation of standard errors for the random effects failed in each case so these random effects were dropped from the final models.

fixed effects for Condition, Peer Position, Peer Shares to Participant, reverse-coded (RC) Participant Rank, reverse-coded (RC) Peer Rank, Participant Exploration, Peer Exploration, Participant Discovery, and Peer Discovery.

Model 3 introduces interactions among elements of the experimental design (Condition, Phase), and the participant- and peer-level explanatory variables. Non-significant two- and three-way interactions between Phase, Condition, and the participant- and peer-level explanatory variables were removed in a backward stepwise fashion starting with the highest-order interactions with the highest p-values. (Non-significant lower-ordered components of significant higher-ordered interactions are retained.) Model 3 provides a significantly better fit than Model 2 [$LR\ \chi^2(25) = 96.07$, $p < 0.000$] and Model 1 [$LR\ \chi^2(35) = 711.30$, $p < 0.000$], so I will focus on the estimates from Model 3.

Table 6.10. Study 3A: Peer Views Explanatory Variables. Maximum likelihood estimates of Three-Level Random-Coefficient models for the number of times participants viewed each of their peers in each Phase of Study 3A. Model 1: Intercept-Slope; Model 2: Main Effects; Model 3: Restricted Interactions. N = 513.

	Model 1		Model 2		Model 3	
	Est	(SE)	Est	(SE)	Est	(SE)
Fixed Effects						
Intercept β_0	9.67***	0.22	8.34***	0.57	8.83***	1.08
Phase 2 β_1	–1.12***	0.06	–1.13***	0.06	–1.37***	0.11
Phase 3 β_2	–0.93***	0.06	–0.96***	0.06	–4.11***	1.00
Dropouts β_3	1.06*	0.44	0.88*	0.43	0.87*	0.43
Abundance β_4			–0.25	0.48	–2.21	1.61
Scarcity β_5			–0.33	0.48	0.34	1.29
Peer Position β_6			–0.19***	0.01	–0.19***	0.01
Peer Shares to Participant β_7			0.09***	0.01	0.10***	0.01
RC Participant Rank β_8			0.33***	0.02	0.19***	0.04
RC Peer Rank β_9			0.02	0.01	0.02	0.01
Participant Exploration β_{10}			0.08	0.11	0.45	0.26
Peer Exploration β_{11}			–0.06	0.10	–0.40	0.22
Participant Discovery β_{12}			–0.14**	0.05	–0.30***	0.10
Peer Discovery β_{13}			0.06	0.04	–0.02	0.10
Abundance × Phase 2 β_{14}					0.31*	0.14
Scarcity × Phase 2 β_{15}					0.20	0.14
Participant Discovery × Phase 2 β_{16}					0.21*	0.22
Abundance × Peer Shares β_{17}					–0.01	0.02
Scarcity × Peer Shares β_{18}					–0.01	0.02
Abundance × RC Participant Rank β_{19}					0.23***	0.06
Scarcity × RC Participant Rank β_{20}					0.22***	0.06
Abundance × Part. Exploration β_{21}					–0.42	0.39
Scarcity × Participant Exploration β_{22}					–0.79**	0.31
Abundance × Peer Exploration β_{23}					0.78*	0.33
Scarcity × Peer Exploration β_{24}					0.36	0.25
Abundance × Peer Discovery β_{25}					0.06	0.05
Scarcity × Peer Discovery β_{26}					0.05	0.13
Abundance × Phase 3 β_{27}					0.17	0.45
Scarcity × Phase 3 β_{28}					–0.40	0.45
Peer Shares × Phase 3 β_{29}					–0.03	0.02
RC Participant Rank × Phase 3 β_{30}					0.12*	0.06
Participant Exploration × Phase 3 β_{31}					1.03***	0.31

Table 6.10. Study 3A: Peer Views Explanatory Variables (Continued). Maximum likelihood estimates of Three-Level Random-Coefficient models for the number of times participants viewed each of their peers in each Phase of Study 3A. Model 1: Intercept-Slope; Model 2: Main Effects; Model 3: Restricted Interactions. N = 513.

	Model 1		Model 2		Model 3	
	Est	(SE)	Est	(SE)	Est	(SE)
Peer Discovery × Phase 3 β_{32}					–0.09	0.17
Abun × Peer Shares × Phase 3 β_{33}					0.04	0.03
Scarcity × Peer Shares × Phase 3 β_{34}					0.07*	0.03
Abun × RC Part. Rank × Phase 3 β_{35}					–0.17*	0.08
Scarc × RC Part. Rank × Phase 3 β_{36}					0.13	0.08
Abun × Peer Discovery × Phase 3 β_{37}					0.58**	0.23
Scarc × Peer Discovery × Phase 3 β_{38}					0.05	0.22
Random Effects						
L3 Random Intercept Variance $\psi_{11}^{(3)}$	1.05	0.58	1.02	0.54	1.03	0.54
L2 Random Intercept Variance $\psi_{11}^{(2)}$	14.81	1.04	13.40	0.94	13.34	0.94
L1 (Residual) Error Variance θ	4.42	0.08	4.08	0.07	4.02	0.07
Log likelihood	–17012		–16704		–16656	
AIC | *BIC*	34037 | 34085		33442 | 33559		33396 | 33686	

♦ * $p \leq 0.05$; ** $p \leq 0.01$; *** $p \leq 0.001$; SE = standard error of the mean
♦ ordinal variables are zero-centered so that the lowest level is equal to zero (e.g. Position 1 = 0, reverse-coded Rank 6 = 0)

Interpreting the coefficients in the regression table is not straightforward, so let's walk through each coefficient step-by-step, starting with the intercept. Start by looking at the value in the very first row in the second-to-last column on the far right of Table 6.10, under the super-heading "Model 3" and the sub-heading "Est." The estimated number of times a Control participant chooses to view a given peer in Phase 1 is 8.83 (z = 8.19, p < 0.000) *if all of the following are true about the participant and the peer*:

1. [Dropouts $\beta_3 = 0$] There are zero dropouts in the participant's group
2. [Peer Position $\beta_6 = 0$] The peer was randomly assigned to Position 1
3. [Peer Shares to Participant $\beta_7 = 0$] The peer did not share her results with the participant on any Trial in the current Phase
4. [RC Participant Rank $\beta_8 = 0$] The participant is the lowest-achieving member of his group (Rank 6)

5. [RC Peer Rank $\beta_9 = 0$] The peer is *also* the lowest-achieving member of the participant's group (Rank 6 – note that this never occurs in the data, there are no ties between participants in any group in any Phase)
6. [Participant Exploration $\beta_{10} = 0$] The participant did not explore any platforms in the current Phase (note that this is strictly impossible because participants are forced to select three platforms on each Trial, so the minimum number of platforms any participant could explore is 3)
7. [Peer Exploration $\beta_{11} = 0$] The peer did not explore any platforms in the current Phase (note that this is strictly impossible for the reasons stated above)
8. [Participant Discovery $\beta_{12} = 0$] The participant never selected any of the true top three highest-valued platforms on any Trial in the current Phase
9. [Peer Discovery $\beta_{13} = 0$] The peer never selected any of the true top three highest-valued platforms on any Trial in the current Phase

Note that the model assumes the participant and her peer can hold the same relative achievement Rank in their group, which never occurs in the data. Note also that the model assumes the participant and her peer can explore zero platforms, which is strictly impossible because participants are forced to select three platforms to include in their pitch before they can move on to the next Trial (so the minimum number of platforms a participant or peer could explore is 3). Hopefully it is clear that, due to these model assumptions, the intercept represents a hypothetical value that is never realized in the actual data.

Now that we've straightened that out, we can move on to interpreting the effects of the remaining coefficients in the regression table. Keep in mind that we are interpreting the effect of each coefficient holding all other coefficients at zero (see the above list for an explanation of what this means for each coefficient), which results in combinations that are never observed in the context of the present experiment. What is important to focus on is the *direction* and *significance* of the effects, not the specific values assigned to the coefficients. We'll start by looking at the main effects of Phase and Condition, and then we'll move to participant- and peer-level explanatory variables.

Phase 1. For a Control participant in Rank 6 with Exploration = 0 and Discovery = 0 and no dropouts in his group, and a peer who never shared with the participant and who is in Position 1 and Rank 6 with Exploration = 0 and Discovery = 0, the estimated number of times the participant chooses to view the peer in Phase 1 is 8.83 ($z = 8.19$, $p < 0.000$). An Abundance participant with the above profile chooses to view a peer with the above profile 6.61 ($z = 5.47$, $p = 0.000$) times in Phase 1, which is lower than the number of times the Control participant views his peer but this difference is not significant ($\beta_4 = -2.21$, $z = -1.37$, $p = 0.170$). A Scarcity participant with the above profile chooses to view a peer with the above profile 9.16 ($z = 12.82$, $p = 0.000$) times in Phase 1, which is higher than the number of times the Control participant views his peer but this different is not significant ($\beta_5 = 0.34$, $z = 0.26$, $p = 0.793$).

Phase 2. In Phase 2, the Control participant views his peer 7.46 times ($z = 6.84$, $p < 0.000$), which is a significant *decrease* from the number of times he viewed his peer in Phase 1 ($\beta_1 = -1.37$, $z = -12.88$, $p < 0.000$). The Scarcity participant views his peer 8.00 times ($z = 11.05$, $p < 0.000$) which is slightly more often than the Control participant views his peer, but this difference is not significant (Scarcity Phase 2 – Control Phase 2 = 0.54, $z = 0.42$, $p = 0.678$). The Abundance participant views his peer 5.55 times ($z = 4.54$, $p < 0.000$), which is less often than the Control participant views his peer, but this difference is not significant (Abundance Phase 2 – Control Phase 2 = –1.91, $z = -1.17$, $p = 0.241$).

Phase 3. In Phase 2, the Control participant views his peer 3.35 times ($z = 2.29$, $p = 0.022$) , which is a significant decrease from the number of times he viewed his peer in Phase 2 ($\beta_2 = -4.11$, $z = -4.13$, $p < 0.000$). The Scarcity participant views his peer 3.50 times ($z = 3.74$, $p < 0.000$) which is slightly more often than the Control participant views his peer, but this difference is not significant (Scarcity Phase 3 – Control Phase 3 = 0.14, $z = 0.11$, $p = 0.914$).

The Abundance participant views his peer 1.61 times ($z = 1.04$, $p = 0.298$), which is less often than the Control participant views his peer, but this difference is not significant (Abundance Phase 3 – Control Phase 3 = –1.74, $z = –1.05$, $p = 0.294$).

Now we'll look at participant and peer characteristics whose effects are stable across Phases and Conditions (no significant interactions with Phase or Condition).

Dropouts, Peer Position, and Reverse-Coded Peer Rank. For each additional dropout in a participant's group, the participant views a given peer an additional 0.87 times ($z = 2.01$, $p = 0.044$) in a given Phase (note that attempts to view dropout peers are excluded from the analysis, so this is an estimated effect on the number of times the participant views an active peer). For each unit increase in Peer Position (each step further away from the top-left position in the button tray), the participant views a given peer –0.19 ($z = –13.29$, $p < 0.000$) *fewer* times in a given Phase. Peer Rank does not have a significant effect on the number of times the participant chooses to view that peer in a given Phase ($\beta_9 = 0.02$, $z = 1.39$, $p = 0.163$).

Finally, we'll look at participant and peer characteristics whose effects vary across Conditions and/or Phases (significant two- and/or three-way interactions between Phase, Condition, and participant and peer characteristics).

Peer Shares to Participant. There is a significant three-way interaction between Condition, Phase 3, and Peer Shares to Participant, which makes it difficult to interpret the lower-order interactions and the main effect of Peer Shares to Participant directly. To understand what is going on here, we'll look at the adjusted marginal predictions for the effect of Peer Shares to Participant in each Condition, in each Phase.

In Phases 1 and 2, the number of times a Control participant views a given peer increases by 0.10 ($z = 6.75$, $p < 0.000$) for each unit increase in Peer Shares to Participant (the number of times the peer shared with the participant in the current Phase). The number of times an Abundance participant views a given peer increases by 0.09 (z = 6.76, p < 0.000) for each unit increase in Peer Shares to Participant, which is not significantly different than the increase observed among Control participants (β_{17} = –0.01, z = –0.38, p = 0.705). The number of times a Scarcity participant views a given peer increases by 0.08 (z = 5.79, p < 0.000) for each unit increase in Peer Shares to Participant, which not significantly different than the increase observed among Control participants (β_{18} = –0.01, z = –0.73, p = 0.464).

In Phase 3, the number of times a Control participant views a given peer increases by 0.06 (z = 3.64, p < 0.000) for each unit increase in Peer Shares to Participant. This increase is not significantly different than that observed among Control participants in Phase 1 or Phase 2 (β_{29} = –0.03, z = –1.42, p = 0.155). The number of times a Scarcity participant views a given peer increases by 0.12 (z = 6.81, p < 0.000) for each unit increase in Peer Shares to Participant. This increase is significantly larger than that observed among Control participants (Peer $\text{Shares}_{\text{SCARCITY}}$ Phase 3 – Peer $\text{Shares}_{\text{CONTROL}}$ Phase 3 = 0.06, z = 2.23, p = 0.026). The number of times an Abundance participant views a given peer increases by 0.10 (z = 5.90, p < 0.000) for each unit increase in Peer Shares to Participant. This increase is not significantly different from that observed among Control participants (Peer $\text{Shares}_{\text{ABUNDANCE}}$ Phase 3 – Peer $\text{Shares}_{\text{CONTROL}}$ Phase 3 = 0.06, z = 1.35, p = 0.176).

Reverse-Coded Participant Rank. There is a significant three-way interaction between Condition, Phase 3, and RC Participant Rank. So, once again, we'll look at the adjusted marginal predictions for the effect of RC Participant Rank in each Condition, in each Phase. In Phases 1 and 2, the number of times a Control participant views a given peer increases by 0.19 (z = 4.83, p < 0.000) for each unit increase in RC Participant Rank (each unit increase in the participant's achievement relative to his peers). The number of times an Abundance participant views a given peer increases by 0.42 (z = 9.57, p < 0.000) for each unit increase in RC Participant Rank, which is a significantly higher increase than that observed among Control participants (β_{19} = 0.23, z = 3.93, p < 0.000). The number of times a Scarcity participant views a given peer increases by 0.41 (z = 9.52, p < 0.000) for each unit increase in RC Participant Rank, which is a significantly higher increase than that observed among Control participants (β_{20} = 0.22, z = 3.83, p < 0.000).

In Phase 3, the number of times a Control participant views a given peer increases by 0.31 (z = 5.98, p < 0.000) for each unit increase in RC Participant Rank. This increase is significantly higher than that observed among Control participants in Phase 1 or Phase 2 (β_{30} = 0.12, z = 2.10, p = 0.036). The number of times a Scarcity participant views a given peer increases by 0.41 (z = 7.46, p < 0.000) for each unit increase in RC Participant Rank. This increase is not significantly different from that observed among Control participants (RC Participant Rank$_{\text{SCARCITY}}$ Phase 3 – RC Participant Rank$_{\text{CONTROL}}$ Phase 3 = 0.10, z = 1.28, p = 0.200). The number of times an Abundance participant views a given peer increases by 0.37 (z = 6.72, p < 0.000) for each unit increase in RC Participant Rank. This increase is not significantly different from that observed among Control participants (RC Participant Rank$_{\text{ABUNDANCE}}$ Phase 3 – RC Participant Rank$_{\text{CONTROL}}$ Phase 3 = 0.06, z = 0.81, p = 0.000).

Participant Exploration. In Phases 1 and 2, the effect of Participant Exploration (the number of unique platforms the participant selected across Trials 1–15) on the number of times a Control participant views a given peer is not significant (β_{10} = 0.45, z = 1.73, p = 0.083). The effect of Participant Exploration on the number of times an Abundance participant views a given peer is not significant either (Participant Exploration$_{\text{ABUNDANCE}}$ = 0.03, z = 0.11, p = 0.912).

However, the effect of Participant Exploration on the number of times a Scarcity participant views a given peer *is* significant. For each unit increase in Participant Exploration, the number of times a Scarcity participant views her peer *decreases* by –0.34 (z = –1.97, p = 0.049).

In Phase 3, the number of times a Control participant views her peer increases by 1.48 (= $\beta_{10} + \beta_{31}$ = 0.45 + 1.03, z = 3.64, p < 0.000) for each unit increase in Participant Exploration. The number of times an Abundance participant views her peer increases by 1.06 (z = 2.49, p = 0.013) for each unit increase in Participant Exploration. The number of times a Scarcity participant views her peer increases by 0.70 (z = 2.67, p = 0.008).

Peer Exploration. The effect of Peer Exploration (the number of unique platforms the peer selected across Trials 1–15) on the number of times a Control participant views a given peer is negative but not significant (β_{11} = –0.40, z = –1.82, p = 0.069). The effect of Participant Exploration on the number of times a Scarcity participant views a given peer also negative and not significant (Peer Exploration$_{\text{SCARCITY}}$ = –0.04, z = –0.35, p = 0.727). The effect of Peer Exploration on the number of times an Abundance participant views a given peer is positive but not significant (Peer Exploration$_{\text{ABUNDANCE}}$ = 0.38, z = 1.52, p = 0.129). There were no differences across Phases.

Participant Discovery. In Phase 1, the number of times a Control participant views a given peer decreases by –0.32 (z = –3.34, p = 0.001) for each unit increase in Participant Discovery (the number of times the participant selects any of the true top three highest-valued platforms across Trials 1–15). In Phase 2, the effect of Participant Discovery on the number of times a Control participant views a given peer is not significant (Participant Discovery$_{\text{CONTROL}}$ Phase 2 = –0.09, z = –1.36, p = 0.173). The interaction between Participant Discovery and Phase 3 was not significant (and was dropped from the model), which tells us that the effect of

Participant Discovery in Phase 3 is the same as in Phase 2 – not significant. There were no differences across Conditions.

Peer Discovery. There is a significant three-way interaction between Condition, Phase 3, and Peer Discovery (the number of times the peer selects any of the true top three highest-valued platforms across Trials 1–15). So, we'll look at the adjusted marginal predictions for the effect of Peer Discovery in each Condition, in each Phase, to understand what's going on. In Phases 1 and 2, the effect of Peer Discovery on the number of times a Control participant views a given peer is negative and nonsignificant ($\beta_{13} = –0.02$, $z = –0.20$, $p = 0.844$). The effect of Peer Discovery on the number of times an Abundance participant views a given peer is positive and nonsignificant (Peer $\text{Discovery}_{\text{ABUNDANCE}}$ Phase 1/2 = 0.04, $z = 0.44$, $p = 0.661$). The effect of Peer Discovery on the number of times a Scarcity participant views a given peer is also positive and nonsignificant (Peer $\text{Discovery}_{\text{SCARCITY}}$ Phase 1/2 = 0.03, $z = 0.38$, $p = 0.705$).

In Phase 3, the effect of Peer Discovery on the number of times a Control participant views a given peer is negative, but still nonsignificant ($\beta_{32} = –0.11$, $z = –0.79$, $p = 0.952$). The effect of Peer Discovery on the number of times a Scarcity participant views a given peer is also negative and nonsignificant (Peer $\text{Discovery}_{\text{SCARCITY}}$ Phase 3 = –0.01, $z = –0.06$, $p = 0.952$). The number of times an Abundance participant views a given peer increases by 0.53 for each unit increase in Peer Discovery (Peer $\text{Discovery}_{\text{ABUNDANCE}}$ Phase 3 = 0.53, $z = 4.05$, $p < 0.000$).

Table 6.11. Study 3A: Summary of Explanatory Variables. Summary of participant- and peer-level explanatory variables, with predicted and observed effects on the number of times a participant chooses to view a given peer in a given Phase of the experiment.

Variable	Predicted Effect (Direction)	Observed Effect (Direction)	Observed Effect (β , 95% CI)
Peer Position	–	–	–0.19 [–0.22, –0.16]
Peer Shares to Participant	+	+	
Phases 1 & 2			
Abundance			0.09 [0.06, 0.11]
Control			0.10 [0.07, 0.12]
Scarcity			0.08 [0.05, 0.11]
Phase 3			
Abundance			0.10 [0.07, 0.13]
Control			0.06 [0.03, 0.10]
Scarcity			0.12 [0.09, 0.16]
RC Participant Rank	+	+	
Phases 1 & 2			
Abundance			0.42 [0.33, 0.50]
Control			0.19 [0.11, 0.27]
Scarcity			0.41 [0.33, 0.50]
Phase 3			
Abundance			0.37 [0.26, 0.48]
Control			0.31 [0.21, 0.41]
Scarcity			0.41 [0.30, 0.51]
RC Peer Rank	+	*not significant*	0.02 [–0.01, 0.05]
Participant Exploration	–	*mixed*	
Phases 1 & 2			
Abundance			0.03 [–0.54, 0.60]
Control			0.45 [–0.06, 0.96]
Scarcity			–0.34 [–0.67, 0.00]
Phase 3			
Abundance			1.06 [0.23, 1.90]
Control			1.48 [0.68, 2.28]
Scarcity			0.70 [0.19, 1.21]
Peer Exploration	+	*not significant*	
Abundance			0.38 [–0.11, 0.86]
Control			–0.40 [–0.84, 0.03]
Scarcity			–0.04 [–0.28, 0.19]
Participant Discovery	– / +	*mixed*	
Phase 1			–0.32 [–0.49, –0.12]
Phases 2 & 3			–0.09 [–0.21, 0.04]

Table 6.11. Study 3A: Summary of Explanatory Variables (*Continued*). Summary of participant- and peer-level explanatory variables, with predicted and observed effects on the number of times a participant chooses to view a given peer in a given Phase of the experiment.

Variable	Predicted Effect (Direction)	Observed Effect (Direction)	Observed Effect (β , 95% CI)
Peer Discovery	+	*mixed*	
Phases 1 & 2			
Abundance			0.04 [–0.15, 0.23]
Control			–0.02 [–0.21, 0.17]
Scarcity			–0.34 [–0.14, 0.21]
Phase 3			
Abundance			0.53 [0.27, 0.79]
Control			–0.11 [–0.38, 0.16]
Scarcity			–0.01 [–0.23, 0.22]

Table 6.11 summarizes the observed effects of participant- and peer-level explanatory variables for the number of times participants view a given peer in a given Phase of Study 3A, and contrasts these with the predicted effects. Consistent with predictions, we found a negative, significant effect of Peer Position – participants viewed a given peer less often the further away the peer's randomly assigned position from the top-left corner of the button tray. We also found a positive, significant effect of the Peer Shares to Participant – participants viewed a given peer more often when the peer shared results more often. We found a positive, significant effect of Reverse-Coded Participant Rank – higher-performing participants viewed their peers more often.

Somewhat surprisingly, the effect of Reverse-Coded Peer Rank was not significant – a peer's achievement level does not have a significant effect on the number of times participants choose to view that peer. The effects of Participant and Peer Exploration and Discovery rates were mostly nonsignificant. There is no strong evidence that either the participant's or their peers' explore-exploit strategies affect the number of times participants view their peers.

6.1.4 Group-Level Results

There are two distinct networks to consider for each experimental participant group. The first is the Shares Network – the network of ties created by each participant's decisions (not) to share his own results with each of his peers on Trials 1–14. The second is the Views Network – the network of ties created by each participant's decisions (not) to view each of his peers' results on Trials 2–15. Participants in Study 3A maintained high levels of sharing with their peers across all Phases and Conditions, so there aren't many insights to be gained from investigating differences in the structure of the Shares Networks. Instead, I am going to focus on the Views Networks, where we see more variability (especially across Phases).

Characterizing the structure of the Views Networks will help us answer three important questions about what's going in within each experimental group in each Phase of the experiment: 1) How much information is exchanged between members of a given group (how often do the members of a given group choose to view each other's results)? 2) Are some members of a given group choosing to view their peers more often than other members of the group? 3) Are some members of a given group viewed more often by their peers than other members of the group?

I will treat the Views Network of each participant group in each Phase of the experiment as a *weighted directed* graph (weighted digraph). Graphs will be constructed separately for each experimental group in each Phase of the experiment to allow us to compare the structure of each group's network across Phases. For each graph (each participant group's Views Network in a given Phase of the experiment), I will calculate six indices that each capture a different characteristic of the graph's structure: Average Degree, Density, Centralization, Out-Degree

Variance, Hierarchy, and In-Degree Variance.[13] There is a lack of consensus in the social network analysis literature around the method for calculating each of these indices. So, I will walk through the method I use to calculate each index, being careful to explain the rationale behind my approach.

I will start by introducing some standard language that I have adapted to the current context from Wasserman and Faust (1994). For a weighted digraph $G_W \coloneqq (N, L, W)$, let $N = \{n_1, n_2, \ldots, n_g\}$ be the set of nodes, n_i, $i = 1,\ldots, g$. Let $L = \{l_1, l_2, \ldots, l_L\}$ be the set of ties (arcs / directed lines) connecting the nodes, and $W = \{w_1, w_2, \ldots, w_L\}$ be the set of weights assigned to each of the ties in L. In the context of Study 3A, the set of nodes $N = \{n_1, n_2, \ldots, n_g\}$ comprise the six participants in each experimental group. So, $|N| = g = 6$.[14] If Participant i (n_i) chooses to view Peer j (n_j) on at least one Trial in a given Phase, the tie from Participant i to Peer j, $l_k \in L$, is assigned the value "1" ($l_k = \langle n_i, n_j \rangle = 1$).

If Participant i (n_i) *does not* choose to view Peer j (n_j) on *any* Trial in a given Phase, the tie from Participant i to Peer j, $l_k \in L$, is assigned the value "0" ($l_k = \langle n_i, n_j \rangle = 0$). The set of weights $W = \{w_1, w_2, \ldots, w_L\}$ assigned to each of the ties in L represent the total number of times a given participant chooses to view a given peer across Trials 2–15 in a given Phase. The value of the weight $w_k \in W$ thus ranges from 0 (Participant i did not choose to view Peer j on *any*

[13] I have chosen to focus on degree-based indices because they are simple, sensitive to small changes in network structure, and can be generalized to weighted digraphs in a relatively straightforward way (Wasserman & Faust, 1994).

[14] Caveat: I exclude active participants' decisions to view peers who dropped out of the experiment, and I also exclude any decisions made by dropout participants before they dropped out of the experiment. For groups that have at least one dropout, I adjust $|N|$ to reflect the number of *active* participants in the group. So, for a group with two dropouts, $|N| = g = 6 - 2 = 4$. No participant group had more than two dropouts. As a reminder: 21 participants across 18 groups were classified as dropouts because they repeatedly failed to submit their responses before the time limits: Abundance = 11 participants, 9 groups; Control = 6 participants, 6 groups; Scarcity = 4 participants, 3 groups.

Trial in a given Phase) to 14 (Participant *i* chose to view Peer *j* on every possible Trial, 2–15, in a given Phase).

A concrete example will help clarify the relationship between *L* and *W*. Consider Participant *i* (n_i) and Peer *j* (n_j) in Phase 1 of the experiment. Participant *i* chooses to view Peer *j* on Trials 2, 4, 6, and 8. In this case, the tie $l_k = \langle n_i , n_j \rangle \in L$ is assigned the value "1" (Participant *i* chose to view Peer *j* at least once). The weight $w_k \in W$ assigned to l_k is equal to 4 (Participant *i* chose to view Peer *j* on exactly 4 Trials in Phase 1).

In the above example, Participant *i* "sends" a tie *to* Peer *j* (Participant *i* chose to view Peer *j'*s results at least once). I will refer to the tie sent *from* Participant *i to* Peer *j* as an "out-going" tie from Participant *i* to Peer *j*. This out-going tie is *directed* from Participant *i* to Peer *j*. The weight, w_k, of this directed, out-going tie, l_k, is equal to 4 (Participant *i* chose to view Peer *j* on 4 Trials in Phase 1). Importantly, neither w_k nor l_k contain any information about Peer *j*'s decisions (not) to view Participant *i*.

Extending the example, suppose Peer *j never* chooses to view Participant *i on any Trial* in Phase 1. In this case, the tie $l_{k'} = \langle n_j , n_i \rangle \in L$ is assigned the value "0," and the weight, $w_{k'}$, of $l_{k'}$ is equal to zero. From the perspective of Peer *j*, $l_{k'} = \langle n_j , n_i \rangle$ is an out-going tie directed *from* himself *to* Participant *i*. But, from the perspective of Participant *i*, $l_{k'} = \langle n_j , n_i \rangle$ is an *in-coming* tie directed *to* himself *from* Peer *j*. Participant *i* "receives" this tie *from* Peer *j*.

This distinction between out-going ties (*from* a given participant *to* a given peer) and in-coming ties (*to* a given participant *from* a given peer) is important. In the context of the present experiment, out-going ties tell us about information the participant seeks/receives from his peers. In-coming ties tell us about information peers seek/receive from the participant.

We'll use the term "centrality" to describe the extent to which a participant initiates connections with (sends ties to, chooses to view) his peers. A participant has higher centrality than his peers if he initiates more connections than his peers do.[15] You can think of centrality as a measure of a given participant's gregariousness, or the extent to which the participant chooses to access social information. We will use out-degree as our actor-level index of centrality.

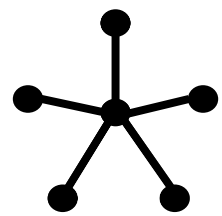
I will define the *out-degree*, $C_{D+}(n_i)$, of Participant *i* as the sum of the weights of all ties *from* Participant *i to* each of his peers in a given Phase (the sum of the number of times Participant *i* chooses to view each of his peers in a given Phase – e.g. if Participant *i* chooses to view Peer *j* on 5 Trials, Peer *j′* on 2 Trials, Peer *j″* on 8 Trials, and his remaining two peers on zero Trials, then Participant *i* has an out-degree of 15 = 5 + 2 + 8 + 0 + 0 in Phase 1).[16]

We can generalize the actor-level centrality index to a group-level index of *centralization* that tells us the extent to which a single actor in the network is responsible for initiating more connections (sending more ties) than all other actors in the network (the extent to which a single participant in a given group chooses to view his peers more often than any of his peers choose to view the participant or each other). To picture a maximally centralized network, imagine a star

[15] Here I am following Wasserman and Faust's (1994) definition of *degree centrality* as a function of an actor's choices to initiate connections with his peers. Note that this is a departure from the definition(s) of centrality suggested by Knoke and Burt (1983), because I am not taking into account in-coming ties (nor am I taking into account any indirect connections that an actor can reach through his neighbors).

[16] I am departing from the suggestion by Wasserman and Faust (1994) that the notion of degree be generalized to weighted graphs by averaging the weights of each tie over all ties directed from a node (for out-degree) or to a node (for in-degree). The reason I am choosing to depart from this suggestion is that I want an actor-level measure of centrality that I can generalize to a group-level measure of centralization. Wasserman and Faust only provide a generalization of the notion of degree centrality to degree centralization for *unweighted* directed graphs. It doesn't make sense to use a standardized measure of degree (the *average* of the weights of all out-going ties from a participant to his peers) with their formulation of degree centralization for *unweighted* directed graphs. Instead, it seems like we ought to use the *sum* of the weights of all out-going ties from a participant to his peers. This "sum of the weights" version of degree for weighted directed graphs is suggested by Barrat et al. (2004), and seems more appropriate for the present application.

graph that has a single central node with ties to each of the other nodes and no ties between any of the other nodes.



The degree centralization of the star graph (above) is equal to 1.0. The degree centralization of all other graphs ranges from 0.0 (all actors have the same degree) to 1.0. It's easier to explain the method for calculating this index if we start with the definition of centralization for an *unweighted* digraph. In an *unweighted* digraph, we only have the set of ties $L = \{l_1, l_2, \ldots, l_L\}$, where each tie $l_k = \langle n_j, n_i \rangle$ takes the value "1" if n_i sends a tie to n_j and "0" if n_i does not send a tie to n_j (there is no set of weights, W). An actor's degree centrality is simply the number of peers in the network to whom the actor has sent a tie ($l_k = \langle n_j, n_i \rangle = 1$). The *centralization* of an unweighted digraph is then a proportion calculated as follows:

- Numerator: The sum of the differences between the maximum *observed* degree centrality in the network (the degree centrality of the actor who has sent the largest number of ties) and the degree centrality of all other actors in the network
- Denominator: The *theoretical* maximum sum of the differences between the degree centrality of the actor who has sent the largest number of ties and the degree centrality of all other actors in the network

More formally, for an unweighted digraph $G \coloneqq (N, L)$, where N is the set of nodes (actors), L is the set of ties, $|N|$ = g = the number of nodes, and n^* is the node with the highest degree centrality, the degree centralization of G is

$$C_{D+}(G) = \frac{\sum_{i=1}^{g}[C_{D+}(n*) - C_{D+}(n_i)]}{max\sum_{i=1}^{g}[C_{D+}(n*) - C_{D+}(n_i)]}$$

In the context of the present experiment, the theoretical maximum sum of the differences between the most central participant in a given group and each of the other participants in that group is 350. This value is obtained when one participant views all 5 of his peers on every possible Trial in a given Phase (participant's degree centrality = 14 + 14 + 14 + 14 + 14 = 70), and each of the 5 peers in the group does not view the participant or any of the other peers on any Trial in a given Phase (each peer's degree centrality = 0 + 0 + 0 + 0 + 0 = 0).[17] When calculating the degree centralization for each participant group's network in each Phase of the present experiment, we set the denominator equal to 350 and the numerator equal to the sum of the differences between the largest observed degree centrality (the largest sum of the number of times a participant viewed each of his peers) and the degree centrality of each of the other participants in the group.[18]

The degree centralization for a weighted digraph ranges from 0.0 (every participant in the group has the same out-degree) to 1.0 (a single participant in the group chooses to view all of his peers on every Trial, and his five peers never choose to view the participant or each other on any Trial).

[17] 350 = (70 – 0) + (70 – 0) + (70 – 0) + (70 – 0) + (70 – 0)

[18] For this and all other group-level indices, the denominator is adjusted for groups with dropouts. For example, in a group with 2 dropouts, the theoretical maximum sum of the differences between the most central participant in a given group and each of the other participants in that group is
126 = (70 – 0) + (70 – 0) + (70 – 0).

We will also look at out-degree *variance*, which gives us a sense of the dispersion or heterogeneity of the degree centralities of the participants in a given group. For a weighted digraph $G_W \coloneqq (N, L, W)$, where $|N|$ = g = the number of nodes in G, the degree variance of G_W is

$$S^2_{D+}(G_W) = \frac{[\sum_{i=1}^{g}(C_{D+}(n_i) - \overline{C}_{D+})^2]}{g}$$

where $\overline{C}_{D+}$ is the average out-degree of the actors in the network, or the sum of the out-degrees of the participants in a given group divided by the number of participants in that group

$$\overline{C}_{D+} = \frac{\sum_{i=1}^{g} C_{D+}(n_i)}{g}$$

The average out-degree, $\overline{C}_{D+}$, is a useful measure in itself, as it gives us a sense of the average number of times participants in a given group choose to view their peers' results in a given Phase. The average out-degree ranges from 0 (none of the participants in a given group choose to view any of their peers on any Trial) to 70 (every participant in a given group chooses to view all 5 of his peers on every possible Trial, 2–15, of a given Phase).

Another useful measure is the *density* of a participant group's network. The density of a weighted digraph G_W is the average value of the weights, $w_k \in W$, attached to the observed (outgoing) ties, $l_k \in L$

$$\Delta(G_W) = \frac{\sum_{w_k}}{g(g-1)}$$

which is the average standardized out-degree or the average strength of an out-going tie between any pair nodes in graph G_W. Density ranges from 0 (none of the participants in a given group choose to view any of their peers on any Trial) to 14 (every participant in a given group chooses to view all 5 of his peers on every possible Trial, 2–15, of a given Phase).

We'll use the term "prestige" to describe the extent to which a participant is the target of connections from (receives ties from, is viewed by) his peers. A participant has higher prestige than his peers if he receives more connections than his peers do.[19] You can think of prestige as a measure of a given participant's popularity, or the extent to which the participant's peers choose him as a source of social information. We will use in-degree as our actor-level index of prestige.

I will define the *in-degree*, $C_{D-}(n_i)$, of Participant i as the sum of the weights of all ties *to* Participant i *from* each of his peers (the sum of the number of times Participant i is viewed by each of his peers in a given Phase – e.g. if Participant i is viewed by Peer j on 3 Trials, Peer j' on 6 Trials, Peer j'' on 9 Trials, and his remaining two peers on zero Trials, then Participant i has an in-degree of 18 = 3 + 6 + 9 + 0 + 0 in Phase 1).

We can generalize the actor-level prestige index to a group-level index of *hierarchy* that tells us the extent to which a single actor in the network is the target of more connections (receives more ties) than all other actors in the network (the extent to which a single participant

[19] This definition of prestige is not commonly used, and is a departure from the definitions of prestige suggested by both Wasserman and Faust (1994) and by Knoke and Burt (1983). Most common indices of an actor's take into account the prestige of the peers who are choosing to connect to that actor. Given the small size of participant networks, and the fact that they tend to be fully-connected (participants tend to view each of their peers at least once in each Phase of the experiment), we don't get much traction by adding this additional level of complexity to our definition of prestige. Defining prestige as the inverse of centrality, gives us a more direct answer to our question about how many peers viewed a given participants' results (and how often they did so), and it eases exposition.

in a given group is viewed by his peers more often than any of his peers are viewed by the participant or by each other). The hierarchy of a graph is a proportion calculated as follows:[20]

- Numerator: The sum of the differences between the maximum *observed* prestige in the network (the prestige of the actor who has received the largest number of ties) and the prestige of all other actors in the network
- Denominator: The *theoretical* maximum sum of the differences between the prestige of the actor who has received the largest number of ties and the prestige of all other actors in the network

In the context of the present experiment, the theoretical maximum sum of the differences between the most prestigious participant in a given group and each of the other participants in that group is 350. This value is obtained when one participant is viewed by all 5 of his peers on every possible Trial in a given Phase (participant's prestige = 14 + 14 + 14 + 14 + 14 = 70), and each of the 5 peers in the group is not viewed by the participant or any of the other peers on any Trial in a given Phase (each peer's prestige = 0 + 0 + 0 + 0 + 0 = 0).[21]

When calculating the hierarchy for each participant group's network in each Phase of the present experiment, we set the denominator equal to 350 and the numerator equal to the sum of the differences between the largest observed prestige (the largest sum of the number of times a participant is viewed by each of his peers) and the prestige of each of the other participants in the group.[22] The hierarchy for a weighted digraph ranges from 0.0 (every participant in the group

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[20] This definition of hierarchy is not commonly used, and is a departure from the definitions of group-level prestige indices suggested by Wasserman and Faust (1994) and of group-level hierarchy indices suggested by Knoke and Burt (1983). The common indices of group-level prestige/hierarchy are based on the actor-level indices that take into account the prestige of the peers who are choosing to connect to a given actor.

[21] 350 = (70 – 0) + (70 – 0) + (70 – 0) + (70 – 0) + (70 – 0)

[22] For this and all other group-level indices, the denominator is adjusted for groups with dropouts. For example, in a group with 2 dropouts, the theoretical maximum sum of the differences between the most central participant in a given group and each of the other participants in that group is
126 = (70 – 0) + (70 – 0) + (70 – 0).

has the same in-degree) to 1.0 (a single participant in the group is viewed by all of his peers on every Trial, and his five peers are never viewed by the participant or each other on any Trial).

The average degree and density are the same regardless of whether we use out-degree or in-degree to calculate these measures. We are dealing with "closed" networks (participants in a given group can only send ties to each other, and can only receive ties from each other), so the total number of views *sent* is equal to the total number of views *received*. We arrive at the same results regardless of whether we use out-degree or in-degree to calculate the average degree and density of such a network.

What patterns do we expect to observe in each of the network indices (summarized in Table 6.12)? This depends on the behavior of individual participants, and pairs of participants, but not on any pre-existing network structure. The network of each participant group begins *de novo* at the start of the experiment. As such, there is no pre-existing network structure that might influence participants' behavior. In other words, at the start of Phase 1 of the present experiment, there is no causal path between network structure and participant behavior because there is no network structure at all.

What's more, a participant cannot observe any aspect of the network structure that arises in her network beyond her peers' decisions to share with her. This rules out structural explanations for participants' behavior that depend on an actor's knowledge of its neighbors' ties (e.g. balance theory, see Cartwright & Harary, 1956; Heider, 1958). So, to form our expectations around the patterns of group-level network structure that might emerge in the present experiment, we should look to behavioral patterns that we observed participant and dyad (pair) levels.

Table 6.12. Group Network Structure Indices. Summary of indices used to characterize the structure of participant group View Networks in Study 3A.

Index	Formula	Interpretation
Average degree	$\overline{C}_D = \frac{\sum_{i=1}^{g} C_D(n_i)}{g}$	The average number of times participants in a given group choose to view their peers (equivalently, the average number of times participants in a given group are viewed by their peers) in a given Phase. Range = [0, 70]
Density	$\Delta(G_W) = \frac{\sum_{w_k}}{g(g-1)}$	The average number of times a given participant chooses to view a given peer (equivalently, the average number of times a given participant is viewed by a given peer) in a given Phase. Range = [0, 14]
Centralization	$C_{D+}(G_W) = \frac{\sum_{i=1}^{g}[C_{D+}(n*) - C_{D+}(n_i)]}{max \sum_{i=1}^{g}[C_{D+}(n*) - C_{D+}(n_i)]}$	The extent to which a single participant in the group chooses to view his peers more often than any of his peers choose to view the participant or each other. Range = [0.0, 1.0]
Out-degree variance	$S_{D+}^2(G_W) = \frac{[\sum_{i=1}^{g}(C_{D+}(n_i) - \overline{C}_{D+})^2]}{g}$	The variability or heterogeneity of the centrality indices of the participants in a given group. Range = [0, 1225]
Hierarchy	$C_{D-}(G_W) = \frac{\sum_{i=1}^{g}[C_{D-}(n*) - C_{D-}(n_i)]}{max \sum_{i=1}^{g}[C_{D-}(n*) - C_{D-}(n_i)]}$	The extent to which a single participant is viewed by his peers more often than any of his peers are viewed by the participant or each other. Range = [0.0, 1.0]
In-degree variance	$S_{D-}^2(G_W) = \frac{[\sum_{i=1}^{g}(C_{D-}(n_i) - \overline{C}_{D-})^2]}{g}$	The variability or heterogeneity of the prestige indices of the participants in a given group Range = [0, 1225]

We found that participants tend to view their peers less often in each subsequent Phase of the experiment. As a result, the Average Degree and Density of a given participant group network should *decrease* across Phases. We also found that the number of times a participant chooses to view her peers increases with the participant's relative achievement level. This relationship produces differences in the out-degrees of the participants in a given group. We can explore how these differences might affect our out-degree-based group-level indices (Centralization and Out-Degree Variance) using a hypothetical example.

Imagine participants A, B, C, D, E, and F comprise experimental group G. Let's start by assuming that each participant in G chooses to view each of her peers on exactly 7 Trials in each Phase of the experiment. Let's also assume that every participant in G has the same Rank (this is not possible in practice, but we want to start here so we have a clear point of comparison). The centrality (out-degree) of each participant in G at the end of Phase 1 is 35 = 5 (peers) × 7 (Trials). The Centralization of group G is 0.0.[23] The Out-Degree Variance of Group G is 0.0.[24]

Now, let's allow each participant in G to take a different achievement level, where A = Rank 1 (highest achievement), B = Rank 2, C = Rank 3, D = Rank 4, E = Rank 5, and F = Rank 6 (lowest achievement). Among Control participants in Phases 1 and 2 of Study 3A, a one-unit increase in (RC) Participant Rank (a one-unit *increase* in achievement) is associated with an increase of 0.19 (z = 4.83, p < 0.000) in the number of times a participant chooses to view a given peer. A participant's out-degree is the sum of the total number of times the participant

[23] The highest centrality is 35. The sum of the differences between the participant with the highest centrality and each of his peers is 0 = (35 – 35) + (35 – 35) + (35 – 35) + (35 – 35) + (35 – 35). The theoretical maximum sum of the differences is 350. The proportion of the sum of the observed differences over the theoretical maximum sum of the differences is 0.0 = 0 / 350.

[24] The mean centrality is 35. The sum of the squared differences between each participant's out-degree and the average out-degree is $0 = (35-35)^2 + (35-35)^2 + (35-35)^2 + (35-35)^2 + (35-35)^2$. The sum of the squared differences divided by the number of participants in group G is 0.0 = 0 / 6.

chose to view each of his peers in a given Phase. So, a one-unit increase in achievement corresponds to an increase of 0.95 (0.19 increase per peer × 5 peers) in a Control participant's out-degree in Phases 1 and 2.

If we assume participant F (Rank 6) in our hypothetical group G chooses to view each of his peers on 7 Trials in Phase 1, then participant F's out-degree at the end of Phase 1 would be 35. The out-degrees of the remaining participants in G would be: E (Rank 5) = 35.95, D (Rank 4) = 36.90, C (Rank 3) = 37.85, B (Rank 2) = 38.80, and A (Rank 1) = 39.75.

The sum of the differences between the out-degree of participant A (the highest-performing participant in group G) and each of his peers (B, C, D, E, F) is equal to 14.25 = 0.95 (A – B) + 1.90 (A – C) + 2.85 (A – D) + 3.80 (A – E) + 4.75 (A – F). The theoretical maximum sum of these differences is 350. So, *assuming no other factors produce differences* in the out-degrees of the participants in group G, the Centralization of such a group in Phase 1 would be 0.04 = 14.25 / 350.

The average (out-)degree in group G would be 37.38. The sum of the squared differences between the out-degree of each participant in G and the average (out-)degree would be 15.79. We divide the sum of the squared differences by 6 (the number of participants in group G) to arrive at the Out-Degree Variance, which is equal to 2.63.

Ignoring any other factors that could possibly affect the number of times a participant chooses to view his peers in Phases 1 and 2 (and any possible interactions between these factors and participant achievement), the positive relationship between achievement and the number of times a participant chooses to view his peers increases the expected Centralization of a given Control group by 0.04 (compared with a hypothetical Control group in which all participants have the same Rank). This relationship also increases the Out-Degree Variance of this group by 2.63.

The increase in peer views associated with a one-unit increase in achievement is larger for Abundance and Scarcity groups than it is for Control groups in Phases 1 and 2 (RC Participant $\text{Rank}_{\text{ABUNDANCE}}$ Phase 1/2= 0.42, $z = 9.57$, $p < 0.000$; RC Participant $\text{Rank}_{\text{SCARCITY}}$ Phase 1/2 = 0.41; $z = 9.52$, $p < 0.000$). If there were no other factors that affect peer views, we would observe that Abundance and Scarcity groups have higher Centralization and Out-Degree Variance than Control groups in Phases 1 and 2. (This is unlikely to be the case, but it's instructive to consider how differences the effect size of a single factor might produce differences in the structure of participant networks across Conditions.)

In Phase 3, the increase in Control participants' peer views associated with a one-unit increase in participant achievement is larger than it was in Phases 1 and 2 (RC Participant $\text{Rank}_{\text{CONTROL}}$ Phase 3 = 0.31, $z = 5.98$, $p < 0.000$) So, we might observe that Control groups have higher Centrality and Out-Degree Variance in Phase 3 than they did in Phases 1 and 2. For Abundance and Scarcity groups in Phase 3, the relationship between participant achievement and peer views is similar to Phases 1 and 2, and similar to that among Control participants in Phase 3 (RC Participant $\text{Rank}_{\text{ABUNDANCE}}$ Phase 3 = 0.37, $z = 6.72$, $p < 0.000$; RC Participant $\text{Rank}_{\text{SCARCITY}}$ Phase 3 = 0.41; $z = 7.46$, $p < 0.000$). If there were no other factors that affect peer views, we would observe that Abundance and Scarcity groups have similar Centralization and Out-Degree Variance to Control groups in Phase 3. (Again, this is unlikely to be the case.)

We also found two factors that affect the number of times a participant is viewed by his peers. The number of times peers choose to view a participant increases with the number of times the participant chooses to share his results. And, the closer the participant's randomly-assigned Position to the top-left location in the button tray (Position 1), the more frequently his peers choose to view him.

Let's explore how one of these factors (participants' randomly-assigned Positions) might affect our in-degree-based group-level indices (Hierarchy and In-Degree Variance) by extending the hypothetical example we used above. We start with participants A, B, C, D, E, and F who comprise experimental group G. Assume that each participant in G is viewed by each of her peers on exactly 7 Trials in each Phase of the experiment. Let's also assume that every participant in G has the same Position (this is strictly impossible in the current experimental design, but once again we want to start here so we have a clear point of comparison). The prestige (in-degree) of each participant in G at the end of a given Phase is 35 = 5 (peers) × 7 (Trials). The Hierarchy of group G is 0.0.[25] The In-Degree Variance of Group G is 0.0.[26]

Now, let's allow each participant in G to take a different Position, where A = Position 1 (top-left location in button tray), B = Position 2, C = Position 3, D = Position 4, E = Position 5, and F = Position 6 (bottom-middle location in button tray). The relationship between Position and the number of views received from peers is constant across Phases and Conditions. A one-unit increase in Position (moving one spot further away from the top-left location of the button tray) is associated with a decrease of –0.19 ($z = –13.29$, $p < 0.000$) in the number of times a participant is viewed by a given peer in a given Phase. A participant's in-degree is the sum of the total number of times the participant was viewed by each of his peers in a given Phase. So, a

[25] The highest prestige is 35. The sum of the differences between the participant with the highest prestige and each of his peers is 0 = (35 – 35) + (35 – 35) + (35 – 35) + (35 – 35) + (35 – 35). The theoretical maximum sum of the differences is 350. The proportion of the sum of the observed differences over the theoretical maximum sum of the differences is 0.0 = 0 / 350.

[26] The mean prestige is 35. The sum of the squared differences between each participant's prestige and the mean prestige score is $0 =(35 – 35)^2 + (35 – 35)^2 + (35 – 35)^2 + (35 – 35)^2 + (35 – 35)^2$. The sum of the squared differences divided by the number of participants in group G is 0.0 = 0 / 6.

one-unit increase in Position corresponds to a decrease of –0.95 (–0.19 decrease per peer × 5 peers) in a participant's in-degree in a given Phase of the experiment.

(Note: The fact that the absolute size of this effect of Position is the same as the absolute size of the effect of Rank is a coincidence. Exploratory analyses found no relationship between Rank and Position. The fact that all of the subsequent calculations in this example yield the same values as we obtained in the example above where we looked at the relationship between Participant Rank and out-degree indices is just a peculiar characteristic of this particular set of data.)

If we assume participant F (Position 6) in our hypothetical group G is viewed by each of his peers on 7 Trials in a given Phase, then participant F's in-degree at the end of a given Phase would be 35. The in-degrees of the remaining participants in G would be: E (Position 5) = 35.95, D (Position 4) = 36.90, C (Position 3) = 37.85, B (Position 2) = 38.80, and A (Position 1) = 39.75.

The sum of the differences between the in-degree of participant A (Position 1) and each of his peers (B, C, D, E, F) is equal to 14.25 = 0.95 (A – B) + 1.90 (A – C) + 2.85 (A – D) + 3.80 (A – E) + 4.75 (A – F). The theoretical maximum sum of these differences is 350. So, *assuming no other factors produce differences* in the in-degrees of the participants in group G, the Hierarchy of such a group in a given Phase would be 0.04 = 14.25 / 350. (Recall that we obtain the same values for Average Degree and Density regardless of whether we use out-degree or in-degree to calculate these indices. So, the Average Degree, or average in-degree, of group G is 37.38.) The sum of the squared differences between the in-degree of each participant in G and the Average Degree is 15.79. We divide the sum of the squared differences by 6 (the number of participants in group G) to arrive at the In-Degree Variance, which is equal to 2.63.

Ignoring any other factors that could possibly affect the number of times a participant is viewed by his peers in a given Phase (and any possible interactions between these factors and participant Position), the negative relationship between Position and the number of times a participant is viewed by his peers increases the expected Hierarchy of a given group by 0.04 (compared with a hypothetical group in which all participants have the same Position). This relationship also increases the In-Degree Variance of this group by 2.63.

The above examples each isolate the effect of a single participant or peer characteristic on the number of times participants view (or are viewed by) their peers, ignoring the possible effects of other participant/peer characteristics, or any interactions between these characteristics. A deep-dive into the relationships among peer characteristics (e.g. constructing participant "profiles"), and the distribution of participant profiles across Phases and Conditions, is beyond the scope of the present analysis. Such a deep-dive would make it possible to construct more precise predictions about the distribution of the values for our six network statistics in Study 3A. For now, we will just move on to a summary of what we actually observed. Table 6.13 presents the average value (and standard deviation) of each View Network index in each Phase and Condition of Study 3A.

Table 6.13. Study 3A: View Network Structure. Average values (and standard deviations) of View Network indices by Phase, Condition. N = 89 (Abundance = 30 groups; Control = 30 groups; Scarcity = 29 groups).

	Phase 1		Phase 2		Phase 3	
	Mean	(SD)	Mean	(SD)	Mean	(SD)
Average Degree						
Abundance	44.94	8.71	40.61	8.81	37.35	9.04
Control	48.99	8.20	42.86	9.82	37.43	9.82
Scarcity	47.12	10.16	41.69	12.33	36.74	13.57
Density						
Abundance	9.80	1.88	8.92	2.19	8.13	1.93
Control	10.29	1.92	9.00	2.21	7.86	2.23
Scarcity	9.68	1.81	8.55	2.33	7.50	2.63
Centralization						
Abundance	0.32	0.14	0.39	0.15	0.42	0.16
Control	0.28	0.15	0.39	0.17	0.47	0.19
Scarcity	0.33	0.15	0.41	0.17	0.45	0.14
Out-Degree Variance						
Abundance	317.37	195.57	375.04	197.85	358.42	182.85
Control	291.07	250.85	322.76	216.19	344.41	180.29
Scarcity	328.71	206.40	362.04	218.22	373.38	204.37
Hierarchy						
Abundance	0.12	0.05	0.11	0.04	0.11	0.04
Control	0.11	0.04	0.10	0.04	0.11	0.03
Scarcity	0.12	0.05	0.12	0.05	0.12	0.05
In-Degree Variance						
Abundance	16.71	10.11	17.52	11.24	17.64	12.60
Control	17.59	12.33	18.81	12.63	22.09	11.24
Scarcity	18.70	11.52	21.06	13.09	21.64	11.77

Figure 6.17 presents the Average Degree of participants groups in each Phase of Study 3A.

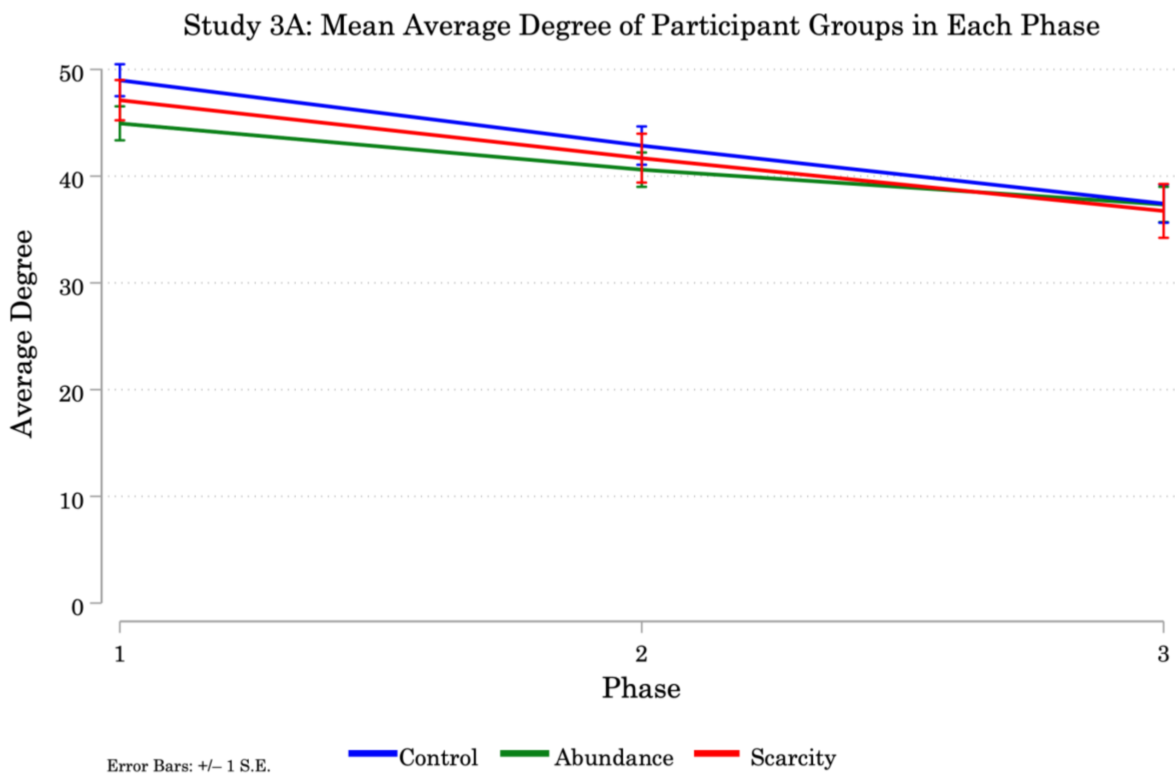

Figure 6.17. Study 3A: Degree. Mean Average Degree of participant groups, by Phase and Condition. Error Bars: +/– 1 S.E. N = 89. Green = Abundance (30 groups); Blue = Control (30 groups); Red = Scarcity (29 groups). Note that the y-axis is truncated. The range of Average Degree = [0, 70]. The Average Degree decreases across Phases in all three Conditions.

Table 6.14 presents the parameter estimates and fit statistics from three different Two-Level Random Coefficient models for the Average Degree of a given participant group in each Phase of Study 3A. Model 1 is the baseline model. The fixed part of Model 1 includes an intercept, piecewise linear slopes for Phases 2 and 3, and a fixed effect for the number of dropouts in a participant's group. The random part of Model 1 includes a random intercept and a random linear slope at the Group level (Level 2). Model 2 includes a fixed effect for Condition. Model 3 introduces interactions among elements of the experimental design (Condition, Phase). Model 3 did not provide a significantly better fit than Model 2 [$LR\ \chi^2(4) = 5.41$, $p = 0.248$], nor did Model 2 provide a better fit than Model 1 [$LR\ \chi^2(2) = 1.89$, $p = 0.388$], so I will focus on the estimates from Model 1.

Table 6.14. Study 3A: Degree. Maximum likelihood estimates of Three-Level Random-Coefficient models for the Average Degree of a given participant group in each Phase. Model 1: Intercept-Slope; Model 2: Main Effects; Model 3: Design Interactions. N = 89 (Abundance = 30 groups; Control = 30 groups; Scarcity = 29 groups).

	Model 1		Model 2		Model 3	
	Est	(SE)	Est	(SE)	Est	(SE)
Fixed Effects						
Intercept β_0	48.16***	1.04	49.82***	1.63	49.90***	1.64
Phase 2 β_1	–5.30***	0.54	–5.30***	0.54	–6.13***	0.92
Phase 3 β_2	–4.54***	0.54	–4.54***	0.54	–5.43***	0.92
Dropouts	–4.84**	1.86	–4.56*	1.88	–4.56*	1.88
Abundance β_3			–3.14	2.26	–3.28	2.28
Scarcity β_4			–2.06	2.38	–2.15	2.28
Abundance × Phase 2 β_5					1.78	1.30
Scarcity × Phase 2 β_6					0.69	1.31
Abundance × Phase 3 β_7					2.17	1.30
Scarcity × Phase 3 β_8					0.49	1.31
Random Effects						
L2 Random Intercept Var $\psi_{11}^{(2)}$	69.05	11.60	67.15	11.32	67.15	11.31
L2 Random Slope Var $\psi_{22}^{(2)}$	7.23	1.93	7.23	1.93	6.54	1.83
L1 (Residual) Error Var θ	9.49	1.42	9.49	1.42	9.48	1.42
Log likelihood	–862		–861		–859	
AIC | *BIC*	1740 | 1769		1743 | 1778		1745 | 1795	

* $p \leq 0.05$; ** $p \leq 0.01$; *** $p \leq 0.001$; SE = standard error of the mean

The Average Degree of participant groups in Phase 1 is 48.16 ($z = 46.43$, $p < 0.000$). In Phase 2, the Average Degree decreases by –5.30 ($z = –9.77$, $p < 0.000$). In Phase 3, Average Degree decreases again by –4.54 ($z = –8.37$, $p < 0.000$). For each additional dropout in a given group, the Average Degree decreases by –4.84 ($z = –2.60$, $p = 0.009$). This decrease is an artefact that results from the exclusion of dropout participants from the data (both attempts made by active participants to view dropout peers, and any attempts made by dropout participants to view their active peers before they left the experiment). The range of the out-degree for a given participant in a group with no dropouts is [0, 70]. In a group with one dropout, the range of the out-degree for a given active participant is [0, 56]. Any attempts to view the one dropout peer on any of the 14 Trials in a given Phase are removed from the data. There is no evidence for a main effect of Condition, or for interactions between Condition and Phase. Participant groups in all three Conditions exhibit the same pattern across Phases.

Figure 6.18 presents the average Density of participant groups in each Phase of Study 3A.

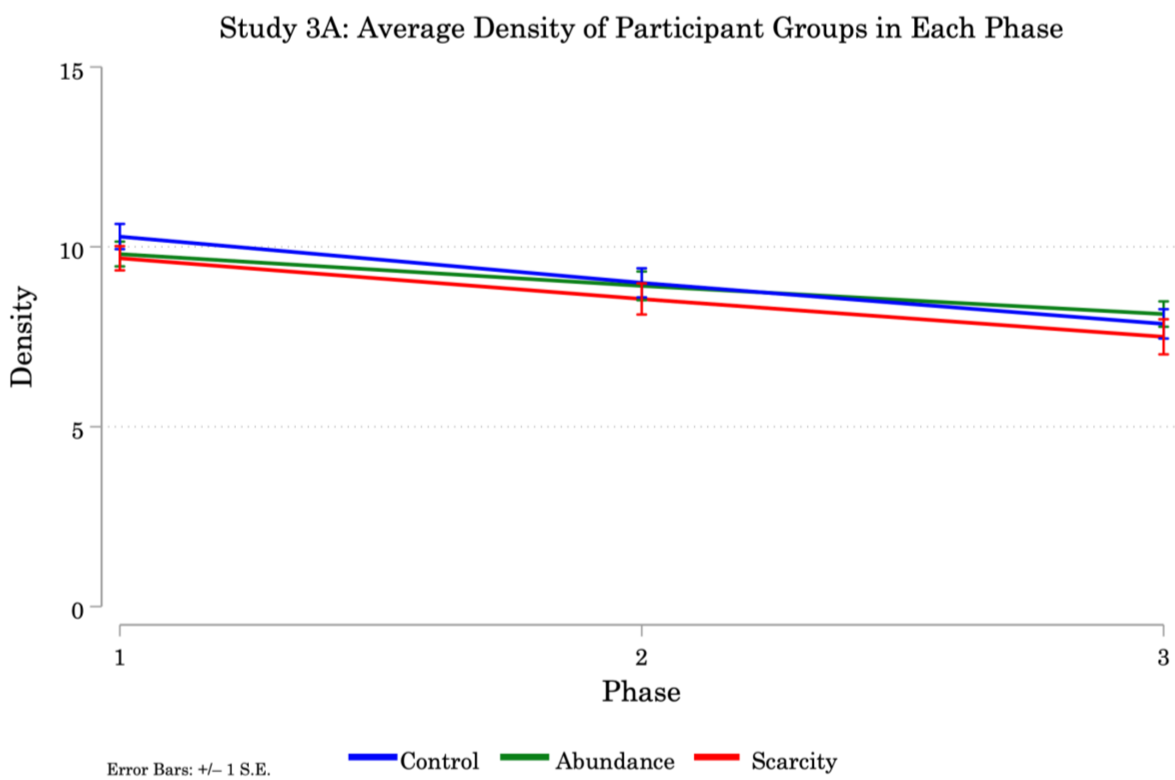

Figure 6.18. Study 3A: Density. Average Density of participant groups, by Phase and Condition. Error Bars: +/– 1 S.E. N = 89. Green = Abundance (30 groups); Blue = Control (30 groups); Red = Scarcity (29 groups). The range of Degree = [0, 14]. Density decreases across Phases in all three Conditions.

Table 6.15. Study 3A: Density. Maximum likelihood estimates of Three-Level Random-Coefficient models for the Density of a given participant group in a given Phase. Model 1: Intercept-Slope; Model 2: Main Effects; Model 3: Design Interactions. N = 89 (Abundance = 30 groups; Control = 30 groups; Scarcity = 29 groups).

	Model 1		Model 2		Model 3	
	Est	(SE)	Est	(SE)	Est	(SE)
Fixed Effects						
Intercept β_0	9.64***	0.21	10.02***	0.34	10.03***	0.34
Phase 2 β_1	–1.10***	0.12	–1.10***	0.12	–1.29***	0.20
Phase 3 β_2	–0.99***	0.12	–0.99***	0.12	–1.14***	0.20
Dropouts β_3	1.22**	0.39	–1.30***	0.39	–1.30***	0.39
Abundance β_4			–0.69	0.47	–0.70	0.47
Scarcity β_5			–0.51	0.47	–0.52	0.47
Abundance × Phase 2 β_6					0.40	0.28
Scarcity × Phase 2 β_7					0.15	0.28
Abundance × Phase 3 β_8					0.36	0.28
Scarcity × Phase 3 β_9					0.09	0.28
Random Effects						
L2 Random Intercept Var $\psi_{11}^{(2)}$	2.92	0.49	2.83	0.48	2.83	0.48
L2 Random Slope Var $\psi_{22}^{(2)}$	0.36	0.09	0.36	0.09	0.33	0.09
L1 (Residual) Error Var θ	0.42	0.06	0.42	0.06	0.42	0.06
Log likelihood	–448		–447		–445	
AIC | *BIC*	912 | 940		913 | 949		917 | 968	

* $p \leq 0.05$; ** $p \leq 0.01$; *** $p \leq 0.001$; SE = standard error of the mean

Table 6.15 presents the parameter estimates and fit statistics from three different Two-Level Random Coefficient models for the Density of a given participant group in each Phase of Study 3A. Model 1 is the baseline model. The fixed part of Model 1 includes an intercept, piecewise linear slopes for Phases 2 and 3, and a fixed effect for the number of dropouts in a participant's group. The random part of Model 1 includes a random intercept and a random linear slope at the Group level (Level 2). Model 2 includes a fixed effect for Condition. Model 3 introduces interactions among elements of the experimental design (Condition, Phase). Model

3 did not provide a significantly better fit than Model 2 [$LR\ \chi^2(4) = 4.06$, $p = 0.398$], and Model 2 did not provide a better fit than Model 1 [$LR\ \chi^2(2) = 2.25$, $p = 0.325$], so I will focus on the estimates from Model 1.

The Density of participant groups in Phase 1 is 9.64 ($z = 45.02$, $p < 0.000$). In Phase 2, the Density decreases by –1.10 ($z = –9.47$, $p < 0.000$). In Phase 3, Density decreases again by –0.99 ($z = –8.53$, $p < 0.000$). For each additional dropout in a given group, the Density *increases* by 1.22 ($z = 3.17$, $p = 0.002$). Density is the average standardized strength of a tie between any two active participants in a given group. Only ties between active participants are considered. The fact that the average standardized tie strength between pairs of active participants increases with the number of dropout participants probably results from the fact that active participants see the message "*Not shared*" each time they attempt to view a dropout pair after the dropout leaves the experiment. After repeatedly observing that the dropout peer has not shared results, active participants re-allocate their attention to their active peers, which increases the average number of times active participants choose to view each of their active peers in a given Phase. There is no evidence for a main effect of Condition, or for interactions between Condition and Phase. Participant groups in all three Conditions exhibit the same pattern across Phases.

Figure 6.19 presents the average Centralization of participant groups in each Phase of Study 3A.

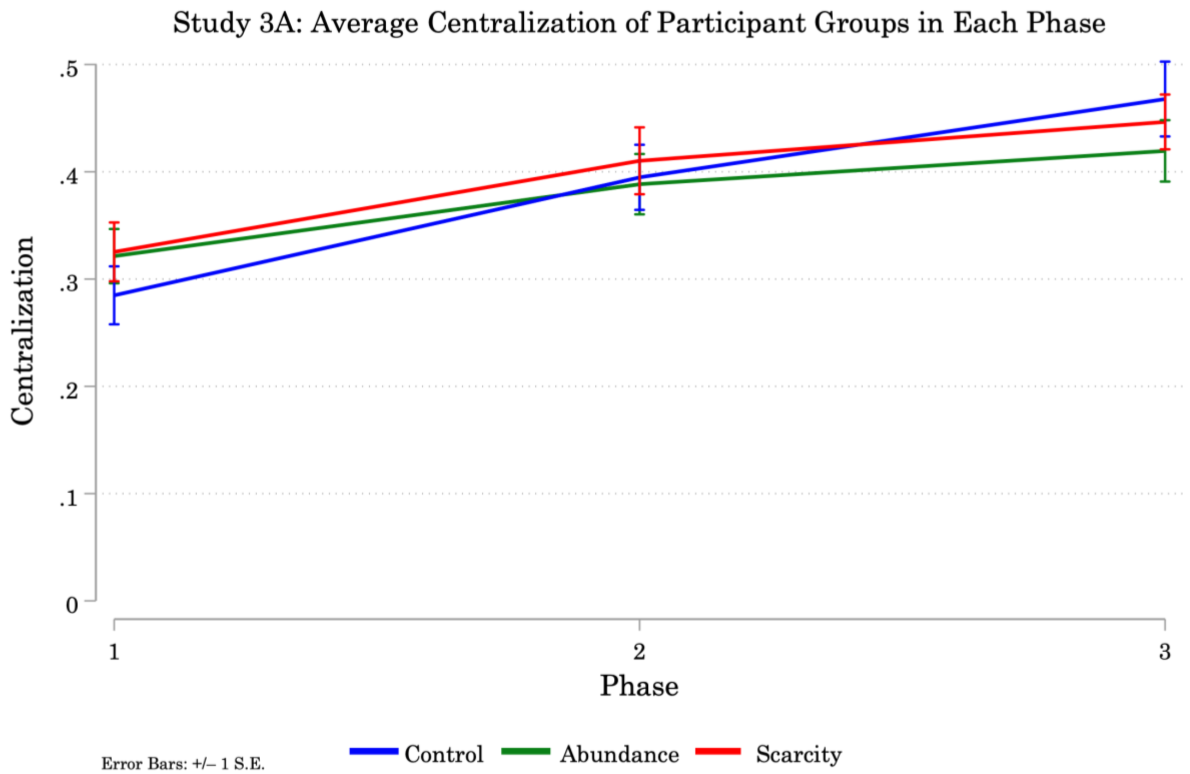

Figure 6.19. Study 3A: Centralization. Average Centralization of participant groups, by Phase and Condition. Error Bars: +/– 1 S.E. N = 89. Green = Abundance (30 groups); Blue = Control (30 groups); Red = Scarcity (29 groups). Note that the y-axis is truncated. The range of Centralization = [0.0, 1.0]. Centralization increases across Phases in all three Conditions.

Table 6.16 presents the parameter estimates and fit statistics from three different Two-Level Random Coefficient models for the Centralization of a given participant group in each Phase of Study 3A. Model 1 is the baseline model. The fixed part of Model 1 includes an intercept, piecewise linear slopes for Phases 2 and 3, and a fixed effect for the number of dropouts in a participant's group. The random part of Model 1 includes a random intercept and a random linear slope at the Group level (Level 2). Model 2 includes a fixed effect for Condition. Model 3 introduces interactions among elements of the experimental design (Condition, Phase). Model 3 does not provide a significantly better fit than Model 2 [$LR\ \chi^2(4) = 5.60$, $p = 0.231$], nor does Model 2 provide a better fit than Model 1 [$LR\ \chi^2(2) = 0.33$, $p = 0.846$], so I will focus on the estimates from Model 1.

Table 6.16. Study 3A: Centralization. Maximum likelihood estimates of Three-Level Random-Coefficient models for the Centralization of a given participant group in a given Phase. Model 1: Intercept-Slope; Model 2: Main Effects; Model 3: Design Interactions. N = 89 (Abundance = 30 groups; Control = 30 groups; Scarcity = 29 groups).

	Model 1		Model 2		Model 3	
	Est	(SE)	Est	(SE)	Est	(SE)
Fixed Effects						
Intercept β_0	0.32***	0.02	0.31***	0.03	0.30***	0.03
Phase 2 β_1	0.09***	0.01	0.09***	0.01	0.11***	0.02
Phase 3 β_2	0.05***	0.01	0.05***	0.01	0.07***	0.02
Dropouts β_3	–0.06*	0.06	–0.06*	0.03	–0.06*	0.03
Abundance β_4			0.02	0.03	0.05	0.04
Scarcity β_5			0.02	0.03	0.04	0.04
Abundance × Phase 2 β_6					–0.04	0.03
Scarcity × Phase 2 β_7					–0.03	0.03
Abundance × Phase 3 β_8					–0.04	0.03
Scarcity × Phase 3 β_9					–0.04	0.03
Random Effects						
L2 Random Intercept Var $\psi_{11}^{(2)}$	0.02	0.00	0.02	0.00	0.02	0.00
L2 Random Slope Var $\psi_{22}^{(2)}$	0.00	0.00	0.00	0.00	0.00	0.00
L1 (Residual) Error Var θ	0.00	0.00	0.00	0.00	0.00	0.00
Log likelihood	–193		–193		–196	
AIC | *BIC*	–369 | –340		–366 | –330		–363 |–313	

* $p \leq 0.05$; ** $p \leq 0.01$; *** $p \leq 0.001$; SE = standard error of the mean

The Centralization of participant groups in Phase 1 is 0.32 ($z = 19.22$, $p < 0.000$). In Phase 2, Centralization increases by 0.09 ($z = 7.44$, $p < 0.000$). In Phase 3, Centralization increases again by 0.05 ($z = 8.53$, $p < 0.000$). As the experiment progresses a greater proportion of the total number of peer views in a given group originates from a single participant. For each additional dropout in a given group, Centralization decreases by –0.06 ($z = –2.02$, $p = 0.044$).

There is no evidence for a main effect of Condition, or for interactions between Condition and Phase. Participant groups in all three Conditions exhibit the same pattern across Phases.

Figure 6.20 presents the average Out-Degree Variance of participant groups in each Phase of Study 3A.

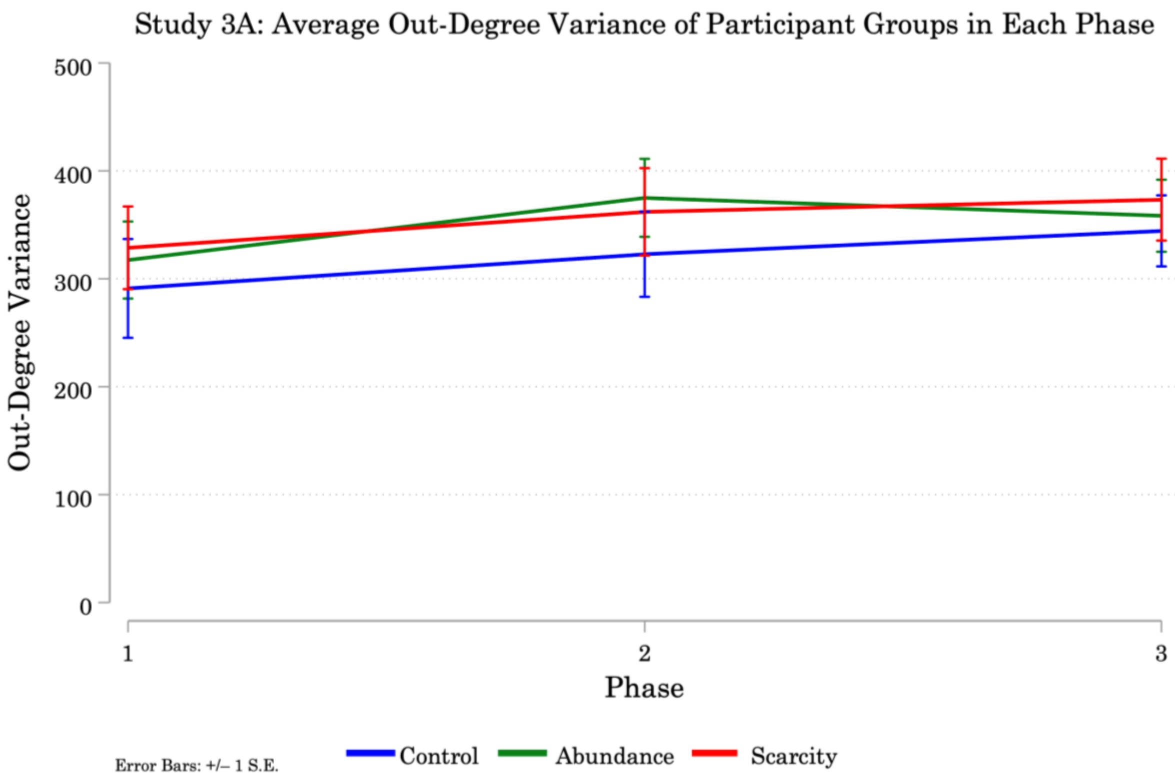

Figure 6.20. Study 3A: Out-Degree Variance. Average Out-Degree Variance of participant groups, by Phase and Condition. Error Bars: +/– 1 S.E. N = 89. Green = Abundance (30 groups); Blue = Control (30 groups); Red = Scarcity (29 groups). Note that the y-axis is truncated. The range of Out-Degree Variance = [0, 1225]. Out-Degree Variance increases slightly across Phases in all three Conditions.

Table 6.17 presents the parameter estimates and fit statistics from three different Two-Level Random Coefficient models for the Out-Degree Variance of a given participant group in each Phase of Study 3A. Model 1 is the baseline model. The fixed part of Model 1 includes an intercept, piecewise linear slopes for Phases 2 and 3, and a fixed effect for the number of dropouts in a participant's group. The random part of Model 1 includes a random intercept and a random linear slope at the Group level (Level 2). Model 2 includes a fixed effect for Condition. Model 3 introduces interactions among elements of the experimental design (Condition, Phase). Model 3 did not provide a significantly better fit than Model 2 [$LR\ \chi^2(4) = 1.98$, $p = 0.740$], and Model 2 did not provide a better fit than Model 1 [$LR\ \chi^2(2) = 2.24$, $p = 0.327$], so I will focus on the estimates from Model 1.

Table 6.17. Study 3A: Out-Degree Variance. Maximum likelihood estimates of Three-Level Random-Coefficient models for the Out-Degree Variance of a given participant group in a given Phase. Model 1: Intercept-Slope; Model 2: Main Effects; Model 3: Design Interactions. N = 89 (Abundance = 30 groups; Control = 30 groups; Scarcity = 29 groups).

	Model 1		Model 2		Model 3	
	Est	(SE)	Est	(SE)	Est	(SE)
Fixed Effects						
Intercept β_0	355.43***	22.80	329.60***	32.16	329.30***	37.08
Phase 2 β_1	40.98**	14.09	40.98**	14.09	31.69	24.13
Phase 3 β_2	5.39	14.09	5.39	14.09	21.65	24.13
Dropouts β_3	–183.20***	33.72	–191.12***	33.94	–191.12***	33.94
Abundance β_4			60.82	40.76	58.15	51.86
Scarcity β_5			22.09	40.77	25.78	52.04
Abundance × Phase 2 β_6					25.98	34.13
Scarcity × Phase 2 β_7					1.64	34.42
Abundance × Phase 3 β_8					–38.27	34.13
Scarcity × Phase 3 β_9					–10.31	34.42
Random Effects						
L2 Rand Int Var $\psi_{11}^{(2)}$	34458.07	5989.77	33723.74	5881.39	33821.31	5876.47
L2 Rand Slope Var $\psi_{22}^{(2)}$	5329.81	1343.71	5329.81	1343.71	5388.54	1339.41
L1 (Resid) Error Var θ	6171.78	925.19	6171.78	925.19	6040.88	905.57
Log likelihood	–1700		–1699		–1698	
AIC | *BIC*	3416 | 3445		3418 | 3453		3424 | 3474	

* $p \leq 0.05$; ** $p \leq 0.01$; *** $p \leq 0.001$; SE = standard error of the mean

The Out-Degree Variance of participant groups in Phase 1 is 355.43 ($z = 15.59$, $p < 0.000$). In Phase 2, Out-Degree Variance increases by 40.98 ($z = 2.91$, $p = 0.004$). Out-Degree Variance stays about the same in Phase 3 ($\beta_2 = 5.39$, $z = 0.38$, $p = 0.702$). For each additional dropout in a given group, Out-Degree Variance decreases by –183.20 ($z = –5.43$, $p < 0.000$). There is no evidence for a main effect of Condition, or for interactions between Condition and Phase. Participant groups in all three Conditions exhibit the same pattern across Phases.

Figure 6.21 presents the average Hierarchy of participant groups in each Phase of Study 3A.

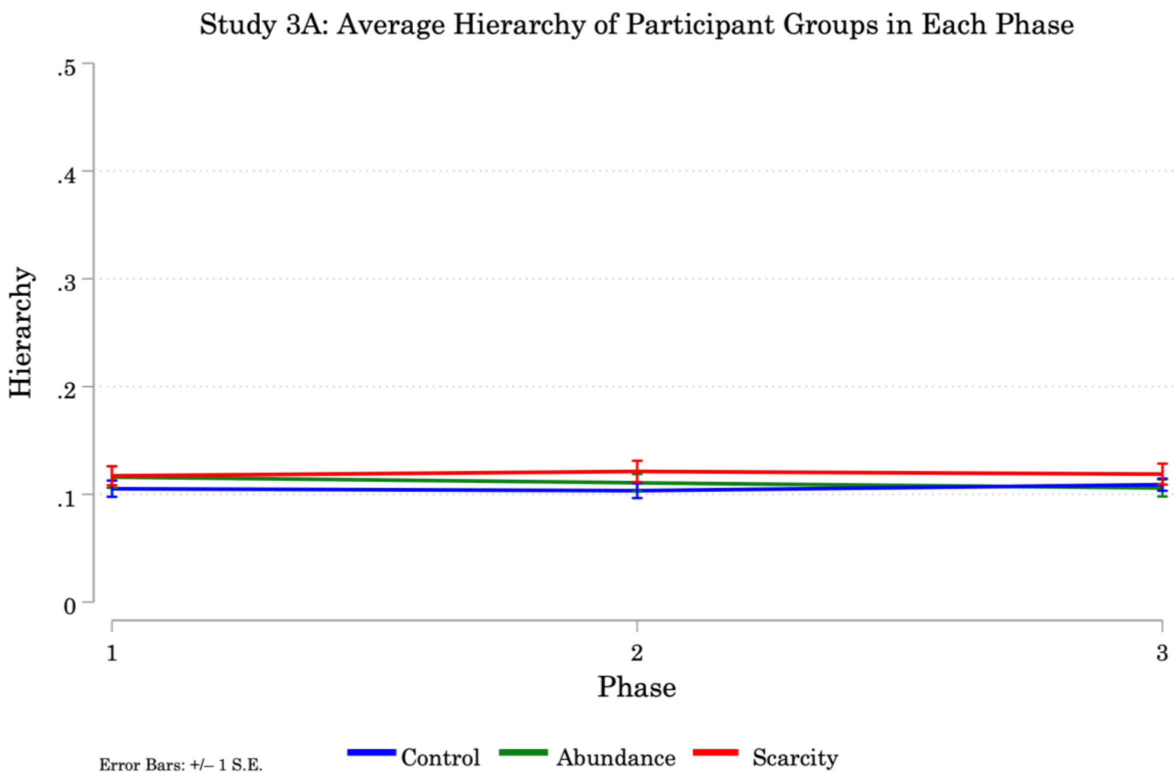

Figure 6.21. Study 3A: Hierarchy. Average Hierarchy of participant groups, by Phase and Condition. Error Bars: +/– 1 S.E. N = 89. Green = Abundance (30 groups); Blue = Control (30 groups); Red = Scarcity (29 groups). Note that the y-axis is truncated. The range of Hierarchy = [0.0, 1.0]. Hierarchy is quite low, and does not change much across Phases in all three Conditions.

Table 6.18. Study 3A: Hierarchy. Maximum likelihood estimates of Three-Level Random-Coefficient models for the Hierarchy of a given participant group in a given Phase. Model 1: Intercept-Slope; Model 2: Main Effects; Model 3: Design Interactions. N = 89 (Abundance = 30 groups; Control = 30 groups; Scarcity = 29 groups).

	Model 1		Model 2		Model 3	
	Est	(SE)	Est	(SE)	Est	(SE)
Fixed Effects						
Intercept β_0	0.11***	0.01	0.10***	0.01	0.10***	0.01
Phase 2 β_1	–0.00	0.00	–0.00	0.00	–0.00	0.00
Phase 3 β_2	–0.00	0.00	–0.00	0.00	0.01	0.01
Dropouts β_3	0.02	0.01	0.02	0.01	0.02	0.01
Abundance β_4			0.00	0.01	0.01	0.01
Scarcity β_5			0.01	0.01	0.01	0.01
Abundance × Phase 2 β_6					–0.00	0.01
Scarcity × Phase 2 β_7					0.01	0.01
Abundance × Phase 3 β_8					–0.01	0.01
Scarcity × Phase 3 β_9					–0.01	0.01
Random Effects						
L2 Random Intercept Var $\psi_{11}^{(2)}$	0.00	0.00	0.00	0.00	0.00	0.00
L2 Random Slope Var (Phase) $\psi_{22}^{(2)}$	0.00	0.00	0.00	0.00	0.00	0.00
L1 (Residual) Error Var θ	0.00	0.00	0.00	0.00	0.00	0.00
Log likelihood	–476		–477		–479	
AIC | *BIC*	–937 | –908		–936 | –900		–930 | –879	

* $p \leq 0.05$; ** $p \leq 0.01$; *** $p \leq 0.001$; SE = standard error of the mean

Table 6.18 presents the parameter estimates and fit statistics from three different Two-Level Random Coefficient models for the Hierarchy of a given participant group in each Phase of Study 3A. Model 1 is the baseline model. The fixed part of Model 1 includes an intercept, piecewise linear slopes for Phases 2 and 3, and a fixed effect for the number of dropouts in a participant's group. The random part of Model 1 includes a random intercept and a random linear slope at the Group level (Level 2). Model 2 includes a fixed effect for Condition. Model 3 introduces interactions among elements of the experimental design (Condition, Phase). Model

3 does not provide a significantly better fit than Model 2 [*LR* $\chi^2(4) = 1.81$, $p = 0.770$], and Model 2 did not provide a better fit than Model 1 [*LR* $\chi^2(2) = 2.89$, $p = 0.236$], so I will focus on the estimates from Model 1.

The Hierarchy of participant groups in Phase 1 is 0.11 ($z = 20.79$, $p < 0.000$). Hierarchy is constant across Phase 2 ($\beta_1 = –0.001$, $z = –0.23$, $p = 0.820$) and Phase 3 ($\beta_2 = –0.001$, $z = –0.12$, $p = 0.907$). For each additional dropout in a given group, Hierarchy increases by 0.02 ($z = 2.06$, $p = 0.039$). There is no evidence for a main effect of Condition, or for interactions between Condition and Phase. Participant groups in all three Conditions exhibit the same pattern across Phases.

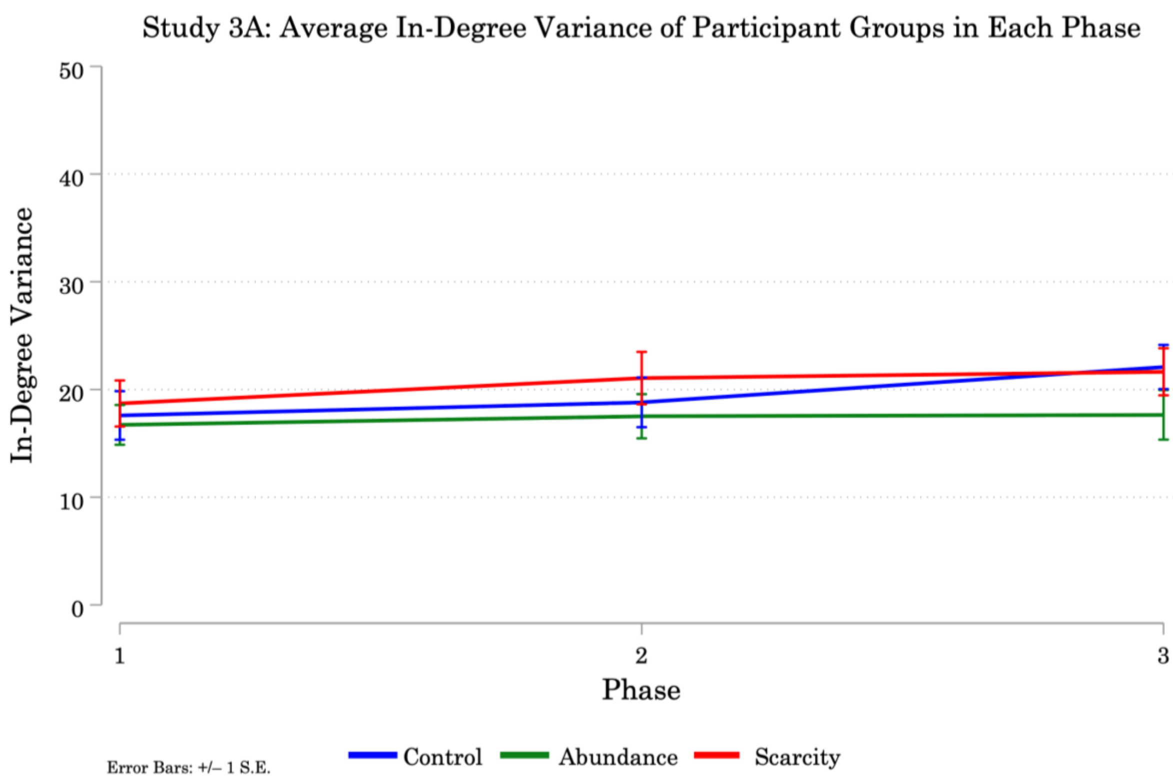

Figure 6.22. Study 3A: In-Degree Variance. Average In-Degree Variance of participant groups, by Phase and Condition. Error Bars: +/– 1 S.E. N = 89. Green = Abundance (30 groups); Blue = Control (30 groups); Red = Scarcity (29 groups). Note that the y-axis is truncated. The range of In-Degree Variance = [0, 1225]. In-Degree Variance is relatively stable across Phases in each Condition.

Figure 6.22 presents the average In-Degree Variance of participant groups in each Phase of Study 3A.

Table 6.19. Study 3A: In-Degree Variance. Maximum likelihood estimates of Three-Level Random-Coefficient models for the In-Degree Variance of a given participant group in a given Phase. Model 1: Intercept-Slope; Model 2: Main Effects; Model 3: Design Interactions. N = 89 (Abundance = 30 groups; Control = 30 groups; Scarcity = 29 groups).

	Model 1		Model 2		Model 3	
	Est	(SE)	Est	(SE)	Est	(SE)
Fixed Effects						
Intercept β_0	18.87***	1.25	18.92***	1.84	18.55***	2.04
Phase 2 β_1	1.45	1.24	1.45	1.24	1.22	2.12
Phase 3 β_2	1.34	1.24	1.34	1.24	3.28	2.12
Dropouts β_3	–5.13	1.96	–4.83	2.00	–4.83	2.00
Abundance β_4			–1.14	2.40	–0.07	2.86
Scarcity β_5			0.79	2.40	0.81	2.86
Abundance × Phase 2 β_6					–0.42	3.00
Scarcity × Phase 2 β_7					1.14	3.03
Abundance × Phase 3 β_8					–3.15	3.00
Scarcity × Phase 3 β_9					–2.70	3.03
Random Effects						
L2 Random Intercept Var $\psi_{11}^{(2)}$	53.07	†	52.97	15.60	53.36	15.54
L2 Random Slope Var $\psi_{22}^{(2)}$	0.45	†	0.40	0.92	0.38	0.89
L1 (Residual) Error Var θ	67.97	†	68.02	7.21	67.28	7.31
Log likelihood	–1002		–1001		–1000	
AIC | BIC	2011 | 2026		2023 | 2058		2029 | 2079	

* $p \leq 0.05$; ** $p \leq 0.01$; *** $p \leq 0.001$; SE = standard error of the mean
† calculation of standard errors for the random effects failed for Model 1

Table 6.19 presents the parameter estimates and fit statistics from three different Two-Level Random Coefficient models for the In-Degree Variance of a given participant group in each Phase of Study 3A. Model 1 is the baseline model. The fixed part of Model 1 includes an intercept, piecewise linear slopes for Phases 2 and 3, and a fixed effect for the number of dropouts in a participant's group. The random part of Model 1 includes a random intercept and a random linear slope at the Group level (Level 2). Model 2 includes a fixed effect for Condition. Model 3 introduces interactions among elements of the experimental design (Condition, Phase). Model 3 does not provide a significantly better fit than Model 2 [$LR\ \chi^2(4) = 1.97$, $p = 0.741$], and Model 2 did not provide a better fit than Model 1 [$LR\ \chi^2(6) = 0.63$, $p = 0.996$], so I will focus on the estimates from Model 1.

The In-Degree Variance of participant groups in Phase 1 is 18.87 ($z = 15.03$, $p < 0.000$). In-Degree Variance is stable across Phase 2 ($\beta_1 = 1.45$. $z = 1.17$, $p = 0.242$) and Phase 3 ($\beta_2 = 1.34$, $z = 1.08$, $p = 0.279$). For each additional dropout in a given group, In-Degree Variance decreases by –5.13 ($z = -2.61$, $p = 0.009$). There is no evidence for a main effect of Condition, or for interactions between Condition and Phase. Participant groups in all three Conditions exhibit the same pattern across Phases.

6.1.5 Discussion

Study 3A was designed to test alternative mechanisms that may drive the contraction in communication network size following a *decrease* in resource values. In Study 3A, participants could learn about the platform values in two ways: 1) through Exploration (sampling platform values by including platforms in their pitch on each Trial), and 2) through side observations (sampling platform values by looking at the pitches made by their peers). Exploration requires a tradeoff between exploring previously unsampled platforms and exploiting the best platforms encountered on previous Trials. Taking side observations of the platform values by viewing the pitches made by peers does not require a tradeoff. However, both the participant and the peer may only view each other's results if they first choose to share those results with one another. I refer to this rule as the "sharing contingency."

The purpose of Study 3A was to test whether a dynamic social process like reciprocity (via the "sharing contingency") moderates the effect of resource shocks on participants' decisions to sample the resource distribution vicariously through the actions (and outcomes) of peers participating in the experiment contemporaneously. I will focus on the comparison between behavior in Phase 1, before any resource shock occurs, and behavior in Phase 2, after Abundance and Scarcity participants experience the first resource shock. For each of the focal dependent variables, I will note any differences between Study 3A and Study 2B.

As a reminder, Control participants experience *no change* in platform values between Phases 1 and 2 (they face the Medium range in every Phase of the experiment). Abundance participants experience a *positive* resource shock in Phase 2 (the Medium range platform values are *higher* than the Low range platform values they faced in Phase 1). Scarcity participants experience a *negative* resource shock in Phase 2 (the Medium range platform values are *lower* than the High range platform values they faced in Phase 1).

6.1.5.1 Exploration

Exploration is defined as the total number of unique platforms participants explored across Trials 1–15 of a given Phase. In other words, Exploration is the number of platforms (out of 20) that the participant included in her pitch on at least one Trial. There are no significant differences between Conditions. Participants in all three Conditions explored significantly fewer platforms in Phase 2 than they did in Phase 1.

No change in platform values produced a *decrease* in Exploration. The same *decrease* in Exploration occurred following an *increase* in platform values. A *decrease* in platform values produced a temporary increase in Exploration on Trial 2, but a global *decrease* in Exploration across the remaining Trials.

In every Phase of the experiment, participants in the Control and Scarcity Conditions of Study 3A explored a similar number of platforms to participants in the corresponding Condition of Study 2B.[27] In Phases 1 and 2, participants in the Abundance Condition explored a similar number of platforms to participants in Study 2B. In Phase 3, Abundance participants in Study 3A explored significantly fewer platforms that Abundance participants in Study 2B.[28]

6.1.5.2 Exploitation

Exploitation is defined as the total number of times that a participant selected any of their Personal-Best platforms across Trials 2–15 of a given Phase. Control participants significantly increased their rates of Exploitation in Phase 2. Abundance participants also increased their rate of Exploitation in Phase 2. Scarcity participants decreased their rate of Exploitation in Phase 2.

No change in platform values produced an *increase* in Exploitation. An *increase* in platform values also produced an *increase* in Exploitation. A *decrease* in platform values produced a *decrease* in Exploitation.

In Phase 1, Control and Abundance participants in Study 3A exploited their Personal-Best platforms with similar frequency to participants in Study 2B. In Phases 2 and 3, Control and Abundance participants exploited their Personal-Best platforms significantly more often than

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[27] CONTROL: Study 3A Control Phase 1 – Study 2B Control Phase 1 = –0.58, z = –1.00, p = 0.319; Study 3A Control Phase 2 – Study 2B Control Phase 2 = –0.67, z = –1.18, p = 0.238; Study 3A Control Phase 3 – Study 2B Control Phase 3 = –1.09, z = –1.84, p = 0.066. SCARCITY: Study 3A Scarcity Phase 1 – Study 2B Scarcity Phase 1 = 0.41, z = 0.69, p = 0.493; Study 3A Scarcity Phase 2 – Study 2B Scarcity Phase 2 = 0.13, z = 0.22, p = 0.827; Study 3A Scarcity Phase 3 – Study 2B Scarcity Phase 3 = –0.01, z = –0.04, p = 0.969.

[28] ABUNDANCE: Study 3A Abundance Phase 1 – Study 2B Abundance Phase 1 = –0.92, z = –1.54, p = 0.125; Study 3A Abundance Phase 2 – Study 2B Abundance Phase 2 = –0.83, z = –1.43, p = 0.152; Study 3A Abundance Phase 3 – Study 2B Abundance Phase 3 = –1.56, z = –2.56, p = 0.010.

participants in Study 2B.[29] Scarcity participants in Study 3A exploited their Personal-Best platforms with similar frequency to Study 2B participants in every Phase of the experiment.[30]

6.1.5.3 *Mental Models*

Mean Absolute Difference is defined as the average absolute value of the difference between participants' estimates of the platform values at the end of each Phase and the true average values of each platform. We'll refer to the Mean Absolute Difference as "average error." Control participants' average error was slightly lower in Phase 2 than in Phase 1, but this difference was not significant. Abundance participants' average error in Phase 2 was significantly higher than in Phase 1. Scarcity participants' average error in Phase 2 was significantly lower than in Phase 1. Scarcity participants' average error was significantly lower than Abundance participants' in Phase 2.

No change in platform values produced *no change* in average error. An *increase* in platform values produced an *increase* in average error. A *decrease* in platform values produced a *decrease* in average error.

Participants in each Condition of Study 3A had similar average error to participants in the corresponding Condition of Study 2B in every Phase of the experiment.[31]

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[29] CONTROL: Study 3A Control Phase 1 – Study 2B Control Phase 1 = 1.78, z = 1.40, p = 0.161; Study 3A Control Phase 2 – Study 2B Control Phase 2 = 3.36, z = 2.70, p = 0.007; Study 3A Control Phase 3 – Study 2B Control Phase 3 = 5.17, z =3.91, p < 0.000. ABUNDANCE: Study 3A Abundance Phase 1 – Study 2B Abundance Phase 1 = 2.25, z = 1.73, p = 0.084; Study 3A Abundance Phase 2 – Study 2B Abundance Phase 2 = 6.02, z = 4.72, p < 0.000; Study 3A Abundance Phase 3 – Study 2B Abundance Phase 3 =4.76, z = 3.51, p < 0.000.

[30] SCARCITY: Study 3A Scarcity Phase 1 – Study 2B Scarcity Phase 1 = 0.68, z = 0.52, p = 0.603; Study 3A Scarcity Phase 2 – Study 2B Scarcity Phase 2 = 1.07, z = 0.83, p = 0.405; Study 3A Scarcity Phase 3 – Study 2B Scarcity Phase 3 = 0.99, z = 0.73, p = 0.467.

[31] CONTROL: Study 3A Control Phase 1 – Study 2B Control Phase 1 = 4.51, z = 0.24, p = 0.809; Study 3A Control Phase 2 – Study 2B Control Phase 2 = –0.12, z = –0.01, p = 0.995; Study 3A Control Phase 3 – Study 2B Control Phase 3 = 3.71, z = 0.12, p = 0.902. SCARCITY: Study 3A Scarcity Phase 1 – Study 2B Scarcity Phase 1 = 27.48, z

6.1.5.4 Rewards

Cumulative Standardized Achievement is the sum of the Standardized Achievement Scores a participant earns across Trials 1–15 of a given Phase. Control participants' scores increased slightly in Phase 2, but this difference was not significant. Abundance participants' scores in Phase 2 were similar to what they earned in Phase 1. Scarcity participants scores were significantly higher in Phase 2 than in Phase 1.

No change in platform values produced *no change* in Cumulative Standardized Achievement scores. An *increase* in platform values also produced *no change* in Cumulative Standardized Achievement Scores. A *decrease* in platform values produced an *increase* in platform values.

Participants in each Condition of Study 3A earned similar scores to participants in the corresponding Condition of Study 2B in every Phase of the experiment.[32]

6.1.5.5 Discovery

Discovery is defined as the number of times a participant selected any of the True Top-Three highest-valued platforms across Trials 1–15 of a given Phase. Control and Abundance

= 1.46, p = 0.145; Study 3A Scarcity Phase 2 – Study 2B Scarcity Phase 2 = 17.17, z = 0.82, p = 0.410; Study 3A Scarcity Phase 3 – Study 2B Scarcity Phase 3 = 9.51, z = 0.31, p = 0.754. ABUNDANCE: Study 3A Abundance Phase 1 – Study 2B Abundance Phase 1 = –4.99, z = –0.27, p = 0.791; Study 3A Abundance Phase 2 – Study 2B Abundance Phase 2 = 0.66, z = 0.03, p = 0.975; Study 3A Abundance Phase 3 – Study 2B Abundance Phase 3 = –6.09, z = –0.20, p = 0.841.

[32] CONTROL: Study 3A Control Phase 1 – Study 2B Control Phase 1 = 37.25 z = 0.82, p = 0.410; Study 3A Control Phase 2 – Study 2B Control Phase 2 = 26.25, z = 0.59, p = 0.558; Study 3A Control Phase 3 – Study 2B Control Phase 3 = 55.06, z = 1.20, p = 0.231. ABUNDANCE: Study 3A Abundance Phase 1 – Study 2B Abundance Phase 1 = 6.38, z = 0.14, p = 0.889; Study 3A Abundance Phase 2 – Study 2B Abundance Phase 2 = 35.41, z = 0.78, p = 0.434; Study 3A Abundance Phase 3 – Study 2B Abundance Phase 3 = –9.96, z = –0.21, p = 0.830. SCARCITY: Study 3A Scarcity Phase 1 – Study 2B Scarcity Phase 1 = –37.45, z = –0.82, p = 0.413; Study 3A Scarcity Phase 2 – Study 2B Scarcity Phase 2 = –17.15, z = –0.38, p = 0.705; Study 3A Scarcity Phase 3 – Study 2B Scarcity Phase 3 = –32.28, z = –0.69, p = 0.487.

participants selected True Top Three platforms with similar frequency in Phase 2 to what they did in Phase 1. Scarcity participants selected True Top-Three platforms significantly more often in Phase 2 than they did in Phase 1.

No change in platform values produced a *no change* in Discovery. An *increase* in platform values produced *no change* in Discovery. A *decrease* in platform values produced an *increase* in Discovery.

Participants in each Condition of Study 3A selected True Top Three platforms with similar frequency to participants in the corresponding Condition of Study 2B in every Phase of the experiment.[33]

6.1.5.6 Side Observations: Peer Results

Sharing. Participants had the option to share their results with their peers on Trials 1–14. Participants had 70 opportunities (= 5 peers × 14 Trials) to share results with their peers. There were no differences between Conditions in any Phase of the experiment. Participants in all three Conditions chose to share with almost every one of their peers on every Trial in every Phase.

There was *no change* in sharing following *no change* in platform values, or following an *increase* or *decrease* in platform values.

Sampling Frequency. Starting on Trial 2 of each Phase, participants had the opportunity to view the pitches made by their five peers on the previous Trial. (The peer's results would

[33] CONTROL: Study 3A Control Phase 1 – Study 2B Control Phase 1 = 1.58, $z = 0.43$, $p = 0.666$; Study 3A Control Phase 2 – Study 2B Control Phase 2 = 1.14, $z = 0.31$, $p = 0.755$; Study 3A Control Phase 3 – Study 2B Control Phase 3 = 3.91, $z = 1.06$, $p = 0.290$. SCARCITY: Study 3A Scarcity Phase 1 – Study 2B Scarcity Phase 1 = –3.20, $z = –0.87$, $p = 0.384$; Study 3A Scarcity Phase 2 – Study 2B Scarcity Phase 2 = 0.52, $z = 0.14$, $p = 0.886$; Study 3A Scarcity Phase 3 – Study 2B Scarcity Phase 3 = 0.46, $z = 0.12$, $p = 0.901$. ABUNDANCE: Study 3A Abundance Phase 1 – Study 2B Abundance Phase 1 = –2.19, $z = –0.59$, $p = 0.552$; Study 3A Abundance Phase 2 – Study 2B Abundance Phase 2 = 3.35, $z = 0.91$, $p = 0.360$; Study 3A Abundance Phase 3 – Study 2B Abundance Phase 3 = 0.16, $z = 0.04$, $p = 0.966$.

only display if *both* the participant *and* the peer chose to share their results with each other.) Participants had a total of 70 opportunities (= 5 peers × 14 Trials) to sample side observations of the platform values by viewing their peers' pitches. There were no differences between Conditions in any Phase of the experiment. Participants in all three Conditions chose to view their peers' results significantly less often in Phase 2 than they did in Phase 1.

No change in platform values produced a *decrease* in the number of times participants chose to view their peers. A *decrease* in platform values produced a *decrease* in the number of times participants chose to view their peers. An *increase* in platform values produced a *decrease* in the number of times participants chose to view their peers.

In Phases 1 and 2, Control and Abundance participants in Study 3A chose to view their peers' results significantly more often than participants in the corresponding Conditions of Study 2B chose to view Exemplar Players. There were no differences in Phase 3.[34]

In every Phase of the experiment, Scarcity participants in Study 3A chose to view their peers' results with similar frequency to Scarcity participants in Study 2B.[35]

Sampling Bias. There were only two peer characteristics found to have a significant effect on the number of times a participant chose to view a given peer. First, participants exhibited the same position-based preference we observed in Studies 2A and 2B. Participants chose to view peers more often the closer the peer's Player button was located to the top-left

[34] CONTROL: Study 3A Control Phase 1 – Study 2B Control Phase 1 = 15.42, z = 3.31, p = 0.001; Study 3A Control Phase 2 – Study 2B Control Phase 2 =11.72, z = 2.51, p = 0.012; Study 3A Control Phase 3 – Study 2B Control Phase 3 = 6.14, z = 1.25, p = 0.210. ABUNDANCE: Study 3A Abundance Phase 1 – Study 2B Abundance Phase 1 = 9.51, z = 2.01, p = 0.044; Study 3A Abundance Phase 2 – Study 2B Abundance Phase 2 = 9.49, z = 2.00, p = 0.045; Study 3A Abundance Phase 3 – Study 2B Abundance Phase 3 = 3.82, z = 0.77, p = 0.440.

[35] SCARCITY: Study 3A Scarcity Phase 1 – Study 2B Scarcity Phase 1 = 7.37, z = 1.55, p = 0.120; Study 3A Scarcity Phase 2 – Study 2B Scarcity Phase 2 = 4.85, z = 1.02, p = 0.307; Study 3A Scarcity Phase 3 – Study 2B Scarcity Phase 3 = 0.10, z = 0.02, p = 0.985.

corner of the button tray. Second, the more frequently a participant's peer chose to share results with the participant, the more frequently the participant chose to view that peer's results.

Peer achievement (realized points earned within a given Phase of the experiment) did not significantly affect participants' decisions. There was no relationship between a peer's relative achievement rank within the group and the number of times the participant chose to view that peer. (Neither was there a relationship between the number of times a participant chose to view a given peer and the peer's *global* achievement across *all* Phases or the peer's achievement in the *previous* Phase.)

Participants with higher achievement (relative to their peers) viewed *all* of their peers more often than participants with lower achievement viewed *any* of their peers.

6.1.5.7 Group Network Structure

Resource shocks did not have a significant effect on the structure of View Networks within each experimental group of participants. The Average Degree and Density of groups in all three Conditions decreases significantly across Phases. This results from an overall decrease in the number of times participants choose to view their peers across Phases.

The Centralization and Out-Degree Variance of participants groups increases significantly across Phases. As the experiment progresses, a greater proportion of the total number of peer views in a given group originates from a single participant.

Group Hierarchy and In-Degree Variance are stable across Phases. No single participant tends to receive a greater proportion of the total number of peer views in a given group.

6.1.5.7 Take-Aways from Study 3A

The biggest take-away from Study 3A is that resource shocks had no effect on participants' willingness to share their results with their peers (participants tended to share with almost every peer on almost every Trial across every Phase), or on the number of times participants chose to view their peers' results.

We introduced "the sharing contingency" to test whether resource shocks altered the structure of communication networks by decreasing expectations of reciprocity and increasing selfish behavior. We find no evidence for such an effect. Neither increasing nor decreasing resource levels had a significant effect on participants' decisions to share with their peers. Participants in all three Conditions shared with almost every one of their peers on almost every Trial in each Phase of the experiment.

Aside from this result, the behavior of participants in Study 3A is consistent with that of participants in Study 2B.

6.2 Study 3B: Groups with Competition

In Study 3A, we *did not* find that a decrease in resource values decreased reciprocity (sharing results) in groups of experimental participants. Study 3B introduces competition, a second component of scarcity that is often present as a confounding variable in past research. The experience of resource scarcity is often coupled with intensified competition for access to resources (Brander & Taylor, 1998; Grossman & Mendoza, 2003). Roux, Goldsmith, and Bonezzi (2015) demonstrated that the effect of a scarcity cue (recalling a situation when resources were scarce) on social preferences was moderated by experimental participants' competitive orientation (Experiment 3). The authors posit that scarcity cues promote generous (prosocial) behavior in the absence of an association with competition, but selfish (antisocial) behavior when an association with competition is present. Scarcity-induced competition decreases reciprocity by undermining trust between exchange partners (Bauernschuster, Falck, and Grosse, 2010), increasing selfish behavior (Cannon, Goldsmith, and Roux, 2019; Roux, Goldsmith, and Bonezzi, 2015), and aggression (Kristofferson et al., 2017).

Participants in Study 3B have the opportunity to earn an additional bonus at the end of the procedure if they are one of the top-3 performers in their group. The bonus amounts are trivial, but produce marked differences in participant behavior compared to the no competition context in Study 3A. Note that this manipulation induces competition *without* increasing uncertainty or ambiguity. This reduces ecological validity (it breaks the correlation among cues that is usually present in the environment), but it allows me to isolate the effect of competition from the effects of resource uncertainty or ambiguity.

To understand why this is important, consider an alternative competition manipulation with higher ecological validity. We could tell participants that each time a platform is selected by more than one person, the points generated by that platform are split evenly among every person who chose that platform. This form of competition increases uncertainty in two ways. First, it increases *expected* uncertainty (variance around a given platform's average value) because collisions (more than one participant selecting the same platform) increase the variance in realized rewards from a given platform across Trials. It also increases ambiguity (*unexpected* uncertainty – ignorance of a given platform's average value) because convergence of multiple participants on the same platform across Trials effectively changes that platform's average value, in expectation.

This version of competition is closer to what happens in real life when resource levels decline. Scarcity is not *just* experienced as a downward shift in average rewards from a given resource, it is *also* experienced as an increase in uncertainty over whether other agents will impede access to that resource. I am choosing to break this link in the experimental environment so that I can look at competition by itself, without confounding the effect of competition with that of uncertainty.

6.2.1 Participants

534 people participated in Study 3B. All participants were recruited online. 168 participants (Female = 110[36]; Average Age = 28, SD = 10) were recruited through the Center for Decision Research (CDR) at the University of Chicago Booth School of Business. 366 participants (Female = 151[37]; Average Age: 38, SD = 11) were recruited through Amazon Mechanical Turk (MTurk).

CDR participants were paid a $10.00 base fee upon completion of the focal procedure, and earned a variable performance-based bonus (Average Bonus: $6.71, SD = $0.35). MTurk participants were paid a $6.00 base fee upon completion of the focal procedure, and earned a variable performance-based bonus (Average Bonus: $6.79, SD = $0.30). MTurk participants also earned an Active Participation Bonus of $4.00 if they consistently submitted their responses before the time limits (described in *3.1.1 Recruitment and Compensation*). Participants complete

[36] Demographic information was not collected from 2 participants in the Abundance Condition recruited through the CDR due to a software platform error. These participants are excluded from subsequent figures and analyses to maintain consistent cases across models. One CDR participant selected “Other” as their gender.
[37] Four MTurk participants selected “Other” as their gender.

the focal procedure in groups of size 6.[38] All participants in a given group were assigned to the same Condition.[39]

Groups were assigned to one of six experimental Conditions (Table 6.20): Abundance (174 participants, 29 groups); Control (180 participants, 30 groups); Scarcity (180 participants, 30 groups). Control, Scarcity, and Abundance carry the same meaning as before, and refer to the trends in platform values described in *Section 3 Common Design Elements* (Abundance = increasing; Control = constant; Scarcity = decreasing).

Table 6.20. Study 3B: Distribution of Participants by Recruiting Source. Count of groups (and participants) in each experimental Condition, by recruiting platform (CDR vs. MTurk).

			CDR		MTurk	
Condition	N (Groups)	N (Ps)	N (Groups)	N (Ps)	N (Groups)	N (Ps)
Abundance	29	174	9	54	20	120
Control	30	180	10	60	20	120
Scarcity	30	180	9	54	21	126
Total	89	534	28	168	61	366

Participants have the opportunity to earn an additional bonus if they are one of the top three highest-scoring members of their group at the end of the procedure. Participants who earn the highest number of points in their group receive an additional bonus of $0.50, second-place participants receive a bonus of $0.30, and third-place participants receive a bonus of $0.10.[40]

[38] After successfully completing the Comprehension Check, participants enter a virtual waiting room. As soon as 6 participants are present in the waiting room, these 6 participants advance to the focal procedure as a group.
[39] Conditions were assigned quasi-randomly across groups.
[40] These bonus amounts were selected based on the expected increase in cumulative rewards for a participant who views five randomly sampled pitches on every Trial (i.e. Random Pitches in Study 2A) versus a participant who views four or fewer randomly sampled pitches on every Trial. To estimate this value, I ran agent-based simulations using common multi-armed bandit decision algorithms (e.g. ϵ–greedy, softmax) and heuristic decision algorithms based on participants' behavior in Study 1. Estimates of the expected increase in cumulative rewards based on these simulations are conservative, because the simulated agents were exposed to randomly sampled pitches, and the average expected value of randomly sampled pitches does not increase across Trials. By contrast, pitches selected

Participants in 4th, 5th, and 6th place do not receive any additional bonus. This bonus opportunity is the only difference between Study 3B and Study 3A.

6.2.2 Procedure

The focal experimental procedure is identical to that in Study 3A, with the addition of the rank-based performance bonus opportunity. The bonus opportunity was described on the final page of the instructions given to participants before the start of the procedure:

> BEST PERFORMER COMPETITION
>
> In addition to earning a bonus for your individual performance on each round, you will also have a chance to earn an additional bonus if you are one of the top 3 performers in your group.
>
> At the end of the game, we will rank everyone in your group based on the total amount of points each person earned across all 45 rounds of the game. The top-ranked person in your group will receive an additional bonus payment of $0.50. The second-place person in your group will receive $0.30. The third-place person in your group will receive $0.10. The fourth-, fifth-, and sixth-place people in your group will not receive any additional bonus payments.

Participants were also reminded of the bonus opportunity at the start of each Phase in the introduction to each Company (see Figure 3.2 for a screenshot of the Company introduction screen). The following reminder appeared at the end of the introduction to each new Company:

> Don’t forget – at the end of The Sales Game, we will rank everyone in your group based on the total amount of points each player earns across all 45 rounds of the game. The top 3 players in your group will earn an additional bonus payment (1st place: $0.50; 2nd place: $0.30; 3rd place: $0.10).

---

by goal-directed agents increase across Trials, making it more likely that the pitches selected on later Trials will contain higher-valued platforms, on average. All this is to say that these bonuses were worth less than the expected increase in cumulative rewards that participants in Study 3 should expect to gain if they choose to view the results of their peers’ versus not.

Aside from these additions to the instructions and Company introduction screens, the experimental procedure is identical to Study 3A. After completing the focal procedure, participants in Study 3B complete the Debrief Questionnaire described in *3.1.3 Procedure*. Participants are also asked to rate the extent to which each of their peers helped or harmed their performance during the focal procedure on a scale of 0 (Very Harmful) to 100 (Very Helpful).

6.2.3 Participant-Level Results

I exclude participants who were marked as dropouts after repeatedly failing to submit their responses before the time limits. 15 participants across 13 groups met this exclusion criteria: Abundance = 4 participants, 4 groups; Control = 3 participants, 3 groups; Scarcity = 8 participants, 6 groups. I also exclude Trials on which participants failed to submit their response before the time limit expired (timeouts).

6.2.3.1 Exploration

Figure 6.23 presents the average number of Never-Seen platforms participants selected on each Trial, in each Phase of Study 3B. In Phase 1, there aren't any consistent differences between Conditions (Abundance participants explore slightly less between Trials 5–10). Over the first few Trials of Phase 2, Scarcity participants explore a higher number of platforms than Control and Abundance participants. Exploration rates across the three Conditions converge around Trial 5. There aren't any consistent differences between Conditions in Phase 3.

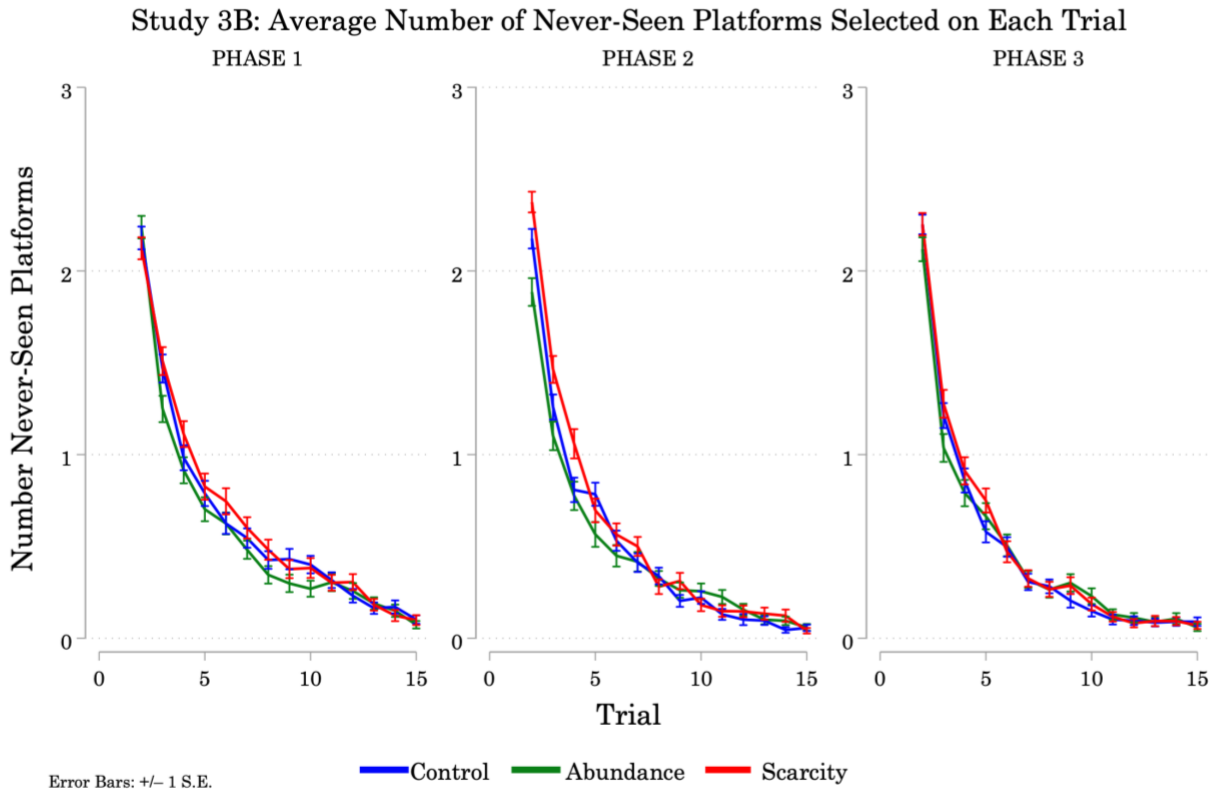

Figure 6.23. Study 3B: Exploration. Average number of Never-Seen platforms selected on each Trial, Phase, and Condition. Error bars = +/– 1 S.E. N = 519. Green = Abundance (170 participants, 29 groups); Blue = Control (177 participants, 30 groups); Red = Scarcity (172 participants, 30 groups). In Phase 1, there aren't any consistent differences between Conditions (Abundance participants explore slightly less between Trials 5–10). Over the first few Trials of Phase 2, Scarcity participants explore a higher number of platforms than Control and Abundance participants. Exploration rates across the three Conditions converge around Trial 5. There aren't any consistent differences between Conditions in Phase 3.

Table 6.21 presents the parameter estimates and fit statistics from three different Three-Level Random Coefficient models for the number of unique platforms participants explored across Trials 1–15 of each Phase in Study 3B. Model 1 is the baseline model, and includes an intercept and piecewise linear slopes for Phases 2 and 3 (in the form of two linear spline functions for the change between Phases 1 and 2, and between Phases 2 and 3). The random part of Model 1 includes a random intercept and random linear slope for Phase at the Group level (Level 3) and at the Participant level (Level 2). Model 2 includes Condition as a fixed effect.

Model 3 introduces interactions among elements of the experimental design (Condition, Phase). Model 3 provides a significantly better fit than Model 2 [$LR\ \chi^2(4) = 11.64$, $p = 0.020$] and Model 1 [$LR\ \chi^2(6) = 18.61$, $p = 0.005$], so I will focus on the predictions from Model 3.

Table 6.21. Study 3B: Exploration. Maximum likelihood estimates of Three-Level Random-Coefficient models for the number of unique platforms participants explored across Trials 1–15 of each Phase. Model 1: Intercept-Slopes; Model 2: Main Effects; Model 3: Design Interactions. N = 519.

	Model 1		Model 2		Model 3	
	Est	(SE)	Est	(SE)	Est	(SE)
Fixed Effects						
Intercept β_0	11.27***	0.17	11.35***	0.27	11.52***	0.29
Phase 2 β_1	–1.13***	0.13	–1.13***	0.13	–1.46***	0.23
Phase 3 β_2	–0.38**	0.13	–0.38**	0.13	–0.38	0.23
Abundance β_3			–0.63	0.37	–0.84*	0.41
Scarcity β_4			0.38	0.37	0.08	0.41
Abundance × Phase 2 β_5					0.23	0.32
Scarcity × Phase 2 β_6					0.74*	0.32
Abundance × Phase 3 β_7					0.46	0.32
Scarcity × Phase 3 β_8					–0.44	0.32
Random Effects						
L3 Random Intercept Var $\psi_{11}^{(3)}$	0.23	0.42	0.01	0.00	0.01	0.01
L3 Random Slope Var $\psi_{22}^{(3)}$	0.08	0.09	0.08	0.08	0.06	0.07
L2 Random Intercept Var $\psi_{11}^{(2)}$	10.49	0.96	10.48	0.88	10.51	0.87
L2 Random Slope Var $\psi_{22}^{(2)}$	0.97	0.23	0.97	0.23	1.00	0.23
L1 (Residual) Error Var θ	3.88	0.24	3.88	0.24	3.82	0.24
Log likelihood	–3954		–3950		–3944	
AIC | *BIC*	7927 | 7981		7924 | 7988		7920 | 8006	

* $p \leq 0.05$; ** $p \leq 0.01$; *** $p \leq 0.001$

In Phase 1, Control participants explored about 11.52 ($z = 40.36$, $p < 0.000$) out of 20 platforms. Scarcity participants explored about the same number of platforms as Controls ($\beta_4 = 0.08$, $z = 0.19$, $p = 0.846$), but Abundance participants explored significantly fewer platforms than Controls ($\beta_3 = –0.84$, $z = –2.07$, $p = 0.039$).

In Phase 2, Control participants explored significantly fewer platforms than they did by the end of Phase 1 ($\beta_1 = -1.46$, $z = -6.49$, $p < 0.000$). Abundance participants explored a similar number of platforms to Controls (Abundance Phase 2 – Control Phase 2 = –0.59, $z = -1.40$, $p = 0.160$), which was significantly less than the number they explored in Phase 1 (Abundance Phase 2 – Abundance Phase 1 = –1.21, $z = -5.24$, $p < 0.000$). Scarcity participants explored a significantly higher number of platforms than Controls (Scarcity Phase 2 – Control Phase 2 = 0.82, $z = 1.97$, $p = 0.048$), but significantly less than the number they explored in Phase 1 (Scarcity Phase 2 – Scarcity Phase 1 = –0.72, $z = -3.15$, $p = 0.002$), but still pitched .

In Phase 3, Control participants explored a similar number of platforms to what they did in Phase 2 ($\beta_2 = -0.38$, $z = -1.70$, $p = 0.089$). Abundance participants explored a similar number of platforms to Controls (Abundance Phase 3 – Control Phase 3= –0.13, $z = -0.27$, $p = 0.785$), which was similar to the number they explored in Phase 2 (Abundance Phase 3 – Abundance Phase 2 = 0.08, $z = 0.33$, $p = 0.741$). Scarcity participants explored a similar number of platforms to Controls (Scarcity Phase 3 – Control Phase 3 = 0.39, $z = 0.84$, $p = 0.402$), which was significantly less than the number of platforms they explored in Phase 2 (Scarcity Phase 3 – Scarcity Phase 2 = –0.82, $z = -3.58$, $p < 0.000$).

6.2.3.2 Exploitation

Figure 6.24 presents the average number of Personal-Best platforms selected by participants on each Trial of each Phase in Study 3B (the number of platforms in the current pitch that have one of the three highest empirical averages based on what the participant has seen so far in the current Phase). In Phases 1 and 2, Scarcity participants exploited their Personal-Best platforms with similar frequency to Controls on the first few Trials, but significantly less often than

Controls across later Trials. In Phase 2, Scarcity participants exploited their Personal-Best platforms significantly less often than Controls across the majority of Trials.

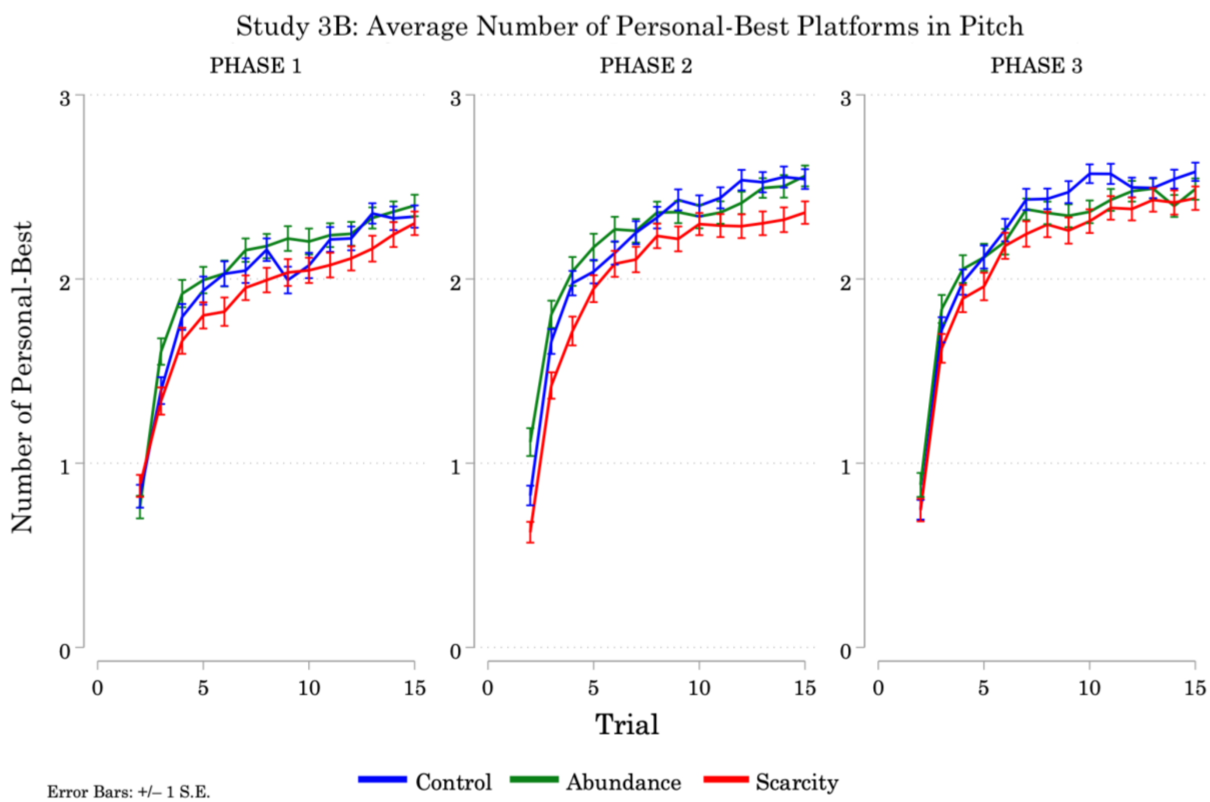

Figure 6.24. Study 3B: Exploitation. Average number of Personal-Best Platforms selected on each Trial, by Phase, Condition. Error bars = +/– 1 S.E. N = 519. Green = Abundance (170 participants, 29 groups); Blue = Control (177 participants, 30 groups); Red = Scarcity (172 participants, 30 groups). Note that the curves begin on Trial 2. On Trial 1, all of the platforms selected have no empirical history. In Phases 1 and 2, Scarcity participants exploited their Personal-Best platforms with similar frequency to Controls on the first few Trials, but significantly less often than Controls across later Trials. In Phase 2, Scarcity participants exploited their Personal-Best platforms significantly less often than Controls across the majority of Trials.

As before, we will look at the cumulative number of times participants exploited their Personal-Best platforms across Trials 2–15 of each Phase. Table 6.22 presents the parameter estimates and fit statistics from three different Three-Level Random Coefficient models for the cumulative number of times participants selected their Personal-Best platforms across Trials 2–15 in a given Phase.

Table 6.22. Study 3B: Exploitation. Maximum likelihood estimates of Three-Level Random-Coefficient models for Average Number of Personal-Best Platforms selected across Trials 2–15 of each Phase. Model 1: Intercept-Slope; Model 2: Main Effects; Model 3: Design Interactions. N = 519.

	Model 1		Model 2		Model 3	
	Est	(SE)	Est	(SE)	Est	(SE)
Fixed Effects						
Intercept β_0	27.12***	0.41	27.72***	0.65	27.47***	0.67
Phase 2 β_1	2.60***	0.28	2.60***	0.28	3.08***	0.48
Phase 3 β_2	0.71**	0.28	0.71**	0.28	0.75	0.48
Abundance β_3			0.16	0.91	0.47	0.96
Scarcity β_4			–1.95*	0.91	–1.52	0.95
Abundance × Phase 2 β_5					–0.37	0.69
Scarcity × Phase 2 β_6					–1.09	0.69
Abundance × Phase 3 β_7					–0.77	0.69
Scarcity × Phase 3 β_8					0.66	0.69
Random Effects						
L3 Random Intercept Var $\psi_{11}^{(3)}$	3.63	2.24	2.68	2.11	2.66	2.10
L3 Random Slope Var $\psi_{22}^{(3)}$	0.46	0.38	0.46	0.38	0.40	0.38
L2 Random Intercept Var $\psi_{11}^{(2)}$	45.51	4.27	45.49	4.27	45.61	4.27
L2 Random Slope Var $\psi_{22}^{(2)}$	1.95	0.96	1.95	0.96	2.03	0.96
L1 (Residual) Error Var θ	18.56	1.15	18.56	1.15	18.41	1.14
Log likelihood	–5104		–5100		–5097	
AIC | *BIC*	10227 | 10280		10224 | 10288		10226 | 10312	

* $p \leq 0.05$; ** $p \leq 0.01$; *** $p \leq 0.001$; SE = standard error of the mean

Model 1 is the baseline model. The fixed part of Model 1 includes an intercept and piecewise linear slopes for Phases 2 and 3. The random part of Model 1 includes a random intercept and a random linear slope for Phase at the Participant level (Level 2) and at the Group level (Level 3). Model 2 includes Condition as a fixed effect. Model 3 introduces two-way interactions between elements of the experimental design (Condition, Phase). Model 3 does not provide a significant improvement over Model 2 [$LR\ \chi^2(4) = 6.18$, $p = 0.186$], but Model 2 does provide a significant improvement over Model 1 [$LR\ \chi^2(2) = 6.56$, $p = 0.038$]. So, I will focus on the estimates from Model 2.

In Phase 1, Control participants exploited their personal-best platforms 27.72 times on average ($z = 42.93$, $p < 0.000$). Abundance participants exploited their personal-best platforms with similar frequency to Controls ($\beta_3 = 0.16$, $z = 0.18$, $p = 0.860$), and Scarcity participants exploited their personal-best platforms significantly less often than Controls ($\beta_4 = -1.95$, $z = -2.18$, $p = 0.030$).

In Phase 2, Control participants exploited their personal-best platforms significantly more often than they did in Phase 1 ($\beta_1 = 2.60$, $z = 9.15$, $p < 0.000$). In Phase 3, Control participants exploited their personal-best platforms significantly more often than they did in Phase 2 ($\beta_2 = 0.71$, $z = 2.51$, $p = 0.012$).

As the interactions between Condition and Phase were not significant, we assume a similar relationship between Conditions in Phases 2 and 3 as in Phase 1: Abundance participants exploited their personal-best platforms with similar frequency to Controls, and Scarcity participants exploited their personal-best platforms significantly less often than Controls.

6.2.3.3 Mental Models

Participants were asked to estimate the average value of each platform after the 8th and 15th Trials of each Phase. Here we will focus on participants' second estimates, following Trial 15. Figure 6.25 plots the average estimated value of each platform against that platform's true average value.

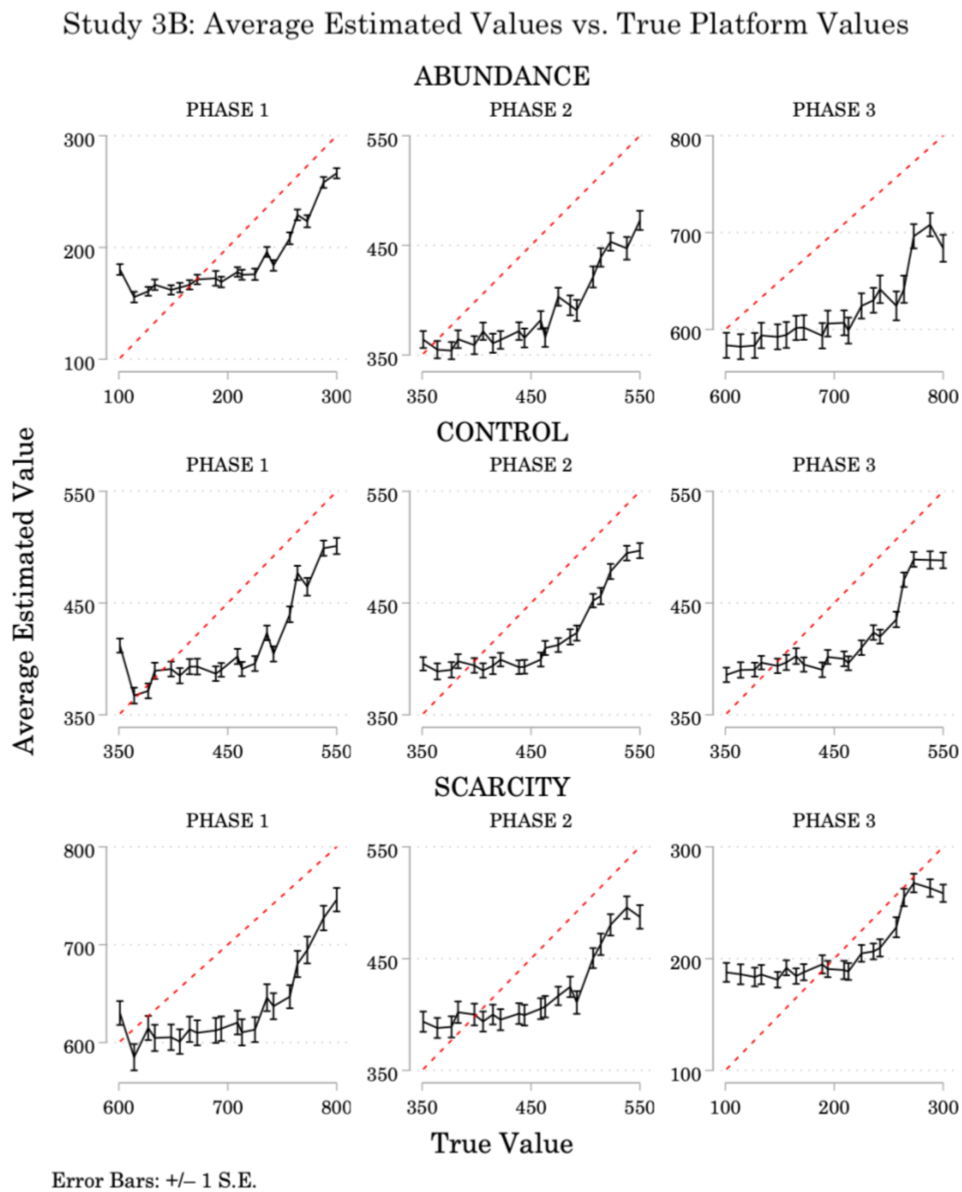

Figure 6.25. Study 3B: Mental Models. Average estimated values versus true average values of each platform, by Phase and Condition. Error bars = +/– 1 S.E. N = 504.[41] Top Row: Abundance (166 participants). Middle Row: Control (175 participants). Bottom Row: Scarcity (163 participants). Results for second estimate made by participants in each Phase (following Trial 15). Average estimated values on y-axes. True average platform values on the x-axes. Red

[41] 13 participants were dropped because they shirked the task (Abundance = 4; Control = 2; Scarcity = 7). Shirking behavior includes entering zeros or alternating single digit numbers (e.g. 1-0-1-0) for at least half of their estimates in at least one Phase of the experiment. 2 Scarcity participants were dropped because at least four of their estimates were extreme outliers (Extreme outliers are defined as estimates that fall more than two times the size of the interquartile range above the 75th percentile, or more than two times the size of the interquartile range below the 35th percentile.)

dotted 45-degree lines mark “perfect agreement” between average values estimated by participants and each platform’s true average value.

The red, dotted 45-degree lines indicate what the shape of each curve would look like if there was perfect agreement between the average estimated values reported by participants and the true values of each platform. One way to think about the accuracy of participants’ estimates is to consider the proximity of the estimates curve to the 45-degree line. Control participants’ average error was similar across Phases 1–3. Abundance participants’ average error increased significantly across Phases, and was significantly higher than Controls in Phases 2 and 3. Scarcity participants’ average error decreased significantly in Phases 2 and 3, and was similar to Controls across Phases 1–3.

Table 6.23 presents the parameter estimates and fit statistics from three different Three-Level Random Coefficient models for the Mean Absolute Deviation between participants’ estimates of each platform’s average value on Trial 15 of each Phase, and the true average value of each platform. Model 1 is the baseline model, and includes an intercept and piecewise linear slopes for Phases 2 and 3. The random part of Model 1 includes a random intercept and random linear slope for Phase at the Group level (Level 3) and at the Participant level (Level 2). Model 2 includes the main effects of Condition. Model 3 introduced interactions among elements of the experimental design (Condition, Phase). Model 3 provides a significantly better fit than Model 2 $LR\ \chi^2(4) = 43.43$, $p < 0.000$] and Model 1 [$LR\ \chi^2(6) = 51.41$, $p < 0.000$], so I will focus on the predictions from Model 3.

Table 6.23. Study 3B: Mental Models. Maximum likelihood estimates of Three-Level Random-Coefficient models for Mean Absolute Deviation of Estimated Values from True Average Values on Trial 15 of each Phase. Model 1: Intercept-Slope; Model 2: Main Effects; Model 3: Design Interactions. N =504.

	Model 1		Model 2		Model 3	
	Est	(SE)	Est	(SE)	Est	(SE)
Fixed Effects						
Intercept β_0	74.45***	5.06	62.07***	7.02	70.70***	8.06
Phase 2 β_1	3.79	3.87	3.79	3.87	–3.96	5.57
Phase 3 β_2	5.02	3.88	5.02	3.88	–0.91	5.63
Abundance β_3			25.99***	8.04	–16.96	11.51
Scarcity β_4			11.79	8.03	27.98*	11.48
Abundance × Phase 2 β_5					38.44***	7.98
Scarcity × Phase 2 β_6					–14.52	7.97
Abundance × Phase 3 β_7					29.53***	8.01
Scarcity × Phase 3 β_8					–11.41	8.02
Random Effects						
L3 Rand Intcpt Var $\psi_{11}^{(3)}$	1246.75	341.49	1508.69	427.96	945.63	295.33
L3 Rand Slope Var $\psi_{22}^{(3)}$	606.97	158.06	606.96	158.02	224.91	101.64
L2 Rand Intcpt Var $\psi_{11}^{(2)}$	4706.39	395.74	4705.75	395.81	4696.68	394.28
L2 Rand Slope Var $\psi_{22}^{(2)}$	1873.58	172.76	1872.36	172.67	1877.06	172.73
Level-1 Error Variance θ	1103.22	70.19	1103.31	70.20	1098.33	69.85
Log likelihood	–8420		–8416		–8395	
AIC | *BIC*	16861 | 16914		16857 | 16921		16821 | 16906	

* $p \leq 0.05$; ** $p \leq 0.01$; *** $p \leq 0.001$

In Phase 1, Control participants' error was 70.70 (z = 8.78, p < 0.000) on average. Abundance participants' error was similar to Controls (β_3 = –16.96, z = –1.47, p = 0.141). Scarcity participants' error was significantly higher than Controls (β_4 = 27.98, z = 2.44, p = 0.015).

In Phase 2, Control participants' error was similar to Phase 1 (β_1 = –3.96, z = –0.71, p = 0.478). Abundance participants' error was significantly higher than Controls (Abundance Phase 2 – Control Phase 2 = 21.48, z = 2.48, p = 0.013), and significantly higher than their error in

Phase 1 (Abundance Phase 2 – Abundance Phase 1 = 34.48, $z = 6.04$, $p < 0.000$). Scarcity participants' error was similar to Controls (Scarcity Phase 2 – Control Phase 2 = 13.46, $z = 1.56$, $p = 0.120$), and significantly lower than their error in Phase 1 (Scarcity Phase 2 – Scarcity Phase 1 = –18.47, $z = –3.24$, $p = 0.001$).

In Phase 3, Control participants' error was similar to Phase 2 ($\beta_2 = –0.91$, $z = –0.16$, $p = 0.871$). Abundance participants' was significantly higher than Controls (Abundance Phase 3 – Control Phase 3 = 51.01, $z = 5.28$, $p < 0.000$), and significantly higher than their error in Phase 2 (Abundance Phase 3 – Abundance Phase 2 = 28.62, $z = 5.02$, $p < 0.000$). Scarcity participants' error was similar to Controls (Scarcity Phase 3 – Control Phase 3 = 2.05, $z = 0.21$, $p = 0.832$), and significantly lower than their error in Phase 2 (Scarcity Phase 3 – Scarcity Phase 2 = –12.32, $z = –2.16$, $p = 0.031$).

Figure 6.26 presents the adjusted marginal predictions for the Mean Absolute Difference between participants' estimates and the true average value of each platform. Notice that Scarcity participants' average error is significantly higher than Abundance participants' average error in Phase 1 (Scarcity Phase 1 – Abundance Phase 1 = 44.94, $z = 3.87$, $p < 0.000$).

When Abundance and Scarcity participants both face the Medium distribution in Phase 2, Abundance and Scarcity participants' average errors are similar (Abundance Phase 2 – Scarcity Phase 2 = 8.01, $z = 0.91$, $p = 0.361$). Scarcity participants' error when they face the Low distribution in Phase 3 is slightly higher than Abundance participants' error when they face the Low distribution in Phase 1, but this difference is not significant (Scarcity Phase 3 – Abundance Phase 1 = 14.39, $z = 1.58$, $p = 0.113$). Scarcity participants' error when they face the High distribution in Phase 1 is significantly lower than Abundance participants' error when they face the High distribution in Phase 3 (Scarcity Phase 1 – Abundance Phase 3 = –18.09, z = –2.18, p = 0.029).

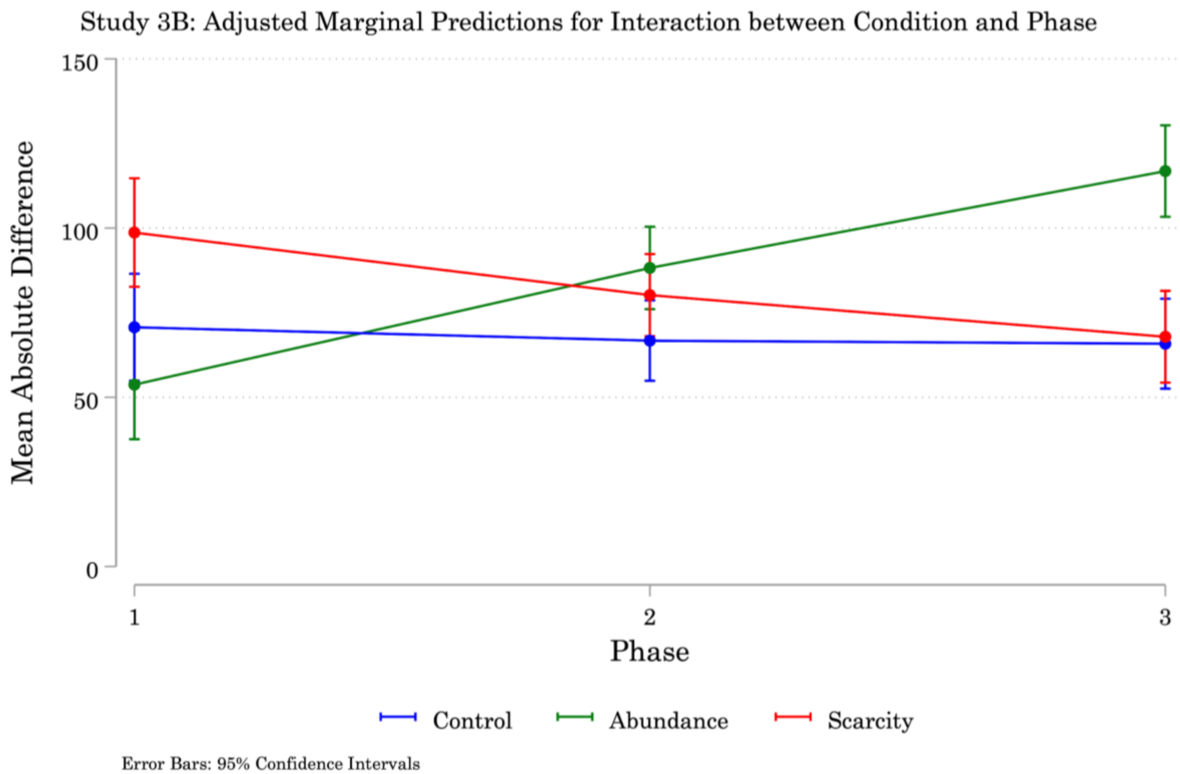

Figure 6.26. Study 3B: Mental Models Interaction. Adjusted marginal predictions for the interaction between Condition and Phase. Error bars = 95% Confidence Interval. N = 519. Green = Abundance (170 participants, 29 groups); Blue = Control (177 participants, 30 groups); Red = Scarcity (172 participants, 30 groups). In Phase 1, Scarcity participants' average error is significantly higher than Abundance and Control participants. In Phase 2, Abundance participants have significantly higher error than Control participants. In Phase 3, Abundance participants have significantly higher error than both Scarcity and Abundance participants. Abundance participants' error increases significantly across Phases 2 and 3. Scarcity participants' error decreases significantly across Phases 2 and 3. Control participants' error is similar across Phases 1–3.

6.2.3.4 Rewards

Figure 6.27 presents participants' Standardized Achievement Scores on each Trial in each Phase of Study 3A. There are no consistent differences between Conditions in Phase 1 or Phase 3. In

Phase 2, Abundance participants achieve significantly lower scores than Controls across a majority of Trials.

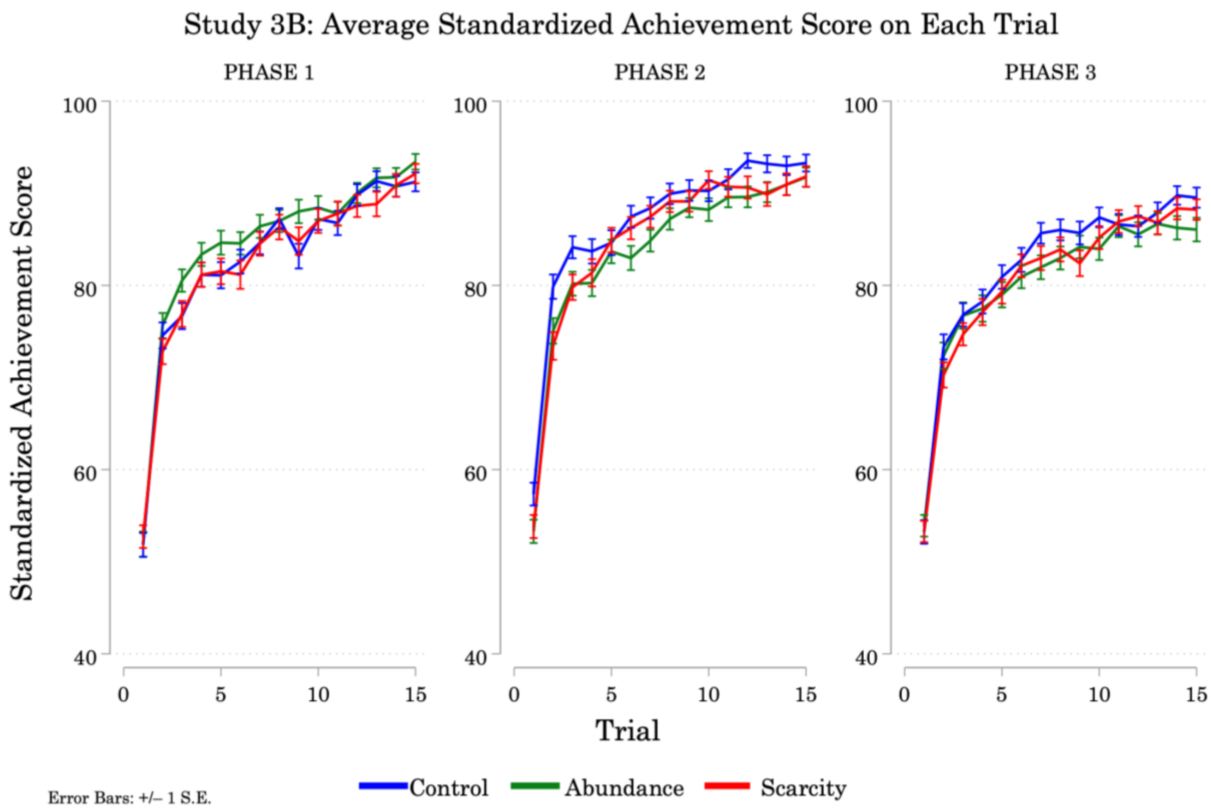

Figure 6.27. Study 3B: Rewards. Average Standardized Achievement Scores on each Trial, by Phase and Condition. N = 519. Green = Abundance (170 participants, 29 groups); Blue = Control (177 participants, 30 groups); Red = Scarcity (172 participants, 30 groups). There are no consistent differences between Conditions in Phase 1 or Phase 3. In Phase 2, Abundance participants achieve significantly lower scores than Controls across a majority of Trials.

Table 6.24 presents the parameter estimates and fit statistics from three different Three-Level Random Coefficient models for the participants' Cumulative Standardized Achievement Scores on Trial 15 of each Phase in Study 3B. Model 1 is the baseline model, and includes two pairwise linear spline functions representing Phase 2 and Phase 3. The random part of Model 1 includes a random intercept and a random linear slope for Phase at the Group level (Level 3), and at the Participant level (Level 2). Model 2 includes fixed effects for Condition. Model 3 includes interactions among elements of the experimental design (Condition, Phase). Model 3 provides a significantly better fit than Model 2 [*LR* $\chi^2(4) = 13.28$, $p = 0.010$] and Model 1 [*LR* $\chi^2(6) = 15.86$, $p = 0.015$], so I will focus on the predictions from Model 3.

Table 6.24. Study 3B: Rewards. Maximum likelihood estimates of Three-Level Random-Coefficient models for participants' Cumulative Standardized Achievement Scores on Trial 15 of each Phase. Model 1: Intercept-Slopes; Model 2: Main Effects; Model 3: Design Interactions. N = 519.

	Model 1		Model 2		Model 3	
	Est	(SE)	Est	(SE)	Est	(SE)
Fixed Effects						
Intercept β_0	1222***	10	1239***	14	1225***	17
Phase 2 β_1	42***	8	42***	8	69***	14
Phase 3 β_2	–59***	8	–59***	8	–72***	14
Abundance β_3			–26	19	6	24
Scarcity β_4			–26	18	–16	24
Abundance × Phase 2 β_5					–62***	19
Scarcity × Phase 2 β_6					–21	19
Abundance × Phase 3 β_7					28	19
Scarcity × Phase 3 β_8					12	19
Random Effects						
L3 Random Intercept Var $\psi_{11}^{(3)}$	3943	1244	3918	1245	3866	1233
L3 Random Slope Var $\psi_{22}^{(3)}$	2126	470	2126	470	2072	462
L2 Random Intercept Var $\psi_{11}^{(2)}$	15475	1726	15474	1726	15665	1722
L2 Random Slope Var $\psi_{22}^{(2)}$	341	494	341	494	456	489
Level-1 Error Var θ	10322	641	10322	641	10092	627
Log likelihood	–9943		–9942		–9935	
AIC | *BIC*	19907 | 19960		19908 | 19972		19903 | 19988	

* $p \leq 0.05$; ** $p \leq 0.01$; *** $p \leq 0.001$

In Phase 1, Control participants accumulated standardized scores of about 1225.13 ($z = 73.94$, $p < 0.000$). Abundance and Scarcity participants accumulated similar scores to Controls ($\beta_3 = 5.57$, $z = 0.24$, $p = 0.814$; $\beta_4 = –15.67$, $z = –0.67$, $p = 0.505$).

In Phase 2, Control participants' scores were significantly higher than in Phase 1 (β_1 = 69.16, z = 5.07, p < 0.000). Abundance participants' scores were significantly lower than Controls (Abundance Phase 2 – Control Phase 2 = –56.81, z = –2.76, p = 0.006), and similar to what they earned in Phase 1 (Abundance Phase 2 – Abundance Phase 1 = 6.78, z = 0.49, p = 0.626). Scarcity participants' scores were similar to Controls (Scarcity Phase 2 – Control Phase 2 = –36.77, z = –1.03, p = 0.072), and significantly higher than their scores in Phase 1 (Phase 2 – Phase 1 = 48.06, z = 3.49, p < 0.000).

In Phase 3, Control participants' scores were significantly lower than in Phase 2 (β_2 = –71.74, z = –5.26, p < 0.000). Abundance and Scarcity participants' scores were similar to Controls (Abundance Phase 3 – Control Phase 3 = –29.15, z = –1.21, p = 0.225; Scarcity Phase 3 – Control Phase 3 = –24.65, z = –1.03, p = 0.303), and significantly lower than their scores in Phase 2 (Abundance Phase 3 – Abundance Phase 2 = –44.08, z = –3.17, p = 0.002; Scarcity Phase 3 – Scarcity Phase 2 = –59.62, z = –4.33, p < 0.000).

6.2.3.5 Discovery

Figure 6.28 presents the average number of True Top Three platforms selected by participants on each Trial in each Phase of Study 3B (the number of platforms in the current pitch that have one of the three highest true average values).

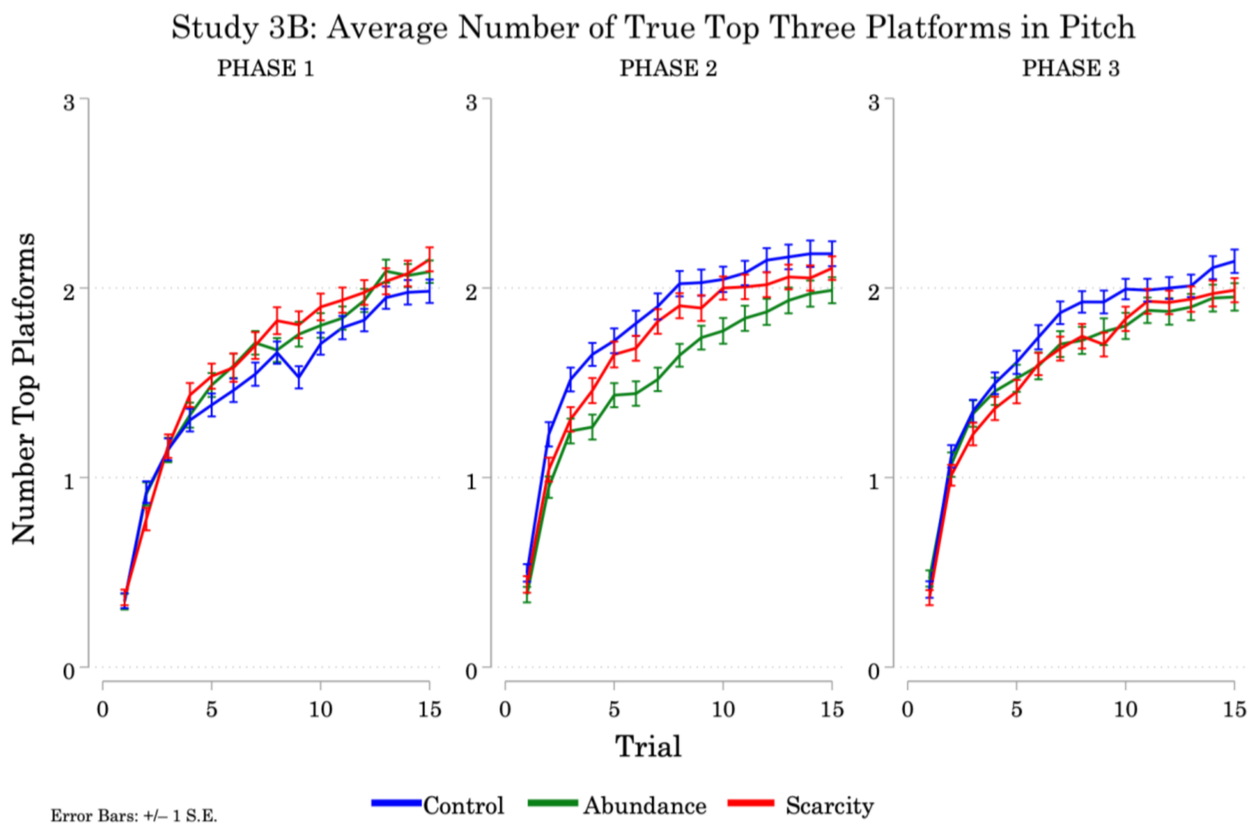

Figure 6.28. Study 3B: Discovery. Average number True Top Three platforms selected on each Trial, by Phase and Condition. Error bars = +/– 1 S.E. N = 519. Green = Abundance (170 participants, 29 groups); Blue = Control (177 participants, 30 groups); Red = Scarcity (172 participants, 30 groups). There are no consistent differences between Conditions in Phase 1 or Phase 3. In Phase 2, Abundance participants selected True Top Three platforms significantly less often than Controls on a majority of Trials. There were no consistent differences between Scarcity and Control participants.

There are no consistent differences between Conditions in Phase 1 or Phase 3. In Phase 2, Abundance participants selected True Top Three platforms significantly less often than Controls on a majority of Trials. There were no consistent differences between Scarcity and Control participants.

As before, we will look at the cumulative number of times participants selected any of the True Top Three platforms across Trials 1–15 of each Phase. Table 6.25 presents the parameter estimates and fit statistics from three different Three-Level Random Coefficient models of the

Number of True Top Three Platforms Selected (Cumulative) across Trials 1–15 in a given Phase. Model 1 is the baseline model. The fixed part of Model 1 includes an intercept and piecewise linear slopes for Phases 2 and 3. The random part of Model 1 includes a random intercept and a random linear slope for Phase at the Participant level (Level 2) and at the Group level (Level 3). Model 2 includes Condition as a fixed effect. Model 3 introduces two-way interactions between elements of the experimental design (Condition, Phase). Model 3 provides a better fit than Model 2 [$LR\ \chi^2(4) = 28.02$, $p < 0.000$] and Model 1 [$LR\ \chi^2(6) = 30.03$, $p < 0.000$], so I will focus on the predictions from Model 3.

In Phase 1, Control participants selected True Top Three platforms 22.29 ($z = 20.92$, $p < 0.000$) times on average. Abundance and Scarcity participants selected True Top Three platforms about the same number of times as did Controls ($\beta_3 = 0.87$, $z = 0.57$, $p = 0.566$; $\beta_4 = 1.56$, $z = 1.04$, $p = 0.301$).

In Phase 2, Control participants selected True Top Three platforms about 27.05 times on average, which is a significant increase over Phase 1 ($\beta_2 = 4.76$, $z = 5.11$, $p < 0.000$). Abundance participants selected True Top Three platforms significantly less often than Controls (Abundance Phase 2 – Control Phase 2 = –4.39, $z = –3.47$, $p = 0.001$), which was similar to the number of times they selected top-three platforms in Phase 1 (Abundance Phase 2 – Abundance Phase 1 = –0.50, $z = –0.53$, $p = 0.594$). Scarcity participants selected True Top Three platforms with similar frequency to Controls (Scarcity Phase 2 – Control Phase 2 = –1.90, $z = –1.51$, $p = 0.131$), which was similar to the number of times they selected True Top Three platforms in Phase 1 (Scarcity Phase 2 – Scarcity Phase 1 = 1.29, $z = 1.38$, $p = 0.167$).

In Phase 3, Control participants selected True Top Three platforms about 25.54 times on average, which was similar to Phase 1 ($\beta_3 = –1.51$, $z = –1.62$, $p = 0.104$). Abundance and

Scarcity participants selected True Top Three platforms with similar frequency to Controls (Abundance Phase 3 – Control Phase 3 = –1.78, z = –1.07, p = 0.284; Scarcity Phase 3 – Control Phase 3 = –2.09, z = –1.26, p = 0.206), which was similar to what they did in Phase 2 (Abundance Phase 3 – Abundance Phase 2 = –1.51, z = –1.62, p = 0.104; Scarcity Phase 3 – Scarcity Phase 2 = –1.70, z = –1.82, p = 0.069).

Table 6.25. Study 3B: Discovery. Maximum likelihood estimates of Two-Level Random-Coefficient models for Number of True Top Three Platforms Selected (Cumulative) by Trial 15 of each Phase. Model 1: Intercept-Slope; Model 2: Main Effects; Model 3: Design Interactions. N = 519.

	Model 1		Model 2		Model 3	
	Est	(SE)	Est	(SE)	Est	(SE)
Fixed Effects						
Intercept β_0	23.10***	0.62	23.84***	0.90	22.29***	1.07
Phase 2 β_1	1.88***	0.55	1.88***	0.55	4.76***	0.93
Phase 3 β_2	–0.73	0.55	–0.73	0.55	–1.51	0.93
Abundance β_3			–1.63	1.15	0.87	1.33
Scarcity β_4			–0.63	1.14	1.56	1.32
Abundance × Phase 2 β_5					–5.26***	1.33
Scarcity × Phase 2 β_6					–3.46**	1.32
Abundance × Phase 3 β_7					2.61*	1.52
Scarcity × Phase 3 β_8					–0.19	1.51
Random Effects						
L3 Random Intercept Var $\psi_{11}^{(3)}$	24.65	5.04	24.76	5.10	24.37	4.98
L3 Random Slope Var $\psi_{22}^{(3)}$	14.31	2.63	14.30	2.63	13.80	2.54
L2 Random Intercept Var $\psi_{11}^{(2)}$	21.17	3.12	21.17	3.12	21.43	3.11
L2 Random Slope Var $\psi_{22}^{(2)}$	0.26	0.24	0.26	0.24	0.27	0.24
L1 (Residual) Error Var θ	36.62	1.68	36.62	0.96	35.67	1.64
Log likelihood	–5436		–5435		–5421	
AIC | *BIC*	10892 | 10945		10894 | 10958		10874 | 10960	

* $p \leq 0.05$; ** $p \leq 0.01$; *** $p \leq 0.001$; SE = standard error of the mean

6.2.3.6 Side Observations: Peer Results

On Trials 1–14 of each Phase, participants had the option to share their results with each of their peers. On Trials 2–15 of each Phase, participants had the option to view each of their peer's results from the previous Trial. If *both* the participant *and* the peer chose to share their results with one another at the end of the previous Trial, the peer's results appeared if the participant clicked on that peer's Player button. If *either* the participant *or* the peer chose *not* to share their results with the other, then the message "*Not shared*" would appear when the participant clicked on the peer's Player button.

Sharing. Figure 6.29 presents the number of peer shares on each Trial in each Phase of Study 3B (the number of peers with whom participants chose to share results on each Trial). Participants make sharing decisions at the end of Trials 1–14 (sharing decisions are not elicited on Trial 15, because participants move on to a different Company and platform list after that Trial). Participants in all three Conditions chose to share with 4–5 of their peers at the start of each Phase. By the end of each Phase, this number decreases to about 3 peers. In Phases 2 and 3, Scarcity participants choose to share with more peers than Control participants across a handful of Trials. (Note that the count includes shares made by active participants to peers who dropped out of the experiment. 15 participants across 13 groups were classified as dropouts for repeatedly failing to submit their responses before the time limits: Abundance = 4 participants, 4 groups; Control = 3 participants, 3 groups; Scarcity = 8 participants, 6 groups. No group had more than two dropouts.)

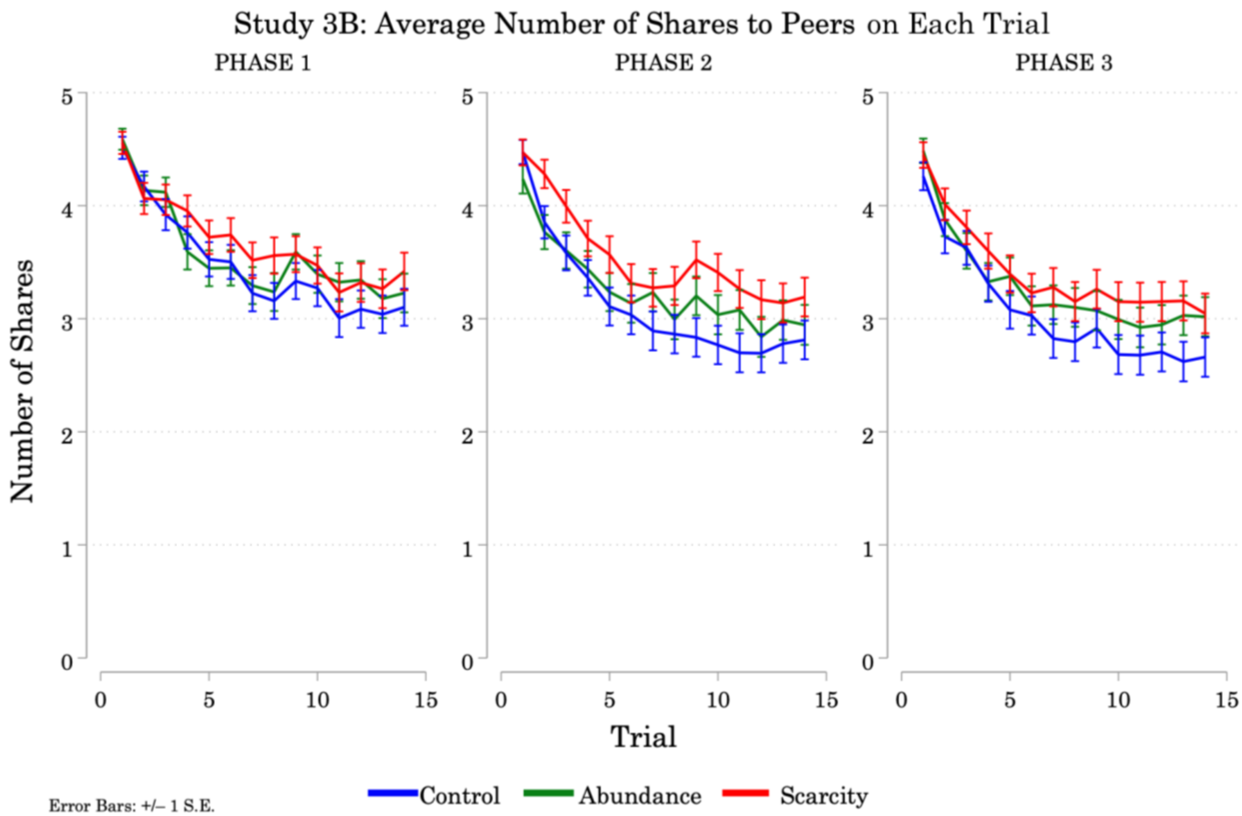

Figure 6.29. Study 3B: Shares to Peers. Average number of shares to peers on each Trial, by Phase and Condition. Error bars = +/– 1 S.E. N = 519. Green = Abundance (170 participants, 29 groups); Blue = Control (177 participants, 30 groups); Red = Scarcity (172 participants, 30 groups). Excludes sharing decisions made by participants who dropped out of the experiment, but includes decisions made by active participants to share with peers who dropped out. Note that participants were not asked to make sharing decisions on the final Trial of each Phase (Trial 15). Participants in all three Conditions shared with 4–5 peers at the start of each Phase, and this number decreases to about 3 peers by the end of each Phase.

Table 6.26 presents the parameter estimates and fit statistics from three different Three-Level Random Coefficient models for the *cumulative* number of times participants chose to share results with their peers across Trials 1–14 of each Phase in Study 3B. The cumulative number of shares to peers ranges from zero (the participant did not share with *any* of her peers on *any* Trial in a given Phase) to 70 (the participant chose to share with *all five* of her peers on *every* possible Trial, 1–14, in a given Phase).

Table 6.26. Study 3B: Shares to Peers. Maximum likelihood estimates of Three-Level Random-Coefficient models for the cumulative number of shares to peers across Trials 1–14 of each Phase. Model 1: Intercept-Slope; Model 2: Main Effects; Model 3: Design Interactions. N = 519.

	Model 1		Model 2		Model 3	
	Est	(SE)	Est	(SE)	Est	(SE)
Fixed Effects						
Intercept β_0	49.83***	1.40	48.56***	2.25	48.69***	2.26
Phase 2 β_1	–3.65***	0.63	–3.65***	0.63	–4.86***	1.08
Phase 3 β_2	–0.74	0.63	–0.74	0.63	–0.79	1.08
Dropouts β_3	–0.70	1.40	–1.33	3.22	–1.34	3.22
Abundance β_4			0.68	3.18	0.86	3.20
Scarcity β_5			3.41	3.19	2.85	3.21
Abundance × Phase 2 β_6					0.63	1.54
Scarcity × Phase 2 β_7					3.02*	1.53
Abundance × Phase 3 β_8					1.15	1.54
Scarcity × Phase 3 β_9					–1.01	1.53
Random Effects						
L3 Random Intercept Var $\psi_{11}^{(3)}$	82.19	23.22	79.98	22.88	79.98	22.88
L2 Random Slope Var $\psi_{22}^{(3)}$	8.14	2.80	8.15	2.80	7.90	2.77
L2 Random Intercept Var $\psi_{11}^{(2)}$	347.85	27.85	347.79	27.84	348.37	27.84
L2 Random Slope Var $\psi_{22}^{(2)}$	22.40	4.43	22.40	4.43	22.77	4.42
L1 (Residual) Error Var θ	68.68	4.26	68.68	4.26	67.99	4.22
Log likelihood	–6434		–6434		–6430	
AIC | *BIC*	12890 | 12949		12893 | 12963		12895 | 12986	

* $p \leq 0.05$; ** $p \leq 0.01$; *** $p \leq 0.001$; SE = standard error of the mean

Model 1 is the baseline model. The fixed part of Model 1 includes an intercept and piecewise linear slopes for Phases 2 and 3. The random part of Model 1 includes a random intercept and a random linear slope for Phase at the Group level (Level 3) and at the Participant level (Level 2). Model 2 includes Condition as a fixed effect. I also include a fixed effect for the number of dropouts in a participants' group. Model 3 introduces interactions among elements of the experimental design (Condition, Phase). Model 3 did not provide a better fit than Model 2

[LR $\chi^2(4) = 6.22$, $p = 0.183$], nor did Model 2 provide a better fit than Model 1 [LR $\chi^2(2) = 1.24$, $p = 0.537$], so I will focus on the predictions from Model 1.

In Phase 1, participants in all three Conditions shared with their peers 49.83 times on average ($z = 35.54$, $p < 0.000$). In Phase 2, participants shared with their peers significantly less often than they did in Phase 1 ($\beta_1 = -3.65$, $z = -5.78$, $p < 0.000$). In Phase 3, participants shared with their peers a similar number of times as they did in Phase 2.

Sampling Frequency. Figure 6.30 presents the average number of peers viewed on each Trial (the number of peers whose Player button the participant clicked at least once in an attempt to view that peer's results from the previous Trial). Participants may choose to view their peers' results on Trials 2-15. Participants in all three Conditions choose to view around 4 of their peers on average at the start of each Phase, and then reduce the number of peers they choose to view across Trials. There is a sharper decrease in the number of peers viewed across Trials in each subsequent Phase of the experiment. (Note that the count of peer views includes attempts to view peers who dropped out of the experiment.)

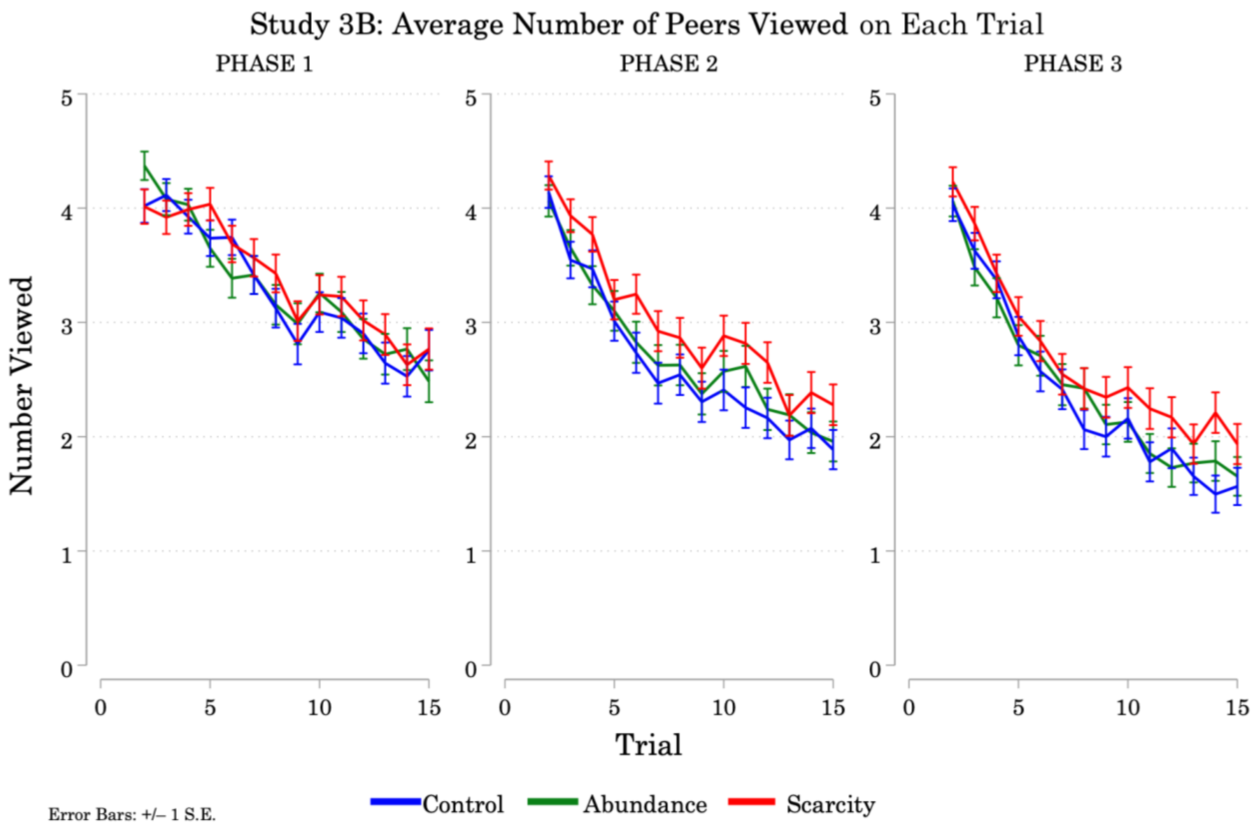

Figure 6.30. Study 3B: Peer Views. Average number of peers viewed across Trials 2–15, by Phase and Condition. Error bars = +/– 1 S.E. N = 519. Green = Abundance (170 participants, 29 groups); Blue = Control (177 participants, 30 groups); Red = Scarcity (172 participants, 30 groups). Excludes viewing decisions made by participants who dropped out of the experiment, but includes decisions made by active participants to view peers who dropped out. Note that participants can only view peer results on Trials 2-15 of each Phase. Participants in all three Conditions choose to view about 4 of their peers on average at the start of each Phase. Participants reduce the number of peers they choose to view across Trials within a given Phase. There is a sharper decrease in the number of peers viewed across Trials in each subsequent Phase of the experiment.

As in Study 3A, the most plausible explanation for the sharp drop in peer views on Trial 9 of Phases 1 and 2 is that participants are experiencing heightened anxiety about the time limits after submitting their Platform Value Estimates at the end of Trial 8.

Table 6.27. Study 3B: Peer Views. Maximum likelihood estimates of Three-Level Random-Coefficient models for the cumulative number of peer views across Trials 2–15 of each Phase. Model 1: Intercept-Slope; Model 2: Main Effects; Model 3: Design Interactions. N = 519.

	Model 1		Model 2		Model 3	
	Est	(SE)	Est	(SE)	Est	(SE)
Fixed Effects						
Intercept β_0	45.24***	1.22	44.36***	1.93	45.10***	1.98
Phase 2 β_1	–6.81***	0.61	–6.81***	0.61	–8.41***	1.04
Phase 3 β_2	–3.84***	0.61	–3.84***	0.61	–3.50***	1.04
Dropouts β_3	0.90	2.77	0.35	2.78	0.35	2.78
Abundance β_4			0.11	2.70	–0.39	2.80
Scarcity β_5			2.80	2.72	1.06	2.81
Abundance × Phase 2 β_6					1.09	1.49
Scarcity × Phase 2 β_7					3.75**	1.48
Abundance × Phase 3 β_8					–0.27	1.49
Scarcity × Phase 3 β_9					–0.74	1.48
Random Effects						
L3 Random Intercept Var $\psi_{11}^{(3)}$	40.01	17.97	39.70	17.95	39.43	17.88
L3 Random Slope Var $\psi_{22}^{(3)}$	1.56	2.25	1.56	2.25	1.14	2.20
L2 Random Intercept Var $\psi_{11}^{(2)}$	371.15	29.91	371.08	29.90	371.64	29.91
L2 Random Slope Var $\psi_{22}^{(2)}$	33.61	5.43	33.61	5.43	33.93	5.43
L1 (Residual) Error Var θ	76.14	4.73	76.14	4.73	75.55	4.69
Log likelihood	–6486		–6485		–6482	
AIC | *BIC*	12994 | 13053		12996 | 13067		12998 | 13089	

* $p \leq 0.05$; ** $p \leq 0.01$; *** $p \leq 0.001$; SE = standard error of the mean

Table 6.27 presents the parameter estimates and fit statistics from three different Three-Level Random Coefficient models for the average *cumulative* Peer Views across Trials 2–15 of each Phase in Study 3B. The cumulative Number of Peer Views ranges from zero (the participant did not view *any* of her peers on *any* Trial in a given Phase) to 70 (the participant viewed all five of her peers on every possible Trial, 2–15, in a given Phase). Model 1 is the baseline model. The fixed part of Model 1 includes an intercept and piecewise linear slopes for Phases 2 and 3. The random part of Model 1 includes a random intercept and a random linear slope for Phase at the Group level (Level 3) and at the Participant level (Level 2). Model 2 includes Condition as a fixed effect. I also include a fixed effect for the number of dropouts in a participants' group. Model 3 introduces interactions among elements of the experimental design (Condition, Phase). Model 3 did not provide a better fit than Model 2 [$LR\ \chi^2(4) = 6.68$, $p = 0.154$], nor did Model 2 provide a better fit than Model 1 [$LR\ \chi^2(2) = 1.29$, $p = 0.524$], so I will focus on the predictions from Model 1.

In Phase 1, participants in all three Conditions viewed their peers 45.24 times on average ($z = 37.20$, $p < 0.000$). Participants viewed their peers significantly less often in Phase 2 than in Phase 1 ($\beta_1 = –6.81$, $z = –11.10$, $p < 0.000$), and significantly less often in Phase 3 than in Phase 2 ($\beta_2 = –3.83$, $z = –86.26$, $p < 0.000$). Unlike in Study 3A, the number of dropouts in a participant's group has no significant effect on the number of times the participant chooses to view her peers.

Sampling Bias. In Study 3A, we found a position-based preference in the number of views received by a given participant. Participants received fewer views from their peers, on average, the further away their Player button was located from the upper-left position in the button tray (Position 1). Higher-achieving participants (those who earned more points than their peers in a given Phase) chose to view their peers more often than lower-achieving participants. We also found that Study 3A participants chose to view peers more often when those peers choose to share their results more often.

We will walk through the same steps we took in Study 3A to investigate the factors that influence participants' decisions to view their peers' results, and the relationship between participants' behavior and the structure of the group-level View Networks.

First, we will look at the number of times participants choose to view each peer in a given Phase, based on that peer's randomly assigned Position in the participant's group (the location of the peer's Player button in the button tray). This will show us whether participants tend to view peers in certain Positions more often than others. Second, we will look at the number of times participants choose to view each peer based on the peer's relative achievement (Rank) in a given Phase. Participants are assigned a relative achievement Rank for each Phase based on the total number of points they earned in that Phase (the sum of the Total Pitch Scores earned across Trials 1–15). Within each group, in each Phase, the participant who earned the highest total number of points is assigned Rank 1, and the participant who earned the lowest total number of points is assigned Rank 6.[42]

Figure 6.31 presents the number of times participants chose to view each of their peers in each Phase of the experiment, based on each peer's randomly-assigned Positions within their groups.

[42] Note that participant Rank is not necessarily constant across Phases, as Ranks are determined by the points earned *within* each Phase.

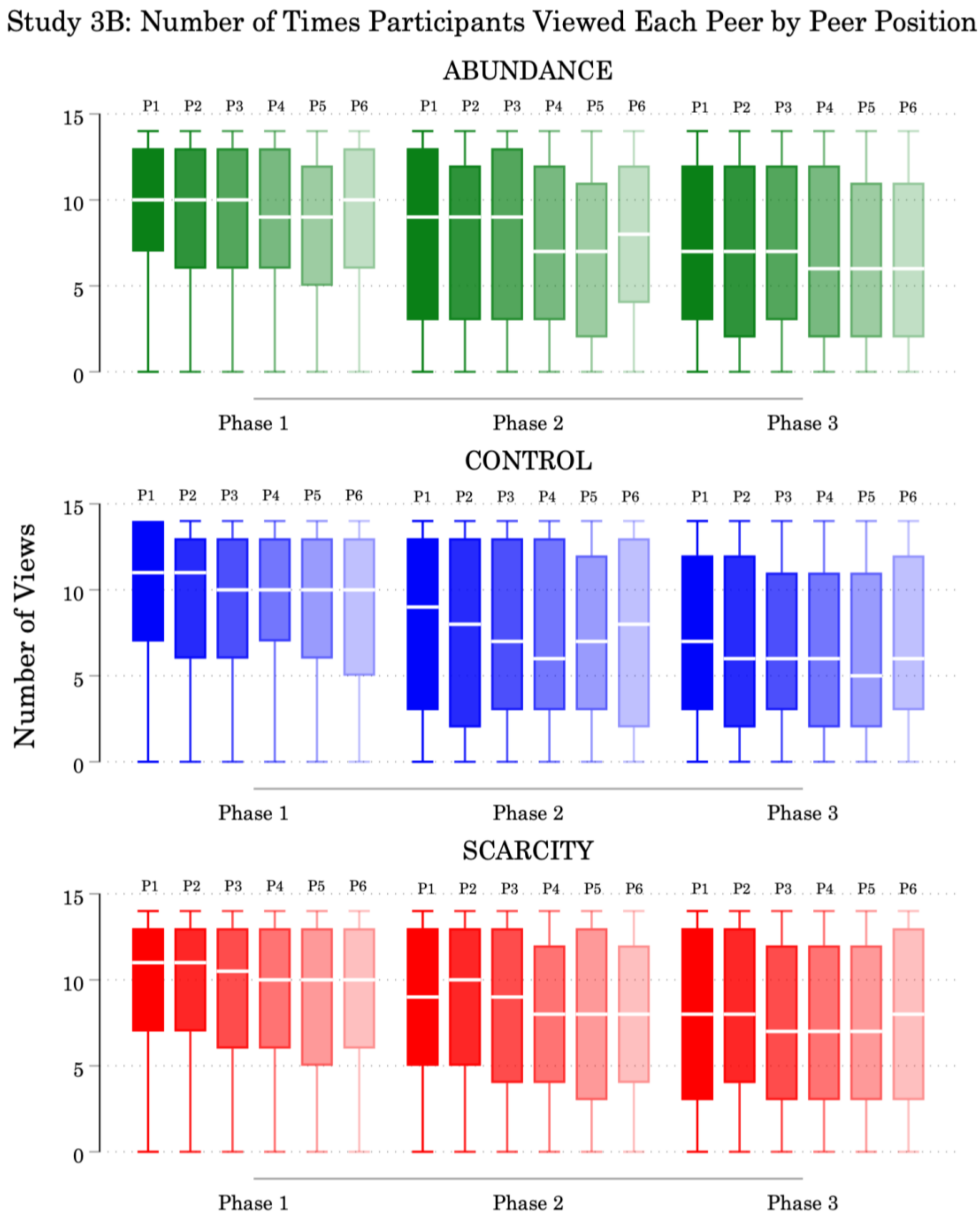

Figure 6.31. Study 3B: Peer Views by Peer Position. Number of times participants viewed each of their peers based on each peer's randomly-assigned Positions, by Phase and Condition. N = 519. Top Row = Abundance (170 participants, 29 groups); Middle Row = Control (177 participants, 30 groups); Bottom Row = Scarcity (172 participants, 30 groups). Excludes attempts to view peers who dropped out of the experiment. Boxes ordered by peer Position, from left to right, within each Phase. P1 = Position 1 (darkest color), P2 = Position 2, P3 = Position 3, P4 = Position 4, P5 = Position 5, P6 = Position 6 (lightest color).

The average number of views ranges from zero (the participant did not view the peer in a given Position on any Trial in a given Phase) to 14 (the participant chose to view the peer in a given Position on every possible Trial, 2–15, in a given Phase). The Abundance Condition (green) is on the top row, the Control Condition (blue) is on the middle row, and the Scarcity Condition (red) is on the bottom row. Each row has three sets of six boxes. Each set of boxes represent one Phase of the experiment (Phase 1 on the far left, Phase 3 on the far right). Each of the six boxes in a given Phase represents a different peer Position, with Position 1 located on the far-left side of each set (darkest color) and Position 6 located on the far-right side of each set (lightest color).

There might be a slight preference for peers whose Player button is located closer to the top-left position in the button tray (Position 1). But the pattern is less consistent than what we saw in Study 3A. It seems like the peer furthest away from the top-left location in the button tray (Position 6, bottom-middle location) is not ignored as often as it was in Study 3A. In other words, the peer in Position 6 never receives the *lowest* number of views, which is something we saw in Study 3A.

Recall that participants could only see their peers' results if both the participant and the peer chose to share with each other. If a participant tried to view the results of a peer who *did not* choose to share with the participant, then the participant would see the message "*Not shared*" when the participant clicked on the peer's Player button. It is possible that participants chose to view peers located closer to the top-left of the button tray because those peers chose to share with the participant more often than peers located closer to the bottom-right of the button tray.

Figure 6.32 presents the number of times each peer shared with a participant, based on the peer's randomly-assigned Position. The number of shares ranges from zero (the peer did not share with the participant on any Trial in a given Phase) to 14 (the peer shared with the participant on every possible Trial, 1–14, in a given Phase). In the Abundance and Control Conditions (top and middle rows), peers in Position 1 seem to share their results slightly more often than peers in Positions 2–6. There don’t seem to be any consistent pattern in the volume of shares received from peers in Positions 2–6.

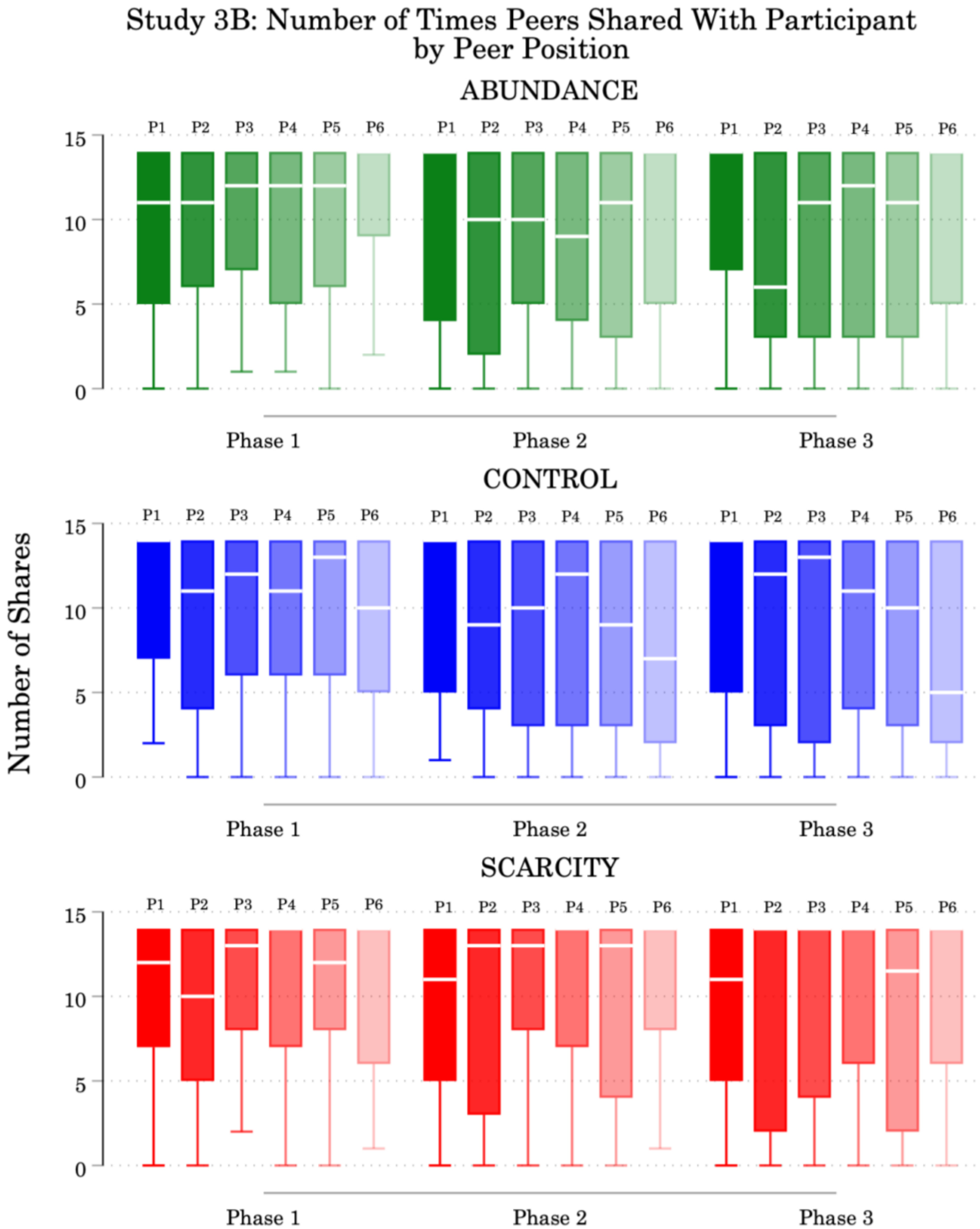

Figure 6.32. Study 3B: Shares from Peers by Peer Position. Number of times peers shared with participants based on peers' randomly-assigned Positions, by Phase and Condition. N = 519. Top Row = Abundance (170 participants, 29 groups); Middle Row = Control (177 participants, 30 groups); Bottom Row = Scarcity (172 participants, 30 groups). Excludes shares received from peers who dropped out of the experiment. Boxes ordered by peer Position, from left to right, within each Phase. P1 = Position 1 (darkest color), P2 = Position 2, P3 = Position 3, P4 = Position 4, P5 = Position 5, P6 = Position 6 (lightest color).

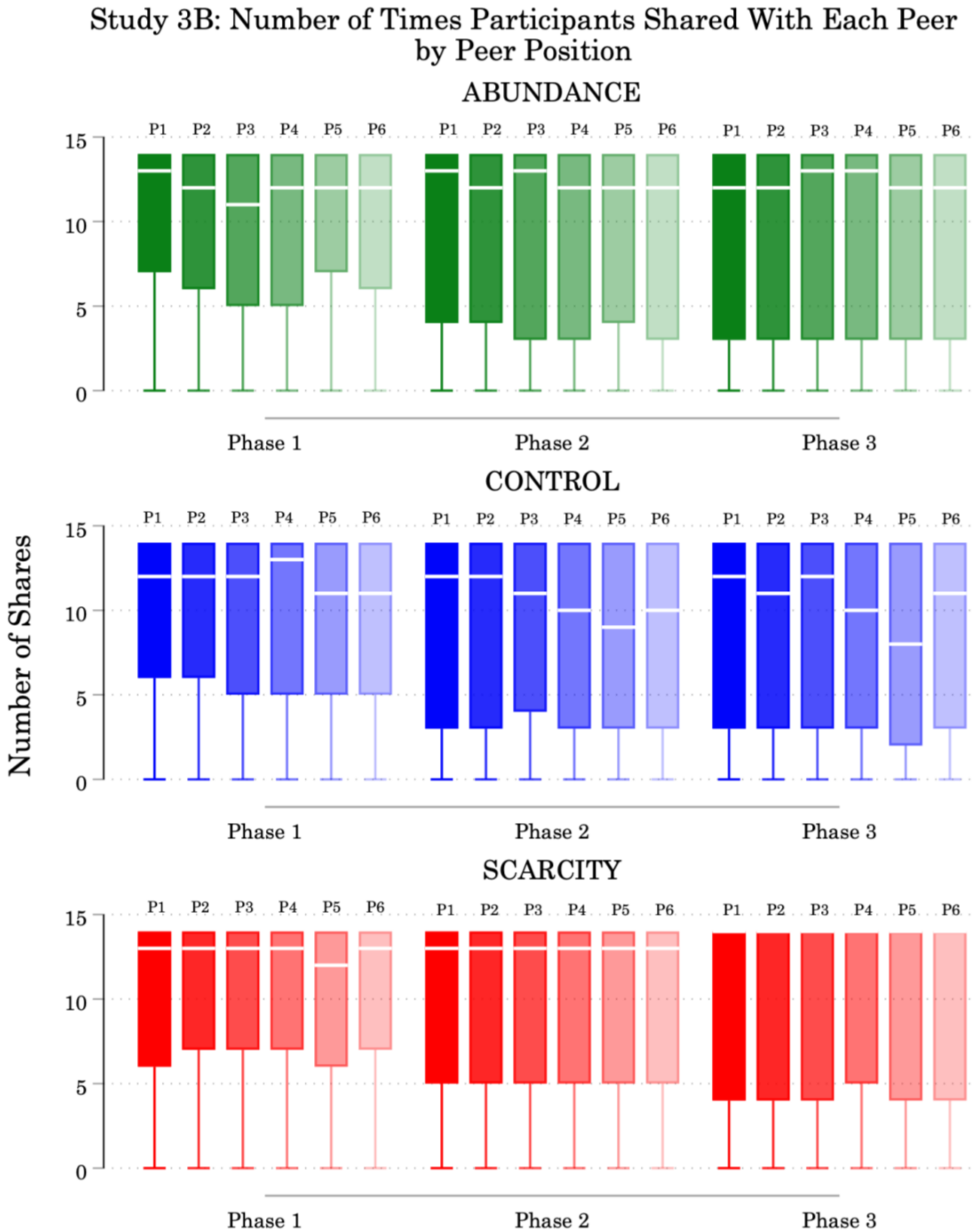

Figure 6.33. Study 3B: Shares to Peers by Peer Position. Number of times participants shared with peers based on peers' randomly-assigned Positions, by Phase and Condition. N = 519. Top Row = Abundance (170 participants, 29 groups); Middle Row = Control (177 participants, 30 groups); Bottom Row = Scarcity (172 participants, 30 groups). Excludes shares sent to peers who dropped out of the experiment. Boxes ordered by peer Position, from left to right, within each Phase. P1 = Position 1 (darkest color), P2 = Position 2, P3 = Position 3, P4 = Position 4, P5 = Position 5, P6 = Position 6 (lightest color).

It's possible that Abundance and Control participants in Position 1 chose to share more often with their peers because their peers chose to share more often with them. Figure 6.33 presents sharing decisions from the opposite perspective - the number of times participants chose to share with each of their peers based on their peers' Positions. There aren't any consistent patterns across Conditions or Phases, but it looks like Abundance participants might have shared with peers in Position 1 slightly more often than they did with other peers in Phase 1. In Phase 2, Control participants might have shared with peers in Positions 1 and 2 slightly more often peers in Positions 3–6.

Next, we will look at the number of times participants chose to view each of their peers based on each peer's relative achievement Rank within a given Phase. Figure 6.34 presents the number of times participants chose to view each of their peers based on each peer's achievement Rank in each Phase of Study 3A. The Abundance Condition (green) is on the top row, the Control Condition (blue) is on the middle row, and the Scarcity Condition (red) is on the bottom row. Each row has three sets of six boxes. Each set of boxes represent one Phase of the experiment (Phase 1 on the far left, Phase 3 on the far right). Each of the six boxes in a given Phase represents a different peer Rank, with Rank 1 (highest achievement in group) located on the far-left side of each set (darkest color) and Rank 6 (lowest achievement in group) located on the far-right side of each set (lightest color).

In the Abundance Condition, it looks like the highest-achieving peer receives slightly less views than the lowest-achieving peer every Phase. In the Scarcity and Control Conditions, it looks like the highest-achieving peer receives slightly less views than the lowest-achieving peer in Phases 1 and 2.

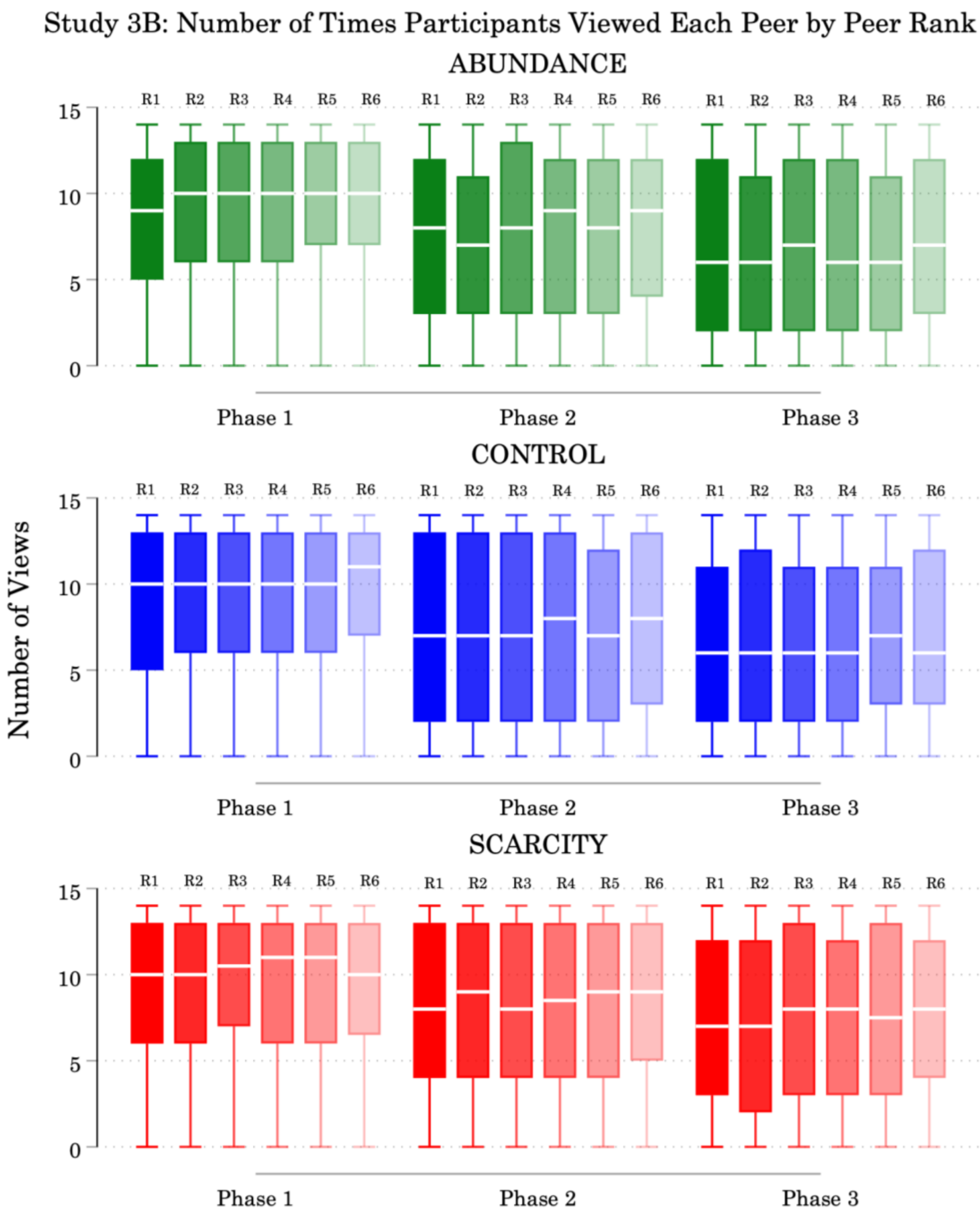

Figure 6.34. Study 3A: Peer Views by Peer Rank. Number of times participants viewed each of their peers based on each peer's achievement Rank, by Phase and Condition. N = 519. Top Row = Abundance (170 participants, 29 groups); Middle Row = Control (177 participants, 30 groups); Bottom Row = Scarcity (172 participants, 30 groups). Excludes attempts to view peers who dropped out of the experiment. Boxes are ordered by peer achievement Rank, from left to right, within each Phase. R1 = Rank 1 (highest achievement), R2 = Rank 2, R3 = Rank 3, R4 = Rank 4, R5 = Rank 5, R6 = Rank 6 (lowest achievement). Note that the on-screen Position of the participant in each Rank varies across groups.

Though it seems like participants view their highest-ranked peer less often, remember the caveat that we discussed in Study 3A. Each participant occupies one of the six Ranks, and a participant cannot view himself. So, each participant's decisions to view his peers are only captured by 5 out of the 6 boxes above a given Phase. This means that Participant X's decisions contribute to the calculation of the interquartile range for the last 5 boxes above each Phase (Ranks 2, 3, 4, 5, and 6), but not to the first box above each Phase (Rank 1). If participants in Rank 1 choose to view *all* of their peers (regardless of Rank) much more often than participants in Rank 6 choose to view *any* of their peers, then it would be impossible for Rank 1 participants to accumulate more views, on average, than Rank 6 participants.

We can explore whether something like this is happening in Study 3B by looking at the average number of times a participant in a given Rank is viewed by each of his peers, based on each peer's Rank (Figure 6.35). Participants (in any Rank) receive more views from the highest-achieving peers in their group (Ranks 1 & 2) than from the lowest-achieving peers in their group (Ranks 5 & 6). This tells us that the highest-achieving participants in a given group choose to view their peers *of every Rank* more often than the lowest-achieving participants in a given group choose to view their peers *of every Rank*.

When we aggregate across participant Ranks (e.g. looking at the number of times a participant *of any Rank* chooses to view a peer *of a specific Rank*) it is difficult to differentiate between patterns driven by peer characteristics (e.g. participants choose to view the lowest-achieving peer, Rank 6, more often) and patterns driven by participant characteristics (e.g. the highest-achieving participant, Rank 1, views all of his peers more often than the lowest-achieving participant, Rank 6, views any of his peers.).

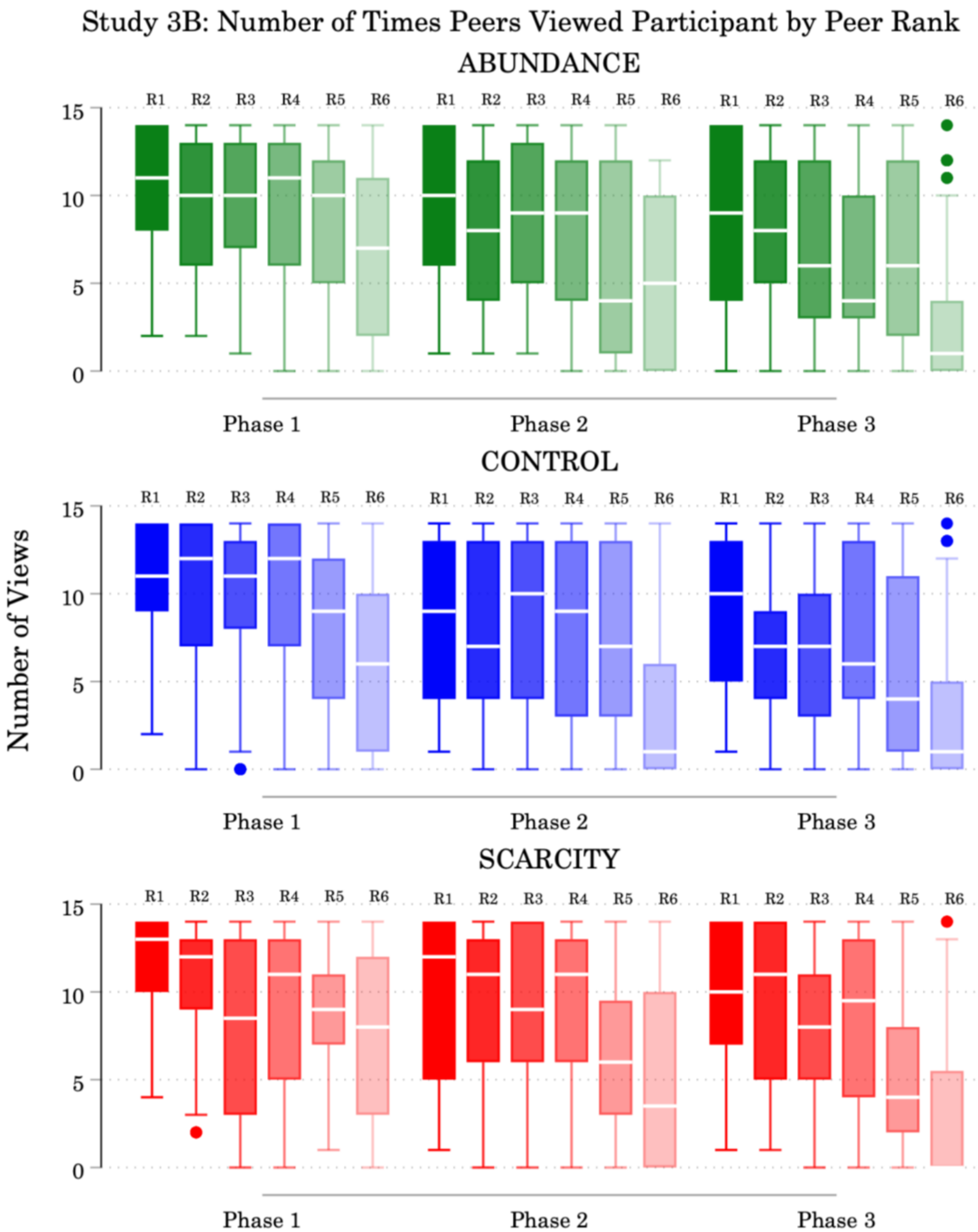

Figure 6.35. Study 3B: Views Received by Peer Rank. Number of times peers viewed participants based on peers' relative achievement Rank, by Phase and Condition. N = 519. Top Row = Abundance (170 participants, 29 groups); Middle Row = Control (177 participants, 30 groups); Bottom Row = Scarcity (172 participants, 30 groups). Excludes views received from peers who dropped out of the experiment. Boxes are ordered by peer achievement Rank, from left to right, within each Phase. R1 = Rank 1 (highest achievement), R2 = Rank 2, R3 = Rank 3, R4 = Rank 4, R5 = Rank 5, R6 = Rank 6 (lowest achievement).

Now we'll take a look at these decisions at the dyad (participant-to-peer) level. This will allow us to take into account both characteristics of the participant, and the peer, and explore the effect of these characteristics on the number of times the participant chooses to view the peer in a given Phase. Let's review the factors we explored in Study 3A, and what we found.

Peer Position. In Study 3A, participants viewed a given peer more often when the peer's randomly-assigned Position was closer to the top-left location in the button tray. We see hints of this position-based preference in Figure 6.21.

Peer Shares. In Study 3A, the number of times a participant viewed a given peer increased with the number of times the peer chose to share with the participant. In Figure 6.22, it seems like Abundance and Control peers in Positions 1 and 2 might share more often than those in higher positions. So, it's possible the position-based preference we observed in Figure 6.21 results from the tendency for peers in Positions 1 and 2 to share more often.

Reverse-Coded Participant / Peer Rank. [Recall that we reverse-code these factors so that an *increase* in achievement is associated with an *increase* in Rank.] In Study 3A, we found that higher-achieving participants (Rank 1 and 2) viewed their peers more often than lower-achieving participants. We did not find any relationship between peer achievement (Peer Rank) and the number of times a participant chooses to view a given peer. However, there was no competition among participants in Study 3A. In the present experiment, participants are competing against their peers for a Rank-based bonus. It's possible that the presence of competition will cause participants to pay more attention to relative performance. As a result, we might observe rank-based preferences in Study 3B participants' viewing decisions.

Participant / Peer Exploration. In Study 3A, the effect of Participant Exploration was mixed. There was no consistent relationship between Participant Exploration and the number of times a participant chose to view his peers in Phase 1 (though Scarcity participants with higher Exploration did tend to view their peers less often). In Phase 3, there was a positive relationship between Participant Exploration and the number of times a participant chose to view his peers. There was no relationship between Peer Exploration and the number of times a participant chose to view a given peer in any Phase of the experiment.

Participant / Peer Discovery. In Phase 1 of Study 3A, there was a negative relationship between Participant Discovery and the number of times a participant chose to view his peers. In Phases 2 and 3, there was no relationship between Participant Discovery and the number of times the participant chose to view his peers. In the Scarcity and Control Conditions, there was no relationship between Peer Discovery and the number of times a participant chose to view a given peer. In the Abundance Condition, there was a positive relationship between Peer Discovery and the number of times a participant chose to view a given peer in Phase 3, but there was no relationship between Peer Discovery and peer views in Phase 1 or 2.

Table 6.28. Participant- and Peer-Level Explanatory Variables (Review). Summary of participant- and peer-level explanatory variables and effects observed on the number of peer views in a given Phase in Study 3A.

Variable	Description	Observed Effect in Study 3A
Peer Position	Peer's randomly-assigned position in the button tray (Position 1 = top left)	–
Peer Shares to Participant	Number of times peer shared with participant in the current Phase	+
RC Participant Rank	Participant's relative achievement Rank within the current Phase (reverse-coded so that Rank 6 = 0, lowest achievement)	+
RC Peer Rank	Peer's relative achievement Rank within the current Phase (reverse-coded so that Rank 6 = 0, lowest achievement)	*not significant*
Participant Exploration	Number of unique platforms participant explored in the current Phase	Phase 1: *mixed* Phase 2: *mixed* Phase 3: +
Peer Exploration	Number of unique platforms peer explored in the current Phase	*not significant*
Participant Discovery	Number of times participant selected any of the true top three highest-valued platforms in the current Phase	Phase 1: – Phase 2: *not significant* Phase 3: *not significant*
Peer Discovery	Number of times peer selected any of the true top three highest-valued platforms in the current Phase	Phase 1: *not significant* Phase 2: *not significant* Phase 3: *mixed*

Table 6.29 presents the parameter estimates and fit statistics from three different Three-Level Random Coefficient models for the number of times participants chose to view a given peer in each Phase of Study 3B. Model 1 is the baseline model. The fixed part of Model 1 includes an intercept, piecewise linear slopes for Phases 2 and 3, and a fixed effect for the number of dropouts in a participant's group. The random part of Model 1 includes a random intercept at the Group level (Level 3) and a random intercept and random linear slope at the

Participant level (Level 2).[43] Model 2 includes fixed effects for Condition, Peer Position, Peer Shares to Participant, reverse-coded (RC) Participant Rank, reverse-coded (RC) Peer Rank, Participant Exploration, Peer Exploration, Participant Discovery, and Peer Discovery.

Model 3 introduces interactions among elements of the experimental design (Condition, Phase), and the participant- and peer-level explanatory variables. Non-significant two- and three-way interactions between Phase, Condition, and the participant- and peer-level explanatory variables were removed in a backward stepwise fashion starting with the highest-order interactions with the highest p-values. (Non-significant lower-ordered components of significant higher-ordered interactions are retained.) Model 3 provides a significantly better fit than Model 2 [$LR\ \chi^2(21) = 166.09$, $p < 0.000$] and Model 1 [$LR\ \chi^2(31) = 920.14$, $p < 0.000$], so I will focus on the estimates from Model 3.

[43] Alternative models were fit with a random linear slope for Phase at the Group level, but calculation of standard errors for the random effects failed so the group-level random slope was dropped from the final models.

Table 6.29. Study 3B: Peer Views Explanatory Variables. Maximum likelihood estimates of Three-Level Random-Coefficient models for the number of times participants viewed each of their peers in each Phase of Study 3A. Model 1: Intercept-Slope; Model 2: Main Effects; Model 3: Restricted Interactions. N = 519.

	Model 1		Model 2		Model 3	
	Est	(SE)	Est	(SE)	Est	(SE)
Fixed Effects						
Intercept β_0	9.07***	0.24	8.01***	0.67	16.19***	1.68
Phase 2 β_1	–1.37***	0.09	–1.30***	0.08	–1.45***	0.26
Phase 3 β_2	–0.76***	0.09	–0.74***	0.08	–0.25	0.24
Dropouts β_3	0.19	0.24	–0.00	0.52	0.01	0.52
Abundance β_4			0.00	0.50	–9.17***	1.93
Scarcity β_5			0.50	0.50	–8.37***	1.81
Peer Position β_6			–0.15***	0.01	–0.16***	0.01
Peer Shares to Participant β_7			0.10***	0.00	0.04***	0.01
RC Participant Rank β_8			0.25***	0.02	0.32***	0.07
RC Peer Rank β_9			0.02	0.01	0.02	0.01
Participant Exploration β_{10}			–0.16	0.17	–2.71***	0.53
Peer Exploration β_{11}			0.03	0.09	0.06	0.09
Participant Discovery β_{12}			0.00	0.06	–0.16	0.09
Peer Discovery β_{13}			0.04	0.04	–0.04	0.06
Abundance × Phase 2 β_{14}					–0.00	0.35
Scarcity × Phase 2 β_{15}					–0.01	0.36
Peer Shares × Phase 2 β_{16}					0.05***	0.01
RC Part Rank × Phase 2 β_{17}					–0.24**	0.08
Abundance × Peer Shares β_{18}					0.05***	0.01
Scarcity × Peer Shares β_{19}					0.01	0.01
Abundance × RC Part Rank β_{20}					0.22*	0.10
Scarcity × RC Part Rank β_{21}					–0.12	0.11
Abundance × Part Exploration β_{22}					2.65***	0.62
Scarcity × Part Exploration β_{23}					2.86***	0.58
Abundance × Part Discovery β_{24}					0.11	0.14
Scarcity × Part Discovery β_{25}					0.43**	0.14
Abundance × Peer Discovery β_{26}					0.19*	0.09
Scarcity × Peer Discovery β_{27}					0.07	0.09
Abundance × Phase 3 β_{28}					–0.44	0.34
Scarcity × Phase 3 β_{29}					–0.97**	0.34
RC Part Rank × Phase 3 β_{30}					–0.19**	0.08

* $p \leq 0.05$; ** $p \leq 0.01$; *** $p \leq 0.001$; SE = standard error of the mean

Table 6.29. Study 3B: Peer Views Explanatory Variables (*Continued*). Maximum likelihood estimates of Three-Level Random-Coefficient models for the number of times participants viewed each of their peers in each Phase of Study 3A. Model 1: Intercept-Slope; Model 2: Main Effects; Model 3: Restricted Interactions. N = 519.

	Model 1		Model 2		Model 3	
	Est	(SE)	Est	(SE)	Est	(SE)
Random Effects						
Abun × RC Part. Rank × Phase 2 β_{31}					0.09	0.11
Scarc × RC Part. Rank × Phase 2 β_{32}					0.24*	0.11
Abun × RC Part. Rank × Phase 3 β_{33}					0.16	0.11
Scarc × RC Part. Rank × Phase 3 β_{34}					0.37***	0.11
Random Effects						
L3 Random Intercept Variance $\psi_{11}^{(3)}$	1.66	0.69	1.10	0.58	1.14	0.59
L2 Random Intercept Variance $\psi_{11}^{(2)}$	16.82	1.17	16.14	1.12	15.96	1.12
L2 Random Slope Variance $\psi_{22}^{(2)}$	2.61	0.18	2.52	0.17	2.51	0.17
L1 (Residual) Error Variance θ	3.08	0.05	2.77	0.32	2.70	0.05
Log likelihood	–16718		–16341		–16258	
AIC | *BIC*	33454 | 33516		32720 | 32851		32596 | 32873	

♦ * $p \leq 0.05$; ** $p \leq 0.01$; *** $p \leq 0.001$; SE = standard error of the mean
♦ ordinal variables are zero-centered so that the lowest level is equal to zero
(e.g. Position 1 = 0, reverse-coded Rank 6 = 0)

Let's start with the Model 3 intercept. The estimated number of times a Control participant chooses to view a given peer in Phase 1 is 16.19 (z = 9.67, p < 0.000). We are getting an estimate that we would never observe in the data because this value represents the number of times a participant would view his peer *if all of the following are true about the participant and the peer*:

1. [Dropouts β_3 = 0] There are zero dropouts in the participant's group
2. [Peer Position β_6 = 0] The peer was randomly assigned to Position 1
3. [Peer Shares to Participant β_7 = 0] The peer did not share her results with the participant on any Trial in the current Phase
4. [RC Participant Rank β_8 = 0] The participant is the lowest-achieving member of his group (Rank 6)
5. [RC Peer Rank β_9 = 0] The peer is *also* the lowest-achieving member of the participant's group (Rank 6 – note that this never occurs in the data, there are no ties between participants in any group in any Phase)

6. [Participant Exploration $\beta_{10} = 0$] The participant did not explore any platforms in the current Phase (note that this is strictly impossible because participants are forced to select three platforms on each Trial, so the minimum number of platforms any participant could explore is 3)
7. [Peer Exploration $\beta_{11} = 0$] The peer did not explore any platforms in the current Phase (note that this is strictly impossible for the reasons stated above)
8. [Participant Discovery $\beta_{12} = 0$] The participant never selected any of the true top three highest-valued platforms on any Trial in the current Phase
9. [Peer Discovery $\beta_{13} = 0$] The peer never selected any of the true top three highest-valued platforms on any Trial in the current Phase

Note that the model assumes the participant and her peer can hold the same relative achievement Rank in their group, which never occurs in the data. Note also that the model assumes the participant and her peer can explore zero platforms, which is strictly impossible because participants are forced to select three platforms to include in their pitch before they can move on to the next Trial (so the minimum number of platforms a participant or peer could explore is 3).

Now we'll move on to each of the remaining coefficients. Keep in mind that we are interpreting the effect of each coefficient holding all other coefficients at zero (see the above list for an explanation of what this means for each coefficient), which results in combinations that are never observed in the context of the present experiment. What is important to focus on is the *direction* and *significance* of the effects, not the specific values assigned to the coefficients. We'll start by looking at the main effects of Phase and Condition, and then we'll move to participant- and peer-level explanatory variables.

Phase 1. For a Control participant in Rank 6 with Exploration = 0 and Discovery = 0 and no dropouts in his group, and a peer who never shared with the participant and who is in Position 1 and Rank 6 with Exploration = 0 and Discovery = 0, the estimated number of times the participant chooses to view the peer in Phase 1 is 16.19 ($z = 8.19$, $p < 0.000$). An Abundance participant with the above profile chooses to view a peer with the above profile 7.02 (z = 6.80, p < 0.000) times in Phase 1, which is significantly lower than the number of times the Control participant views his peer (β_4 = –9.17, z = –4.75, p < 0.000). A Scarcity participant with the above profile chooses to view a peer with the above profile 7.83 (z = 9.92, p < 0.000) times in Phase 1, which is also significantly lower than the number of times the Control participant views his peer (β_5 = –8.37, z = –4.62, p < 0.000).

This huge difference between the Control Condition and the Abundance and Scarcity Conditions doesn't seem right. We don't see such a big difference between Conditions in any of the figures we explored earlier in this section. What's driving this difference is the relationship between Participant Exploration (β_{10}) and peer views. In the Control Condition, the number of times a participant views a given peer *decreases* by –2.71 (z = –5.07, p < 0.000) for each unit increase in Participant Exploration (each additional platform the participant chooses to include in at least one of his pitches). In the other two Conditions, the relationship between Participant Exploration and peer views is not significant (Participant Exploration$_{\text{ABUNDANCE}}$ Phase 1 = –0.06, z = –0.20, p = 0.845; Participant Exploration$_{\text{SCARCITY}}$ Phase 1 = 0.15, z = 0.68, p = 0.500).

The lowest value Participant Exploration can actually take in the present experiment is 3 (participants must select at least 3 platforms in order to advance beyond Trial 1). If we set Participant Exploration to its minimum empirical value (3), the estimated number of times a Control participant chooses to view a given peer is 8.06 (z = 16.36, p < 0.000). The estimate for an Abundance participant is 6.85 (z = 13.72, p < 0.000), which is still significantly less than the Control participant (Abundance Phase 1 – Control Phase 1 = –1.22, z = –2.06, p = 0.040) but this difference is much smaller than what we get when we allow Participant Exploration to equal zero. The estimate for a Scarcity participant is 8.28 (z = 16.30, p < 0.000), which is not significantly different than the estimate for the Control participant (Scarcity Phase 1 – Control Phase 1 = 0.22, $z = 0.36$, $p = 0.716$).

Phase 2. For a Control participant in Rank 6 with Exploration = 3 and Discovery = 0 and no dropouts in his group, and a peer who never shared with the participant and who is in Position 1 and Rank 6 with Exploration = 0 and Discovery = 0, the estimated number of times the participant chooses to view the peer in Phase 2 is 6.61 ($z = 14.17$, $p < 0.000$). This is significantly lower than in Phase 1 ($\beta_1 = -1.45$, $z = -5.62$, $p < 0.000$). An Abundance participant with the above profile chooses to view a peer with the above profile 5.39 ($z = 11.38$, $p < 0.000$) times in Phase 2, which is significantly lower than the number of times the Control participant views his peer (Abundance Phase 2 – Control Phase 2 = –1.22, $z = -2.24$, $p = 0.025$). A Scarcity participant with the above profile chooses to view a peer with the above profile 6.82 ($z = 14.22$, $p < 0.000$) times in Phase 2, which is not significantly different than the number of times the Control participant views his peer (Scarcity Phase 2 – Control Phase 2 = 0.21, $z = 0.38$, $p = 0.701$).

Phase 3. For a Control participant in Rank 6 with Exploration = 3 and Discovery = 0 and no dropouts in his group, and a peer who never shared with the participant and who is in Position 1 and Rank 6 with Exploration = 0 and Discovery = 0, the estimated number of times the participant chooses to view the peer in Phase 3 is 6.36 ($z = 12.33$, $p < 0.000$), which is not significantly different than Phase 2 ($\beta_2 = -0.25$, $z = -1.05$, $p = 0.294$). An Abundance participant with the above profile chooses to view a peer with the above profile 4.70 ($z = 8.96$, $p < 0.000$) times in Phase 1, which is significantly lower than the number of times the Control participant views his peer (Abundance Phase 3 – Control Phase 3 = –1.66, $z = -2.63$, $p = 0.009$). A Scarcity participant with the above profile chooses to view a peer with the above profile 5.60 ($z = 10.61$, p

< 0.000) times in Phase 3, which is not significantly different than the number of times the Control participant views his peer (Scarcity Phase 3 – Control Phase 3 = –0.76, $z = -1.21$, $p = 0.228$).

Now we'll look at participant and peer characteristics whose effects are stable across Phases and Conditions (no significant interactions with Phase or Condition).

Dropouts, *Peer Position*, *Reverse-Coded Peer Rank*, and *Peer Exploration*. The number of dropouts in a participant's group did not significantly affect the number of times a participant chose to view his peers ($\beta_3 = 0.01$, $z = 0.02$, $p = 0.984$). For each unit increase in Peer Position (each step further away from the top-left position in the button tray), the participant views a given peer –0.16 ($z = -13.60$, $p < 0.000$) *fewer* times in a given Phase. Peer Rank does not have a significant effect on the number of times the participant chooses to view that peer in a given Phase ($\beta_9 = 0.02$, $z = 1.39$, $p = 0.163$). Peer Exploration does not have a significant effect on the number of times the participant chooses to view a given peer ($\beta_{11} = 0.06$, $z = 0.66$, $p = 0.510$).

Finally, we'll look at participant and peer characteristics whose effects vary across Conditions and/or Phases (significant two- and/or three-way interactions between Phase, Condition, and participant and peer characteristics).

Peer Shares to Participant. In Phase 1, the number of times a Control participant views a given peer increases by 0.04 ($z = 4.20$, $p < 0.000$) for each unit increase in the number of times a peer shares with the participant. The number of times an Abundance participant views a given peer increases by 0.09 ($z = 8.53$, $p < 0.000$), which is significantly larger than the increase exhibited by Control participants (Peer Shares$_{\text{ABUNDANCE}}$ Phase 1 – Peer Shares$_{\text{CONTROL}}$ Phase 1 = 0.05, $z = 4.42$, $p < 0.000$). The number of times a Scarcity participant views a given peer increases by 0.05 ($z = 4.98$, $p < 0.000$), which is not significantly different than the increase exhibited by Control participants ($\text{Peer Shares}_{\text{SCARCITY}}$ Phase 1 – $\text{Peer Shares}_{\text{CONTROL}}$ Phase 1 = 0.01, $z = 0.93$, $p = 0.353$).

In Phase 2, the number of times a Control participant views a given peer increases by 0.09 ($z = 11.85$, $p < 0.000$) for each unit increase in the number of times a peer shares with the participant. This increase is significantly larger than in Phase 1 ($\beta_{16} = 0.05$, $z = 5.35$, $p < 0.000$). The number of times an Abundance participant views a given peer increases by 0.14 ($z =17.01$, $p < 0.000$), which is significantly larger than the increase exhibited by Control participants ($\text{Peer Shares}_{\text{ABUNDANCE}}$ Phase 2 – $\text{Peer Shares}_{\text{CONTROL}}$ Phase 2 = 0.05, $z = 4.42$, $p < 0.000$). The number of times a Scarcity participant views a given peer increases by 0.10 ($z = 12.18$, $p < 0.000$), which is not significantly different than the increase exhibited by Control participants ($\text{Peer Shares}_{\text{SCARCITY}}$ Phase 2 – $\text{Peer Shares}_{\text{CONTROL}}$ Phase 2 = 0.01, $z = 0.93$, $p = 0.353$). The effect of Peer Shares in Phase 3 was the same as in Phase 2.

Reverse-Coded Participant Rank. There is a significant three-way interaction between Condition, Phase 2, and RC Participant Rank. There is also a significant three-way interaction between Condition, Phase 3, and RC Participant Rank. So, we'll look at the adjusted marginal predictions for the effect of RC Participant Rank in each Condition, in each Phase, to understand what's going on here.

In Phase 1, the number of times a Control participant views a given peer increases by 0.32 ($z = 4.34$, $p < 0.000$) for each unit increase in RC Participant Rank. The number of times an Abundance participant views a given peer increases by 0.54 ($z = 7.33$, $p < 0.000$) for each unit increase in RC Participant Rank, which is a significantly higher increase than that observed among Control participants ($\beta_{20} = 0.22$, $z = 2.12$, $p = 0.034$). The number of times a Scarcity participant views a given peer increases by 0.20 ($z = 2.65$, $p = 0.008$) for each unit increase in

RC Participant Rank, which lower than the increase observed among Control participants, but this difference is not significant (β_{21} = –0.12, z = –1.13, p = 0.260).

In Phase 2, the number of times a Control participant views a given peer increases by 0.08 (z = 1.72, p = 0.085) for each unit increase in RC Participant Rank. This increase is significantly lower than that observed among Control participants in Phase 1 (β_{17} = –0.24, z = –3.14, p = 0.002). The number of times an Abundance participant views a given peer increases by 0.38 (z = 8.43, p < 0.000) for each unit increase in RC Participant Rank. This increase is significantly higher that observed among Control participants (RC Participant $\text{Rank}_{\text{ABUNDANCE}}$ Phase 2 – RC Participant $\text{Rank}_{\text{CONTROL}}$ Phase 2 = 0.31, z = 4.79, p < 0.000). The number of times a Scarcity participant views a given peer increases by 0.20 (z = 4.47, p < 0.000) for each unit increase in RC Participant Rank. This increase is higher than that observed among Control participants, but the difference is only marginally significant (RC Participant $\text{Rank}_{\text{SCARCITY}}$ Phase 2 – RC Participant $\text{Rank}_{\text{CONTROL}}$ Phase 2 = 0.12, z = 1.91, p = 0.056).

In Phase 3, the number of times a Control participant views a given peer decreases by –0.12 (z = –1.49, p = 0.136) for each unit increase in RC Participant Rank, but this decrease is not significant (β_{30} = –0.19, z = –2.58, p = 0.010). The number of times an Abundance participant views a given peer increases by 0.35 (z = 4.45, p < 0.000) for each unit increase in RC Participant Rank. This increase is significantly higher that observed among Control participants (RC Participant $\text{Rank}_{\text{ABUNDANCE}}$ Phase 3 – RC Participant $\text{Rank}_{\text{CONTROL}}$ Phase 3 = 0.47, z = 4.22, p < 0.000). The number of times a Scarcity participant views a given peer increases by 0.37 (z = 4.80, p < 0.000) for each unit increase in RC Participant Rank. This increase is significantly higher than that observed among Control participants (RC Participant $\text{Rank}_{\text{SCARCITY}}$ Phase 3 – RC Participant $\text{Rank}_{\text{CONTROL}}$ Phase 3 = 0.49, z = 4.44, p < 0.000).

Participant Exploration. The number of times a Control participant views a given peer decreases by –2.71 (z = –5.07, $p < 0.000$) for each unit increase in Participant Exploration. The effect of Participant Exploration on the number of times an Abundance participant views a given peer is not significant (Participant $\text{Exploration}_{\text{ABUNDANCE}}$ = –0.06, z = –0.20, p = 0.845). The effect of Participant Exploration on the number of times a Scarcity participant views a given peer is not significant either (Participant $\text{Exploration}_{\text{SCARCITY}}$ = 0.15, z = 0.68, p = 0.500).

Participant Discovery. For each unit increase in Participant Discovery (the number of times the participant selects any of the true top three highest-valued platforms across Trials 1–15) the number of times a Control participant views a given peer decreases by –0.16 (z = –1.76, p < 0.079), but this decrease is not significant. The effect of Participant Discovery on the number of times an Abundance participant views a given peer is also negative and nonsignificant (Participant $\text{Discovery}_{\text{ABUNDANCE}}$ = –0.05, z = –0.50, p = 0.614). The effect of Participant Discovery on the number of times a Scarcity participant views a given peer is positive and significant (Participant $\text{Discovery}_{\text{SCARCITY}}$ = 0.27, z = 2.64, p < 0.008). A unit increase in the number of times a Scarcity participant selects any of the true top three highest-valued platforms is associated with an increase of 0.27 in the number of times a Scarcity participant views a given peer.

Peer Discovery. For each unit increase in Peer Discovery (the number of times a peer selects any of the true top three highest-valued platforms across Trials 1–15) the number of times a Control participant views that peer decreases by –0.04 (z = –0.72, p = 0.472), but this decrease is not significant. The effect of Peer Discovery on the number of times a Scarcity participant views a given peer is positive but not significant (Participant $\text{Discovery}_{\text{SCARCITY}}$ = 0.03, z = 0.39, p = 0.700), which is not significantly different than the (nonsignificant) effect observed among

Control participants (β_{27} = 0.07, z = 0.77, p = 0.441). For each unit increase in Peer Discovery, an Abundance participant views that peer an additional 0.15 times (z = –0.50, p = 0.614) which is significantly higher than the effect observed among Control participants (β_{26} = 0.19, z = 2.06, p = 0.039). Abundance participants view a peer more often when that peer selects any of the top three highest-valued platforms more often.

Table 6.30. Study 3B: Summary of Explanatory Variables. Summary of participant- and peer-level explanatory variables, with observed effects (Study 3A, Study 3B) on the number of times a participant chooses to view a given peer in a given Phase of the experiment.

Variable	Study 3A: Observed Effect (Direction)	Study 3A: Observed Effect (β , 95% CI)	Study 3B: Observed Effect (Direction)	Study 3B: Observed Effect (β , 95% CI)
Peer Position	–	–0.19 [–0.22, –0.16]	–	–0.16 [–0.18, –0.13]
Peer Shares	+		+	
Phases 1				
Abundance		0.09 [0.06, 0.11]		0.09 [0.07, 0.11]
Control		0.10 [0.07, 0.12]		0.04 [0.02, 0.06]
Scarcity		0.08 [0.05, 0.11]		0.08 [0.03, 0.07]
Phases 2				
Abundance		0.09 [0.06, 0.11]		0.14 [0.12, 0.15]
Control		0.10 [0.07, 0.12]		0.09 [0.08, 0.11]
Scarcity		0.08 [0.05, 0.11]		0.10 [0.09, 0.12]
Phase 3				
Abundance		0.10 [0.07, 0.13]		0.14 [0.12, 0.15]
Control		0.06 [0.03, 0.10]		0.09 [0.08, 0.11]
Scarcity		0.12 [0.09, 0.16]		0.10 [0.09, 0.12]
RC Part Rank	+		*mixed*	
Phase 1				
Abundance		0.42 [0.33, 0.50]		0.54 [0.40, 0.68]
Control		0.19 [0.11, 0.27]		0.32 [0.18, 0.46]
Scarcity		0.41 [0.33, 0.50]		0.20 [0.05, 0.35]
Phase 2				
Abundance		0.42 [0.33, 0.50]		0.38 [0.29, 0.47]
Control		0.19 [0.11, 0.27]		0.08 [–0.01, 0.17]
Scarcity		0.41 [0.33, 0.50]		0.20 [0.11, 0.29]
Phase 3				
Abundance		0.37 [0.26, 0.48]		0.35 [0.29, 0.47]
Control		0.31 [0.21, 0.41]		–0.12 [–0.27, 0.04]
Scarcity		0.41 [0.30, 0.51]		0.37 [0.22, 0.52]
RC Peer Rank	*not significant*	0.02 [–0.01, 0.05]	*not significant*	0.02 [–0.00, 0.04]
Part Exploration	*mixed*		*mixed*	
Phases 1 & 2				
Abundance		0.03 [–0.54, 0.60]		–0.06 [–0.66, 0.54]
Control		0.45 [–0.06, 0.96]		–2.71 [–3.76, –1.66]
Scarcity		–0.34 [–0.67, 0.00]		0.15 [–0.29, 0.60]
Phase 3				
Abundance		1.06 [0.23, 1.90]		–0.06 [–0.66, 0.54]
Control		1.48 [0.68, 2.28]		–2.71 [–3.76, –1.66]
Scarcity		0.70 [0.19, 1.21]		0.15 [–0.29, 0.60]

Table 6.30. Study 3B: Summary of Explanatory Variables *(Continued*). Summary of participant- and peer-level explanatory variables, with observed effects (Study 3A, Study 3B) on the number of times a participant chooses to view a given peer in a given Phase of the experiment.

Variable	Study 3A: Observed Effect (Direction)	Study 3A: Observed Effect (β , 95% CI)	Study 3B: Observed Effect (Direction)	Study 3B: Observed Effect (β , 95% CI)
Peer Exploration	*not significant*		*not significant*	
Phases 1, 2, & 3				0.06 [–0.11, 0.23]
Abundance		0.38 [–0.11, 0.86]		
Control		–0.40 [–0.84, 0.03]		
Scarcity		–0.04 [–0.28, 0.19]		
Part Discovery	*mixed*		*mixed*	
Phase 1		–0.32 [–0.49, –0.12]		
Abundance				–0.05 [–0.25, 0.15]
Control				–0.16 [–0.34, 0.02]
Scarcity				0.27 [0.07, 0.47]
Phases 2 & 3		–0.09 [–0.21, 0.04]		
Abundance				–0.05 [–0.25, 0.15]
Control				–0.16 [–0.34, 0.02]
Scarcity				0.27 [0.07, 0.47]
Peer Discovery	*mixed*		*mixed*	
Phases 1 & 2				
Abundance		0.04 [–0.15, 0.23]		0.14 [0.01, 0.27]
Control		–0.02 [–0.21, 0.17]		–0.04 [–0.16, 0.08]
Scarcity		–0.34 [–0.14, 0.21]		0.03 [–0.10, 0.15]
Phase 3				
Abundance		0.53 [0.27, 0.79]		0.14 [0.01, 0.27]
Control		–0.11 [–0.38, 0.16]		–0.04 [–0.16, 0.08]
Scarcity		–0.01 [–0.23, 0.22]		0.03 [–0.10, 0.15]

6.2.4 Group-Level Results

To investigate differences in the structure of participant groups' View Networks, we will look at the same six network indices as we did in Study 3A. Refer to Table 6.12 in Section 6.1 for a reminder of each index's formulation and interpretation.[44] Table 6.31 presents the average value (and standard deviation) of each View Network index in each Phase and Condition of Study 3B.

***Table 6.31*. Study 3B: View Network Structure.** Average values (and standard deviations) of View Network indices by Phase, Condition. N = 89 (Abundance = 29 groups; Control = 30 groups; Scarcity = 30 groups).

	Phase 1		Phase 2		Phase 3	
	Mean	(SD)	Mean	(SD)	Mean	(SD)
Average Degree						
Abundance	43.70	10.61	36.55	12.44	32.95	11.79
Control	44.36	11.70	36.09	13.23	32.63	12.01
Scarcity	43.76	9.61	39.30	11.02	35.39	10.38
Density						
Abundance	8.97	2.00	7.46	2.33	6.71	2.22
Control	9.05	2.29	7.38	2.69	6.66	2.39
Scarcity	9.31	2.01	8.35	2.31	7.52	2.17
Centralization						
Abundance	0.37	0.16	0.45	0.19	0.46	0.16
Control	0.37	0.15	0.45	0.17	0.45	0.15
Scarcity	0.36	0.16	0.43	0.18	0.45	0.16
Out-Degree Variance						
Abundance	301.13	174.90	385.19	178.84	374.46	209.48
Control	368.54	223.56	418.55	215.47	381.29	198.27
Scarcity	330.39	219.69	373.03	206.16	402.19	178.07
Hierarchy						
Abundance	0.10	0.06	0.11	0.05	0.11	0.06
Control	0.10	0.04	0.11	0.05	0.11	0.05
Scarcity	0.11	0.05	0.10	0.05	0.12	0.04
In-Degree Variance						
Abundance	15.11	11.36	19.88	19.94	22.11	21.71
Control	14.98	9.71	18.04	13.40	21.81	15.92
Scarcity	17.16	10.24	17.40	12.26	20.86	11.23

[44] As in Study 3A, I exclude active participants' decisions to view peers who dropped out of the experiment, and I also exclude any decisions made by dropout participants before they dropped out of the experiment. For groups that have at least one dropout, I adjust $|N|$ to reflect the number of *active* participants in the group. So, for a group with two dropouts, $|N| = g = 6 - 2 = 4$. No participant group had more than two dropouts. As a reminder: 15 participants across 13 groups met this exclusion criteria: Abundance = 4 participants, 4 groups; Control = 3 participants, 3 groups; Scarcity = 8 participants, 6 groups.

Figure 6.36 presents the Average Degree of participants groups in each Phase of Study 3B.

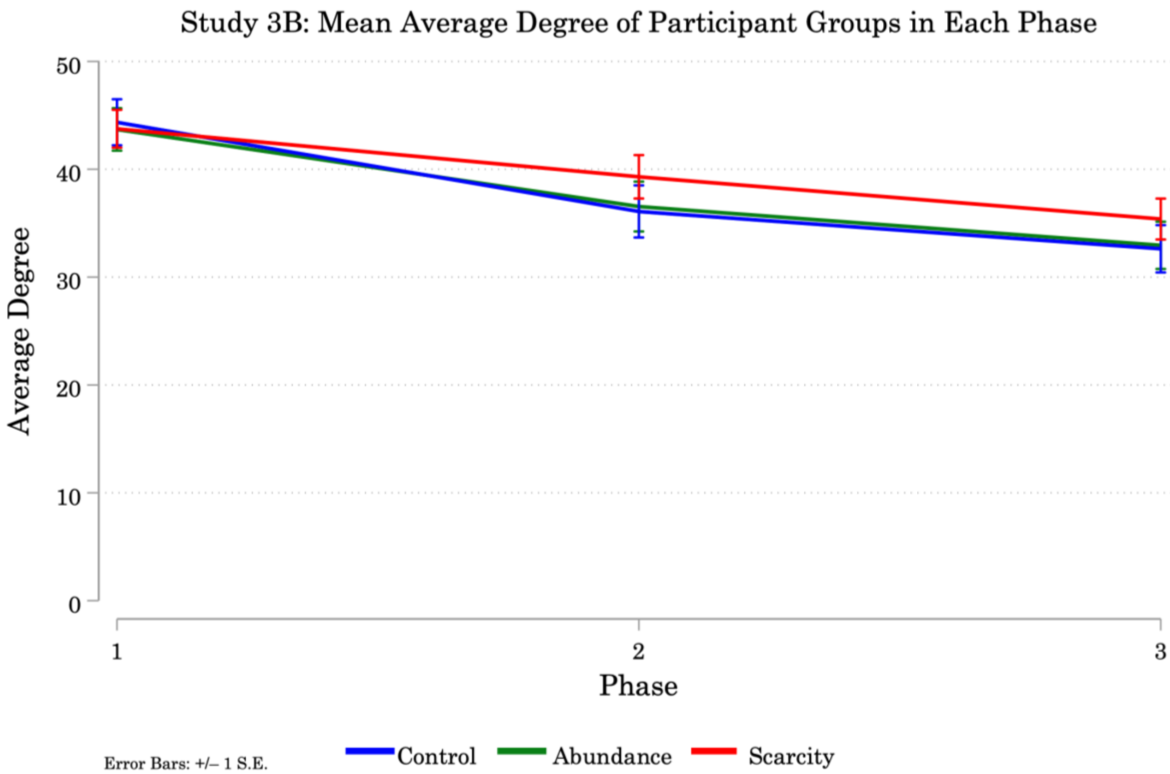

Figure 6.36. Study 3B: Degree. Mean Average Degree of participant groups, by Phase and Condition. Error Bars: +/– 1 S.E. N = 89. Green = Abundance (29 groups); Blue = Control (30 groups); Red = Scarcity (30 groups). Note that the y-axis is truncated. The range of Average Degree = [0, 70]. The Average Degree decreases across Phases in all three Conditions.

Table 6.32 presents the parameter estimates and fit statistics from three different Two-Level Random Coefficient models for the Average Degree of a given participant group in each Phase of Study 3B. Model 1 is the baseline model. The fixed part of Model 1 includes an intercept, piecewise linear slopes for Phases 2 and 3, and a fixed effect for the number of dropouts in a participant's group. The random part of Model 1 includes a random intercept and a random linear slope at the Group level (Level 2). Model 2 includes a fixed effect for Condition.

Model 3 introduces interactions among elements of the experimental design (Condition, Phase). Model 3 did not provide a significantly better fit than Model 2 [*LR* $\chi^2(4) = 7.08$, $p = 0.132$], nor did Model 2 provide a better fit than Model 1 [*LR* $\chi^2(2) = 1.15$, $p = 0.562$], so I will focus on the estimates from Model 1.

Table 6.32. Study 3B: Degree. Maximum likelihood estimates of Three-Level Random-Coefficient models for the Average Degree of a given participant group in each Phase. Model 1: Intercept-Slope; Model 2: Main Effects; Model 3: Design Interactions. N = 89 (Abundance = 29 groups; Control = 30 groups; Scarcity = 30 groups).

	Model 1		Model 2		Model 3	
	Est	(SE)	Est	(SE)	Est	(SE)
Fixed Effects						
Intercept β_0	45.26***	1.18	44.41***	1.87	45.19***	1.91
Phase 2 β_1	–6.62***	0.62	–6.62***	0.62	–8.27***	1.04
Phase 3 β_2	–3.66***	0.62	–3.66***	0.62	–3.46***	1.04
Dropouts β_3	–7.84**	2.48	–8.29**	2.50	–8.29***	2.05
Abundance β_4			0.18	2.61	–0.35	2.71
Scarcity β_5			2.59	2.62	0.78	2.71
Abundance × Phase 2 β_6					1.12	1.48
Scarcity × Phase 2 β_7					3.81**	1.47
Abundance × Phase 3 β_8					–0.14	1.48
Scarcity × Phase 3 β_9					–0.45	1.47
Random Effects						
L2 Random Intercept Var $\psi_{11}^{(2)}$	94.40	16.00	94.10	15.98	94.33	15.91
L2 Random Slope Var $\psi_{22}^{(2)}$	5.75	2.18	5.75	2.18	5.52	2.10
L1 (Residual) Error Var θ	14.00	2.10	14.00	2.10	13.46	2.02
Log likelihood	–895		–894		–891	
AIC | *BIC*	1806 | 1835		1809 | 1845		1810 | 1860	

* $p \leq 0.05$; ** $p \leq 0.01$; *** $p \leq 0.001$; SE = standard error of the mean

The Average Degree of participant groups in Phase 1 is 45.26 ($z = 38.35$, $p < 0.000$). In Phase 2, the Average Degree decreases by –6.62 ($z = –10.75$, $p < 0.000$). In Phase 3, Average Degree decreases again by –3.66 ($z = –5.94$, $p < 0.000$).

For each additional dropout in a given group, the Average Degree decreases by –7.84 (z = –3.16, p = 0.002). This decrease is an artefact that results from the exclusion of dropout participants from the data (both attempts made by active participants to view dropout peers, and any attempts made by dropout participants to view their active peers before they left the experiment). The range of the out-degree for a given participant in a group with no dropouts is [0, 70]. In a group with one dropout, the range of the out-degree for a given active participant is [0, 56]. Any attempts to view the one dropout peer on any of the 14 Trials in a given Phase are removed from the data.

There is no evidence for a main effect of Condition, or for interactions between Condition and Phase. Participant groups in all three Conditions exhibit the same pattern across Phases.

Figure 6.37 presents the average Density of participant groups in each Phase of Study 3B.

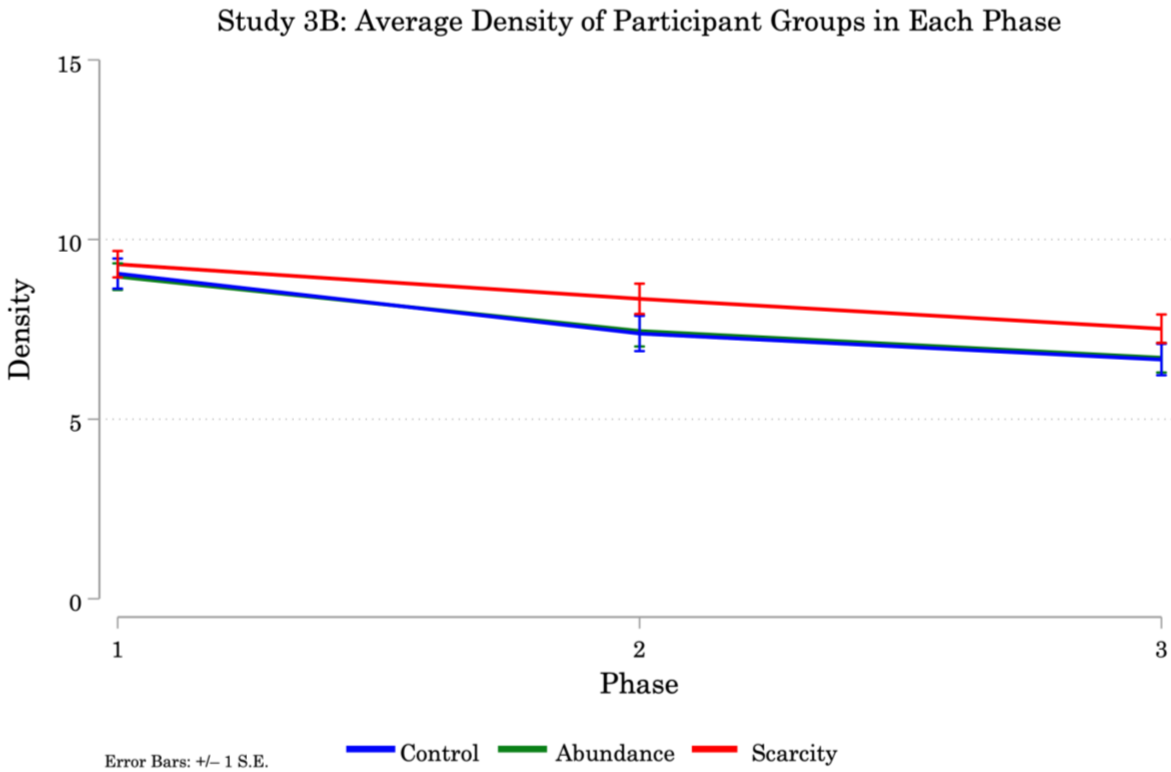

Figure 6.37. Study 3B: Density. Average Density of participant groups, by Phase and Condition. Error Bars: +/– 1 S.E. N = 89. Green = Abundance (29 groups); Blue = Control (30 groups); Red = Scarcity (230 groups). The range of Degree = [0, 14]. Density decreases across Phases in all three Conditions.

Table 6.33 presents the parameter estimates and fit statistics from three different Two-Level Random Coefficient models for the Density of a given participant group in each Phase of Study 3B. Model 1 is the baseline model. The fixed part of Model 1 includes an intercept, piecewise linear slopes for Phases 2 and 3, and a fixed effect for the number of dropouts in a participant's group. The random part of Model 1 includes a random intercept and a random linear slope at the Group level (Level 2). Model 2 includes a fixed effect for Condition. Model 3 introduces interactions among elements of the experimental design (Condition, Phase). Model 3 did not provide a significantly better fit than Model 2 [$LR\ \chi^2(4) = 5.76$, $p = 0.218$], and Model

2 did not provide a better fit than Model 1 [$LR\ \chi^2(2) = 1.29$, $p = 0.524$], so I will focus on the estimates from Model 1.

Table 6.33. Study 3B: Density. Maximum likelihood estimates of Three-Level Random-Coefficient models for the Density of participant groups in each Phase. Model 1: Intercept-Slope; Model 2: Main Effects; Model 3: Design Interactions. N = 89 (Abundance = 29 groups; Control = 30 groups; Scarcity = 30 groups).

	Model 1		Model 2		Model 3	
	Est	(SE)	Est	(SE)	Est	(SE)
Fixed Effects						
Intercept β_0	9.06***	0.25	8.90***	0.39	9.03***	0.40
Phase 2 β_1	–1.38***	0.13	–1.38***	0.13	–1.67***	0.22
Phase 3 β_2	–0.77***	0.13	–0.77***	0.13	–0.73***	0.22
Dropouts β_3	0.33	0.52	0.22	0.52	0.22	0.52
Abundance β_4			–0.02	0.54	–0.09	0.56
Scarcity β_5			–0.54	0.55	0.22	0.56
Abundance × Phase 2 β_6					0.16	0.31
Scarcity × Phase 2 β_7					0.70	0.31
Abundance × Phase 3 β_8					–0.02	0.31
Scarcity × Phase 3 β_9					–0.11	0.31
Random Effects						
L2 Random Intercept Var $\psi_{11}^{(2)}$	4.11	0.69	4.09	0.69	4.10	0.69
L2 Random Slope Var$\psi_{22}^{(2)}$	0.27	0.10	0.27	0.10	0.27	0.09
L1 (Residual) Error Var θ	0.59	0.09	0.59	0.09	0572	0.09
Log likelihood	–476		–475		–473	
AIC | *BIC*	912 | 940		913 | 949		917 | 968	

* $p \leq 0.05$; ** $p \leq 0.01$; *** $p \leq 0.001$; SE = standard error of the mean

The Density of participant groups in Phase 1 is 9.06 ($z = 36.85$, $p < 0.000$). In Phase 2, the Density decreases by –1.38 ($z = –10.80$, $p < 0.000$). In Phase 3, Density decreases again by –0.77 ($z = –6.02$, $p < 0.000$). The number of dropouts in a given group does not affect the group's Density ($\beta_3 = 0.33$, $z = 0.64$, $p = 0.521$). In Study 3A, we saw that Density increased significantly with the number of dropouts in a given group. We hypothesized that active participants in groups with dropouts re-allocate their attention to their active peers, which increases the average number of times active participants choose to view each of their active peers in a given Phase.

In Study 3B, the number of peers a participant chooses to view decreases significantly more across Trials, and across Phases, than it does in Study 3A. So, we probably don't see any effect of dropouts here because participants are already constricting the number of peers they view, unlike in Study 3A where participants maintain relatively high frequencies of peer views across Trials and Phases. There is no evidence for a main effect of Condition, or for interactions between Condition and Phase. Participant groups in all three Conditions exhibit the same pattern across Phases.

Figure 6.38 presents the average Centralization of participant groups in each Phase of Study 3B.

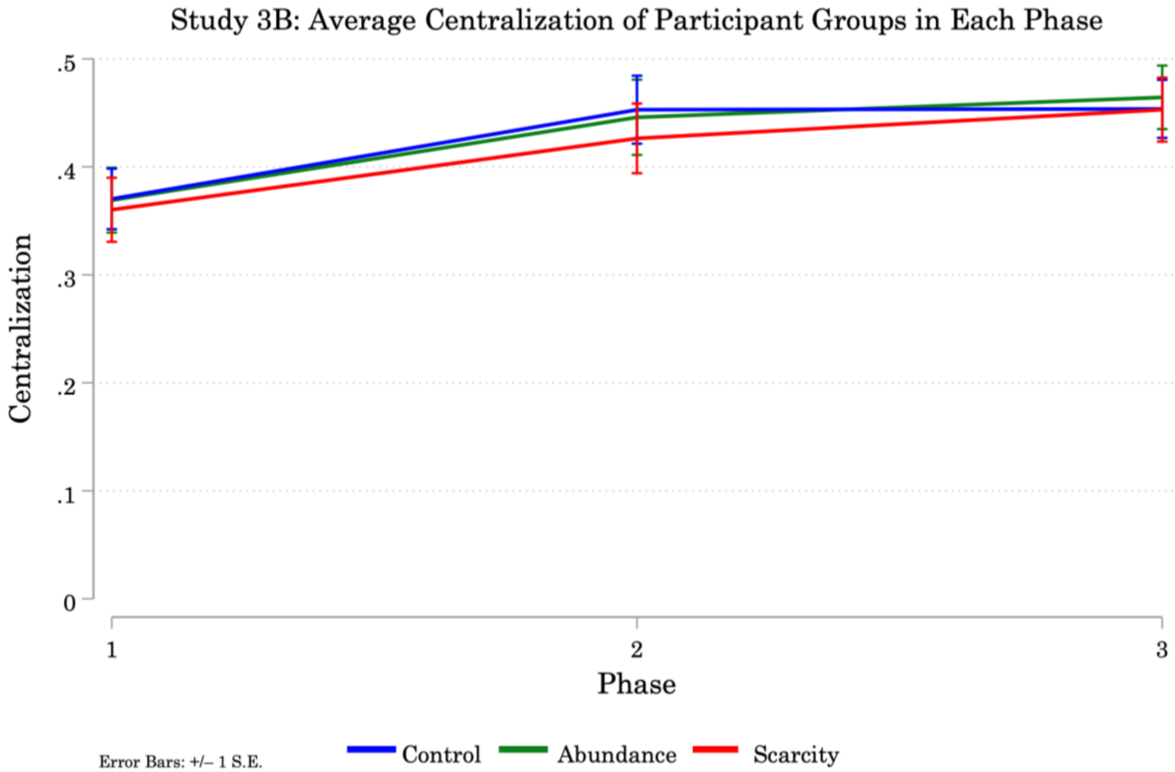

Figure 6.38. Study 3B: Centralization. Average Centralization of participant groups, by Phase and Condition. Error Bars: +/– 1 S.E. N = 89. Green = Abundance (29 groups); Blue = Control (30 groups); Red = Scarcity (30 groups). Note that the y-axis is truncated. The range of Centralization = [0.0, 1.0]. Centralization increases between Phases 1 and 2 in all three Conditions.

Table 6.34 presents the parameter estimates and fit statistics from three different Two-Level Random Coefficient models for the Centralization of a given participant group in each Phase of Study 3B. Model 1 is the baseline model. The fixed part of Model 1 includes an intercept, piecewise linear slopes for Phases 2 and 3, and a fixed effect for the number of dropouts in a participant's group. The random part of Model 1 includes a random intercept and a random linear slope at the Group level (Level 2). Model 2 includes a fixed effect for Condition. Model 3 introduces interactions among elements of the experimental design (Condition, Phase). Model 3 does not provide a significantly better fit than Model 2 [*LR* $\chi^2(4) = 0.67$, $p = 0.955$], nor does Model 2 provide a better fit than Model 1 [$LR\ \chi^2(2) = 0.15$, $p = 0.929$], so I will focus on the estimates from Model 1.

Table 6.34. Study 3B: Centralization. Maximum likelihood estimates of Three-Level Random-Coefficient models for the Centralization of a given participant group in a given Phase. Model 1: Intercept-Slope; Model 2: Main Effects; Model 3: Design Interactions. N = 89 (Abundance = 29 groups; Control = 30 groups; Scarcity = 30 groups).

	Model 1		Model 2		Model 3	
	Est	(SE)	Est	(SE)	Est	(SE)
Fixed Effects						
Intercept β_0	0.37***	0.02	0.31***	0.03	0.30***	0.03
Phase 2 β_1	0.08***	0.01	0.09***	0.01	0.11***	0.02
Phase 3 β_2	0.02	0.01	0.05***	0.01	0.07***	0.02
Dropouts β_3	–0.01	0.03	–0.06*	0.03	–0.06*	0.03
Abundance β_4			0.02	0.03	0.05	0.04
Scarcity β_5			0.02	0.03	0.04	0.04
Abundance × Phase 2 β_6					–0.04	0.03
Scarcity × Phase 2 β_7					–0.03	0.03
Abundance × Phase 3 β_8					–0.04	0.03
Scarcity × Phase 3 β_9					–0.04	0.03
Random Effects						
L2 Random Intercept Var $\psi_{11}^{(2)}$	0.02	0.00	0.02	0.00	0.02	0.00
L2 Random Slope Var $\psi_{22}^{(2)}$	0.00	0.00	0.00	0.00	0.00	0.00
L1 (Residual) Error Var θ	0.01	0.00	0.00	0.00	0.00	0.00
Log likelihood	–161		–161		–161	
AIC | *BIC*	–305 | –276		–301 | –265		–294 |–244	

* $p \leq 0.05$; ** $p \leq 0.01$; *** $p \leq 0.001$; SE = standard error of the mean

The Centralization of participant groups in Phase 1 is 0.37 ($z = 19.22$, $p < 0.000$). In Phase 2, Centralization increases by 0.08 ($z = 5.33$, $p < 0.000$). In Phase 3, Centralization is the same as in Phase 2 ($\beta_2 = 0.02$, $z = 1.08$, $p = 0.280$). As the experiment progresses a greater proportion of the total number of peer views in a given group originates from a single participant. The number of dropouts in a given group does not effect that group's Centralization

(β_3 = –0.01, z = –0.17, p = 0.863). There is no evidence for a main effect of Condition, or for interactions between Condition and Phase. Participant groups in all three Conditions exhibit the same pattern across Phases.

Figure 6.39 presents the average Out-Degree Variance of participant groups in each Phase of Study 3B.

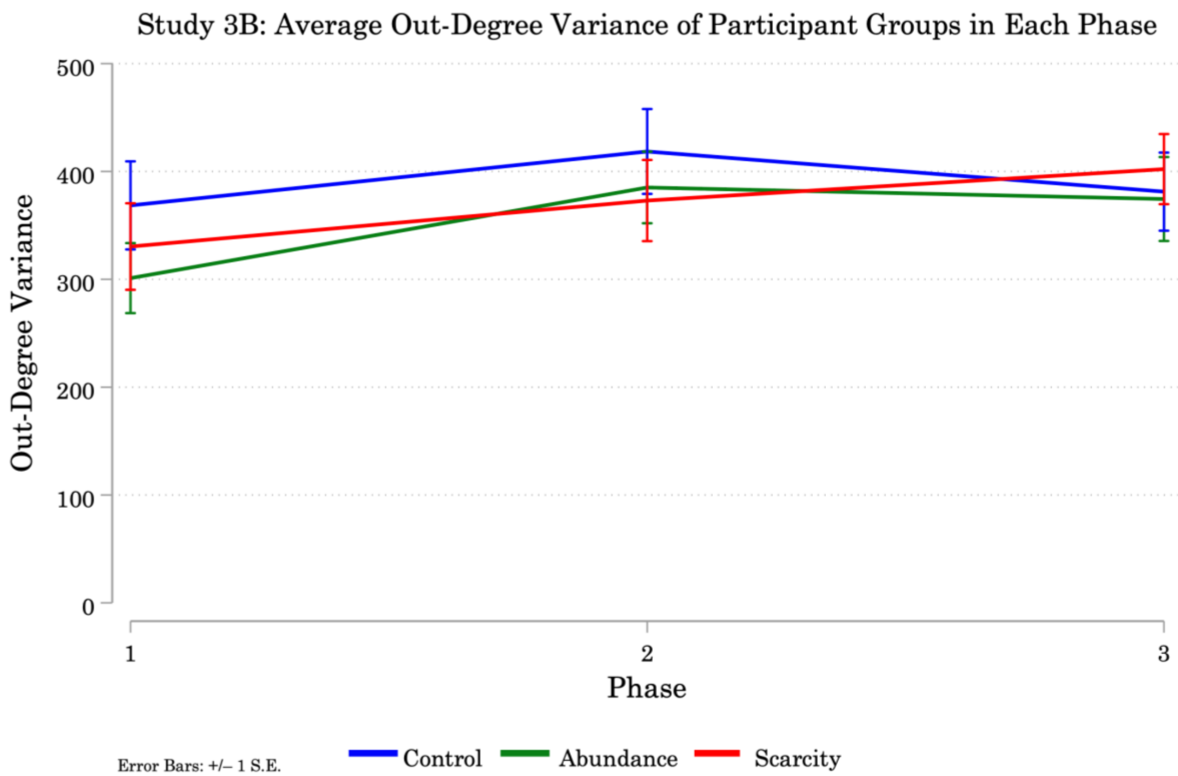

Figure 6.39. Study 3B: Out-Degree Variance. Average Out-Degree Variance of participant groups, by Phase and Condition. Error Bars: +/– 1 S.E. N = 89. Green = Abundance (29 groups); Blue = Control (30 groups); Red = Scarcity (30 groups). Note that the y-axis is truncated. The range of Out-Degree Variance = [0, 1225]. Out-Degree Variance increases between Phases 1 and 2 in all three Conditions.

Table 6.35 presents the parameter estimates and fit statistics from three different Two-Level Random Coefficient models for the Out-Degree Variance of a given participant group in each Phase of Study 3B. Model 1 is the baseline model. The fixed part of Model 1 includes an intercept, piecewise linear slopes for Phases 2 and 3, and a fixed effect for the number of dropouts in a participant's group. The random part of Model 1 includes a random intercept and a random linear slope at the Group level (Level 2). Model 2 includes a fixed effect for Condition. Model 3 introduces interactions among elements of the experimental design (Condition, Phase). Model 3 did not provide a significantly better fit than Model 2 [*LR* $\chi^2(4) = 3.52$, $p = 0.475$], and Model 2 did not provide a better fit than Model 1 [*LR* $\chi^2(2) = 0.79$, $p = 0.674$], so I will focus on the estimates from Model 1.

Table 6.35. Study 3B: Out-Degree Variance. Maximum likelihood estimates of Three-Level Random-Coefficient models for the Out-Degree Variance of a given participant group in a given Phase. Model 1: Intercept-Slope; Model 2: Main Effects; Model 3: Design Interactions. N = 89 (Abundance = 29 groups; Control = 30 groups; Scarcity = 30 groups).

	Model 1		Model 2		Model 3	
	Est	(SE)	Est	(SE)	Est	(SE)
Fixed Effects						
Intercept β_0	359.46***	22.26	365.37***	31.58	384.11***	36.60
Phase 2 β_1	58.62**	17.46	58.62**	17.46	50.01	29.77
Phase 3 β_2	–6.22	17.46	–6.22	17.46	–37.25	29.77
Dropouts	–152.75***	38.42	–155.68***	38.80	–155.68***	38.79
Abundance β_3			–25.91	40.45	–61.51	51.93
Scarcity β_4			8.98	40.60	–12.20	51.87
Abundance × Phase 2 β_5					34.05	42.46
Scarcity × Phase 2 β_6					–7.37	42.09
Abundance × Phase 3 β_7					26.53	42.46
Scarcity × Phase 3 β_8					66.41	42.09
Random Effects						
L2 Rand Intcpt Var $\psi_{11}^{(2)}$	29598.51	5939.49	29268.83	5918.64	29199.47	5850.49
L2 Rand Slope Var $\psi_{22}^{(2)}$	5613.15	1833.91	5613.15	1833.91	5525.87	1799.59
L1 (Resid) Error Var θ	10752.08	1611.81	10752.08	1611.81	10526.93	1578.05
Log likelihood	–1735		–1735		–1733	
AIC | *BIC*	3486 | 3515		3489 | 3525		3494 | 3544	

* $p \leq 0.05$; ** $p \leq 0.01$; *** $p \leq 0.001$; SE = standard error of the mean

The Out-Degree Variance of participant groups in Phase 1 is 359.46 (z = 16.15, p < 0.000). In Phase 2, Out-Degree Variance increases by 58.62 (z = 3.36, p = 0.001). Out-Degree Variance stays about the same in Phase 3 (β_2 = –6.22, z = –0.36, p = 0.722). For each additional dropout in a given group, Out-Degree Variance decreases by –152.75(z = –3.98, p < 0.000). There is no evidence for a main effect of Condition, or for interactions between Condition and Phase. Participant groups in all three Conditions exhibit the same pattern across Phases.

Figure 6.40 presents the average Hierarchy of participant groups in each Phase of Study 3B.

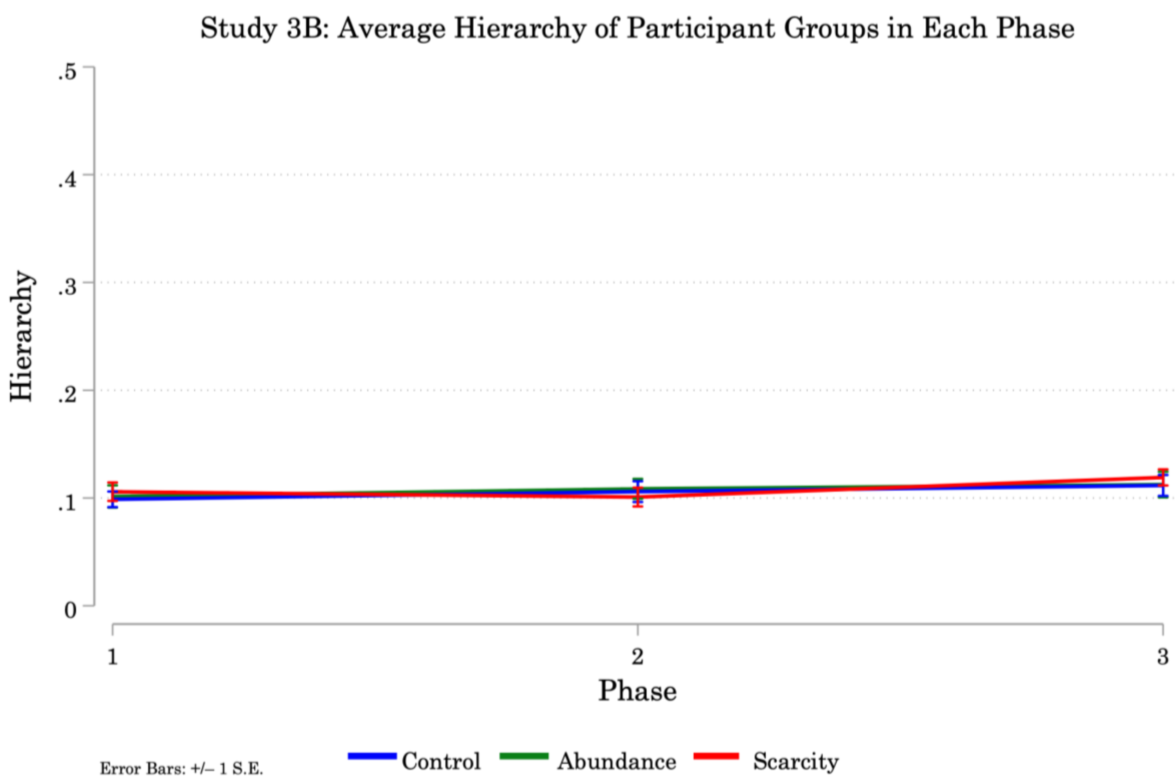

Figure 6.40. Study 3B: Hierarchy. Average Hierarchy of participant groups, by Phase and Condition. Error Bars: +/– 1 S.E. N = 89. Green = Abundance (29 groups); Blue = Control (30 groups); Red = Scarcity (30 groups). Note that the y-axis is truncated. The range of Hierarchy = [0.0, 1.0]. Hierarchy is quite low, and does not change much across Phases in all three Conditions.

Table 6.36 presents the parameter estimates and fit statistics from three different Two-Level Random Coefficient models for the Hierarchy of a given participant group in each Phase of Study 3B. Model 1 is the baseline model. The fixed part of Model 1 includes an intercept, piecewise linear slopes for Phases 2 and 3, and a fixed effect for the number of dropouts in a participant's group. The random part of Model 1 includes a random intercept and a random linear slope at the Group level (Level 2). Model 2 includes a fixed effect for Condition. Model 3 introduces interactions among elements of the experimental design (Condition, Phase). Model 3 does not provide a significantly better fit than Model 2 [$LR\ \chi^2(4) = 2.19$, $p = 0.700$], and Model 2 did not provide a better fit than Model 1 [$LR\ \chi^2(2) = 0.05$, $p = 0.975$], so I will focus on the estimates from Model 1.

The Hierarchy of participant groups in Phase 1 is 0.10 ($z = 19.47$, $p < 0.000$). Hierarchy is constant across Phase 2 ($\beta_1 = 0.003$, $z = 0.59$, $p = 0.558$) and Phase 3 ($\beta_2 = 0.009$, $z = 1.80$, $p = 0.072$). The number of dropouts in a given group does not affect that group's Hierarchy ($\beta_3 = 0.007$, $z = 2.06$, $p = 0.039$). There is no evidence for a main effect of Condition, or for interactions between Condition and Phase. Participant groups in all three Conditions exhibit the same pattern across Phases.

Table 6.36. Study 3B: Hierarchy. Maximum likelihood estimates of Three-Level Random-Coefficient models for the Hierarchy of a given participant group in a given Phase. Model 1: Intercept-Slope; Model 2: Main Effects; Model 3: Design Interactions. N = 89 (Abundance = 29 groups; Control = 30 groups; Scarcity = 30 groups).

	Model 1		Model 2		Model 3	
	Est	(SE)	Est	(SE)	Est	(SE)
Fixed Effects						
Intercept β_0	0.10***	0.01	0.10***	0.01	0.10***	0.01
Phase 2 β_1	0.00	0.01	0.00	0.01	0.01	0.01
Phase 3 β_2	0.01	0.01	0.01	0.01	0.01	0.01
Dropouts β_3	0.01	0.01	0.01	0.01	0.01	0.01
Abundance β_4			0.00	0.01	0.00	0.01
Scarcity β_5			0.00	0.01	0.01	0.01
Abundance × Phase 2 β_6					–0.00	0.01
Scarcity × Phase 2 β_7					–0.01	0.01
Abundance × Phase 3 β_8					–0.00	0.01
Scarcity × Phase 3 β_9					0.01	0.01
Random Effects						
L2 Random Intercept Var $\psi_{11}^{(2)}$	0.00	0.00	0.00	0.00	0.00	0.00
L2 Random Slope Var $\psi_{22}^{(2)}$	0.00	0.00	0.00	0.00	0.00	0.00
L1 (Residual) Error Var θ	0.00	0.00	0.00	0.00	0.00	0.00
Log likelihood	–451		–451		–452	
AIC | *BIC*	–886 | –857		–882 | –846		–876 | –826	

* $p \leq 0.05$; ** $p \leq 0.01$; *** $p \leq 0.001$; SE = standard error of the mean

Figure 6.41 presents the average In-Degree Variance of participant groups in each Phase of Study 3B.

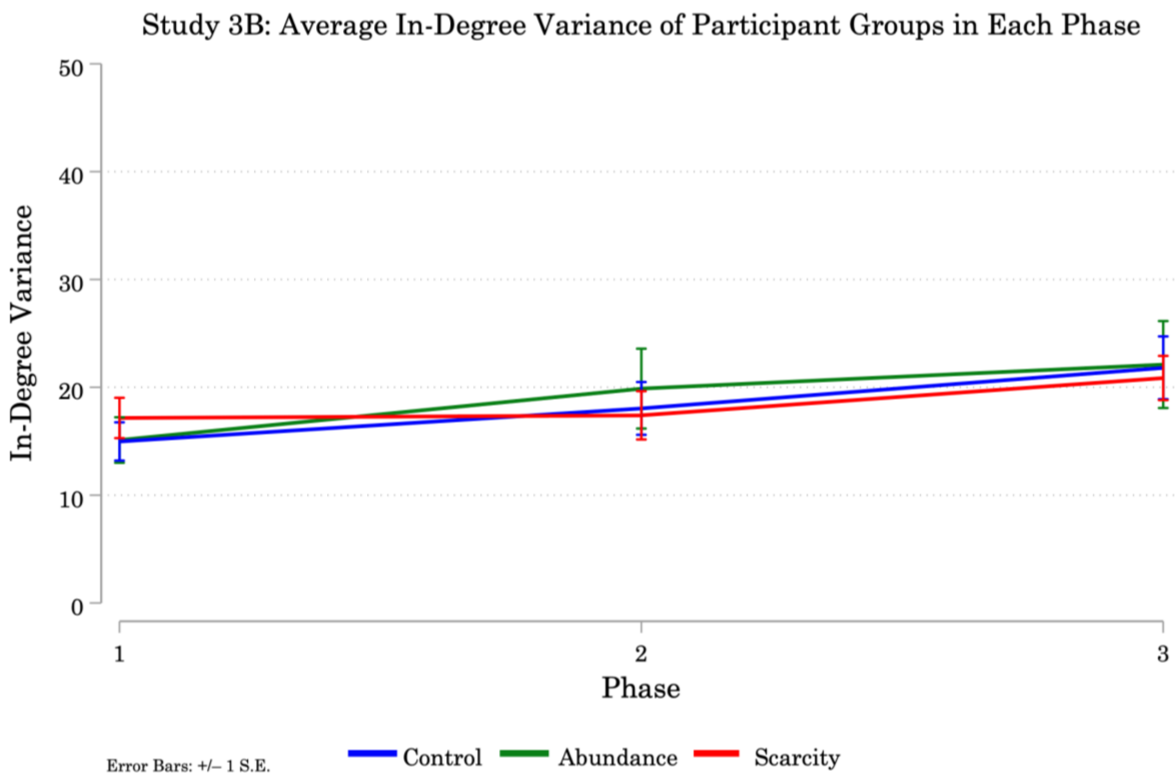

Figure 6.41. Study 3B: In-Degree Variance. Average In-Degree Variance of participant groups, by Phase and Condition. Error Bars: +/– 1 S.E. N = 89. Green = Abundance (29 groups); Blue = Control (30 groups); Red = Scarcity (30 groups). Note that the y-axis is truncated. The range of In-Degree Variance = [0, 1225]. In-Degree Variance increases between Phases 2 and 3 in each Condition.

Table 6.37 presents the parameter estimates and fit statistics from three different Two-Level Random Coefficient models for the In-Degree Variance of a given participant group in each Phase of Study 3A. Model 1 is the baseline model. The fixed part of Model 1 includes an intercept, piecewise linear slopes for Phases 2 and 3, and a fixed effect for the number of dropouts in a participant's group. The random part of Model 1 includes a random intercept and a random linear slope at the Group level (Level 2). Model 2 includes a fixed effect for Condition. Model 3 introduces interactions among elements of the experimental design (Condition, Phase). Model 3 does not provide a significantly better fit than Model 2 [$LR\ \chi^2(4) = 1.53$, $p = 0.821$], and Model 2 did not provide a better fit than Model 1 [$LR\ \chi^2(2) = 0.44$, $p = 0.804$], so I will focus on the estimates from Model 1.

Table 6.37. Study 3B: In-Degree Variance. Maximum likelihood estimates of Three-Level Random-Coefficient models for the In-Degree Variance of a given participant group in a given Phase. Model 1: Intercept-Slope; Model 2: Main Effects; Model 3: Design Interactions. N = 89 (Abundance = 30 groups; Control = 30 groups; Scarcity = 29 groups).

	Model 1		Model 2		Model 3	
	Est	(SE)	Est	(SE)	Est	(SE)
Fixed Effects						
Intercept β_0	16.13***	1.19	15.37***	1.79	15.22***	1.94
Phase 2 β_1	2.67	1.57	2.67	1.57	3.06	2.69
Phase 3 β_2	3.16*	1.57	3.16*	1.57	3.77	2.69
Dropouts β_3	–2.22	2.29	–2.45	2.32	–2.45	2.32
Abundance β_4			0.80	2.42	0.23	2.75
Scarcity β_5			1.60	2.42	2.59	2.75
Abundance × Phase 2 β_6					1.70	3.83
Scarcity × Phase 2 β_7					–2.82	3.80
Abundance × Phase 3 β_8					–1.54	3.83
Scarcity × Phase 3 β_9					–0.31	3.80
Random Effects						
L2 Random Intercept Var $\psi_{11}^{(2)}$	19.01	18.65	18.37	18.59	19.06	18.49
L2 Random Slope Var $\psi_{22}^{(2)}$	31.91	13.71	31.91	13.71	31.80	13.60
L1 (Residual) Error Var θ	93.45	14.00	93.45	14.01	92.53	13.87
Log likelihood	–1053		–1053		–1052	
AIC | *BIC*	2122 | 2151		2126 | 2162		2132 | 2183	

* $p \leq 0.05$; ** $p \leq 0.01$; *** $p \leq 0.001$; SE = standard error of the mean
† calculation of standard errors for the random effects failed for Model 1

The In-Degree Variance of participant groups in Phase 1 is 16.73 ($z = 13.57$, $p < 0.000$). In-Degree Variance in Phase 2 is higher than in Phase 1, but this increase is not significant ($\beta_1 = 2.67$, $z = 1.70$, $p = 0.089$). In-Degree Variance is significantly higher in Phase 3 than in Phase 2 ($\beta_2 = 3.16$, $z = 2.02$, $p = 0.044$). The number of dropouts in a given group does not have a significant effect on In-Degree Variance ($\beta_3 = –2.22$, $z = 2.29$, $p = 0.333$). There is no evidence for a main effect of Condition, or for interactions between Condition and Phase. Participant groups in all three Conditions exhibit the same pattern across Phases.

6.2.5 Discussion

The purpose of Study 3B was to test whether reciprocity (via the "sharing contingency") moderates the effect of resource shocks on people's appetite for social information in the presence of competition. In Study 3B, participants could learn about the platform values in two ways: 1) through Exploration (sampling platform values by including platforms in their pitch on each Trial), and 2) through side observation (sampling platform values by looking at the pitches made by their peers). Exploration requires a tradeoff between exploring previously unsampled platforms and exploiting the best platforms encountered on previous Trials. Taking side observations of the platform values by viewing the pitches made by peers does not require a tradeoff. However, both the participant and the peer may only view each other's results if they first choose to share those results with one another. This is what I referred to as the "sharing contingency," in the discussion of Study 3A.

Competition was induced among participants in each experimental group of Study 3A. Participants could earn a trivial bonus if they earned one of the top three cumulative scores in their group (first place = $0.50; second place = $0.30; third place = $0.10). These bonus amounts were selected based on the expected increase in cumulative rewards for a participant who views five randomly sampled pitches on every Trial (i.e. Random Pitches in Study 2A) versus a participant who views four or fewer randomly sampled pitches on every Trial. To estimate this value, I ran agent-based simulations using common multi-armed bandit decision algorithms (e.g. ϵ–greedy, softmax) and heuristic decision algorithms based on participants' behavior in Study 1.

Estimates of the expected increase in cumulative rewards based on these simulations are conservative, because the simulated agents were exposed to randomly sampled pitches, and the average expected value of randomly sampled pitches does not increase across Trials. By contrast, pitches selected by goal-directed agents increase across Trials, making it more likely that the pitches selected on later Trials will contain higher-valued platforms, on average.

All this is to say that these bonuses were worth less than the expected increase in cumulative rewards that participants in Study 3 should expect to gain if they choose to view the results of their peers' versus not.

I will focus on the comparison between behavior in Phase 1, before any resource shock occurs, and behavior in Phase 2, after Abundance and Scarcity participants experience the first resource shock. For each of the focal dependent variables, I will note any differences between Study 3B and Study 3A. As a reminder, Control participants experience *no change* in platform values between Phases 1 and 2 (they face the Medium range in every Phase of the experiment). Abundance participants experience a *positive* resource shock in Phase 2 (the Medium range platform values are *higher* than the Low range platform values they faced in Phase 1). Scarcity participants experience a *negative* resource shock in Phase 2 (the Medium range platform values are *lower* than the High range platform values they faced in Phase 1).

6.2.5.1 Exploration

Exploration is defined as the total number of unique platforms participants explored across Trials 1–15 of a given Phase. In other words, Exploration is the number of platforms (out of 20) that the participant included in her pitch on at least one Trial. There are no significant differences between Conditions. Participants in all three Conditions explored significantly fewer platforms in Phase 2 than they did in Phase 1.

No change in platform values produced a *decrease* in Exploration. The same decrease in Exploration occurs following an *increase* in platform values. A *decrease* in platform values produced a temporary increase in Exploration, followed by a global *decrease* in Exploration.

In every Phase of the experiment, participants in each Condition of Study 3B explored a similar number of platforms to participants in the corresponding Condition of Study 3A.[45]

6.2.5.2 Exploitation

Exploitation is defined as the total number of times that a participant selected one of the platforms with the top three highest empirical averages across Trials 2–15 of a given Phase. A platform's "empirical average" is the average of the *realized* values that the participant has observed for that platform over all preceding Trials. There were no significant differences between Conditions. Participants in all three Conditions exploited their Personal-Best platforms with similar frequency across all three Phases of the experiment.

No change in platform values produced an *increase* in Exploitation. An *increase* in platform values also produced an *increase* in Exploitation. A *decrease* in platform values produced a temporary decrease in Exploitation, followed by a global *increase* in Exploitation.

[45] CONTROL: Study 3B Control Phase 1 – Study 3A Control Phase 1 = 0.65, z = 1.54, p = 0.125; Study 3B Control Phase 2 – Study 3A Control Phase 2 = 0.25, z = 0.62, p = 0.536; Study 3B Control Phase 3 – Study 3A Control Phase 3 = 0.29, z = 0.72, p = 0.472. ABUNDANCE: Study 3B Abundance Phase 1 – Study 3A Abundance Phase 1 = –0.08, z = –0.17, p = 0.861; Study 3B Abundance Phase 2 – Study 3A Abundance Phase 2 = –0.58, z = –1.40, p = 0.160; Study 3B Abundance Phase 3 – Study 3A Abundance Phase 3 = –0.14, z = –0.34, p = 0.737. SCARCITY: Study 3B Scarcity Phase 1 – Study 3A Scarcity Phase 1 = –0.26, z = –0.61, p = 0.544; Study 3B Scarcity Phase 2 – Study 3A Scarcity Phase 2 = –0.03, z = –0.08, p = 0.933; Study 3B Scarcity Phase 3 – Study 3A Scarcity Phase 3 = –0.33, z = –0.80, p = 0.423.

In every Phase of the experiment, participants in each Condition of Study 3B exploited their Personal-Best platforms a similar number of times as did participants in the corresponding Condition of Study 3A.[46]

6.2.5.3 Mental Models

Mean Absolute Difference is defined as the average absolute value of the difference between participants' estimates of the platform values at the end of each Phase and the true average values of each platform. We'll refer to the Mean Absolute Difference as "average error." Control participants' average error was slightly lower in Phase 2 than in Phase 1, but this difference was not significant. Abundance participants' average error in Phase 2 was significantly higher than in Phase 1. Scarcity participants' average error in Phase 2 was lower than in Phase 2, but this difference was not significant. Scarcity and Abundance participants had similar average errors in Phase 2.

No change in platform values produced *no change* in average error. An *increase* in platform values produced an *increase* in average error. A *decrease* in platform values produced a *decrease* in average error.

Participants in each Condition of Study 3B had similar average error to participants in Study 3A in every Phase of the experiment.[47]

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[46] CONTROL: Study 3B Control Phase 1 – Study 3A Control Phase 1 = –0.98, z = –1.00, p = 0.319; Study 3B Control Phase 2 – Study 3A Control Phase 2 = 0.18, z = 0.19, p = 0.853; Study 3B Control Phase 3 – Study 3A Control Phase 3 =–052, z = –0.54, p = 0.589. ABUNDANCE: Study 3B Abundance Phase 1 – Study 3A Abundance Phase 1 = –0.23, z = –0.23, p = 0.818; Study 3B Abundance Phase 2 – Study 3A Abundance Phase 2 = 0.36, z = 0.37, p = 0.710; Study 3B Abundance Phase 3 – Study 3A Abundance Phase 3 = 0.98, z = 0.61, p = 0.543. SCARCITY: Study 3B Scarcity Phase 1 – Study 3A Scarcity Phase 1 = –0.70, z = –0.70, p = 0.481; Study 3B Scarcity Phase 2 – Study 3A Scarcity Phase 2 = 0.53, z = 0.55, p = 0.585; Study 3B Scarcity Phase 3 – Study 3A Scarcity Phase 3 = –0.70, z = –0.70, p = 0.481.

[47] CONTROL: Study 3B Control Phase 1 – Study 3A Control Phase 1 = 0.71, z = 0.07, p = 0.942; Study 3B Control Phase 2 – Study 3A Control Phase 2 = 2.35, z = 0.26, p = 0.796; Study 3B Control Phase 3 – Study 3A Control

6.2.5.4 Rewards

Cumulative Standardized Achievement is the sum of the standardized achievement scores a participant earns across Trials 1–15 of a given Phase. There were no significant differences between Conditions. Participants in all three Conditions earned similar scores in Phase 2 to what they did in Phase 1.

No change in platform values produced an *increase* in Cumulative Standardized Achievement scores. An *increase* in platform values produced *no change* in Cumulative Standardized Achievement scores. A *decrease* in platform values produced an *increase* in Cumulative Standardized Achievement scores.

Abundance and Scarcity participants in Study 3B earned similar scores to participants in the corresponding Condition of Study 3A in every Phase of the experiment.[48] In Phases 1 and 3, Control participants in Study 3B earned significantly lower scores than Control participants in Study 3A. In Phase 2, there was no significant difference between Control participants in Study 3B and Control participants in Study 2A.[49]

Phase 3 = 0.65, z = 0.06, p = 0.954. SCARCITY: Study 3B Scarcity Phase 1 – Study 3A Scarcity Phase 1 =1.89, z = 0.19, p = 0.849; Study 3B Scarcity Phase 2 – Study 3A Scarcity Phase 2 = 7.08, z = 0.77, p = 0.444; Study 3B Scarcity Phase 3 – Study 3A Scarcity Phase 3 = 2.88, z = 0.25, p = 0.799. ABUNDANCE: Study 3B Abundance Phase 1 – Study 3A Abundance Phase 1 = –4.06, z = –0.41, p = 0.683; Study 3B Abundance Phase 2 – Study 3A Abundance Phase 2 = –7.04, z = –0.76, p = 0.447; Study 3B Abundance Phase 3 – Study 3A Abundance Phase 3 = –8.28, z = –0.73, p = 0.466.

[48] ABUNDANCE: Study 3B Abundance Phase 1 – Study 3A Abundance Phase 1 = –18.11, z = –0.85, p = 0.396; Study 3B Abundance Phase 2 – Study 3A Abundance Phase 2 = –30.63, z = –1.47, p = 0.141; Study 3B Abundance Phase 3 – Study 3A Abundance Phase 3 = 4.47, z = 0.20, p = 0.838. SCARCITY: Study 3B Scarcity Phase 1 – Study 3A Scarcity Phase 1 = –24.45, z = 1.15, p = 0.251; Study 3B Scarcity Phase 2 – Study 3A Scarcity Phase 2 = –7.92, z = –0.38, p = 0.703; Study 3B Scarcity Phase 3 – Study 3A Scarcity Phase 3 = –24.15, z = –1.11, p = 0.269.

[49] CONTROL: Study 3B Control Phase 1 – Study 3A Control Phase 1 = –63.10, z = –3.00, p = 0.003; Study 3B Control Phase 2 – Study 3A Control Phase 2 = –2.65, z = –0.13, p = 0.897; Study 3B Control Phase 3 – Study 3A Control Phase 3 = –45.58, z = –2.11, p = 0.035.

6.2.5.5 Discovery

Discovery is defined as the number of times a participant selected any of the True Top-Three highest-valued platforms across Trials 1–15 of a given Phase. Control and Scarcity participants selected True Top Three platforms with similar frequency in Phase 2 as they did in Phase 1. Abundance participants selected True Top-Three platforms significantly less often in Phase 2 as they did in Phase 1.

No change in platform values produced an *increase* in Discovery. A *decrease* in platform values produced *no change* in Discovery. An *increase* in platform values produced a *decrease* in Discovery.

In every Phase of the experiment, Abundance participants in Study 3B selected the True Top-Three platforms with similar frequency to Abundance participants in Study 3A.[50] In Phases 1 and 3, Control participants in Study 3B selected True Top Three platforms significantly less often than Control participants in Study 3A (there was no significant difference in Phase 2).[51] In Phase 3, Scarcity participants in Study 3B selected True Top Three platforms significantly less often than Scarcity participants in Study 3A (there was no significant difference in Phase 1 or Phase 2).[52]

[50] ABUNDANCE: Study 3B Abundance Phase 1 – Study 3A Abundance Phase 1 = –0.74, z = –0.56, p = 0.575; Study 3B Abundance Phase 2 – Study 3A Abundance Phase 2 = –1.83, z = –1.41, p = 0.158; Study 3B Abundance Phase 3 – Study 3A Abundance Phase 3 = 0.87, z = 0.64, p = 0.525.

[51] CONTROL: Study 3B Control Phase 1 – Study 3A Control Phase 1 = –4.92, z = –3.78, p < 0.000; Study 3B Control Phase 2 – Study 3A Control Phase 2 = 0.25, z = 0.19, p = 0.847; Study 3B Control Phase 3 – Study 3A Control Phase 3 = –3.26, z = –2.41, p = 0.016.

[52] SCARCITY: Study 3B Scarcity Phase 1 – Study 3A Scarcity Phase 1 = –0.98, z = –0.75, p = 0.455; Study 3B Scarcity Phase 2 – Study 3A Scarcity Phase 2 = 0.25, z = 0.19, p = 0.847; Study 3B Scarcity Phase 3 – Study 3A Scarcity Phase 3 = –3.13, z = –2.29, p = 0.022.

6.2.5.6 Side Observations: Peer Results

Sharing. Participants had the option to share their results with their peers on Trials 1–14. Participants had 70 opportunities (= 5 peers × 14 Trials) to share results with their peers. There were no significant differences between Conditions in any Phase of the experiment (Scarcity participants shared with their peers slightly more often than participants in the other two Conditions, but this difference was not significant). Participants in all three Conditions chose to share with almost every one of their peers at the start of each Phase, and then reduced the number of peers with whom they shared across Trials.

There was *no change* in sharing following *no change* in platform values, or following an *increase* or *decrease* in platform values.

Participants in each Condition of Study 3B shared with their peers significantly less often than participants in the corresponding Condition of Study 3A, in every Phase of the experiment.[53]

Sampling Frequency. Starting on Trial 2 of each Phase, participants had the opportunity to view the pitches made by their five peers on the previous Trial. (The peer's results would only display if *both* the participant *and* the peer chose to share their results with each other.) Participants had a total of 70 opportunities to sample side observations of the platform values by viewing their peers' pitches (70 opportunities = 5 peers × 14 Trials). There were no differences

[53] CONTROL: Study 3B Control Phase 1 – Study 3A Control Phase 1 = –11.56, z = –4.15, p < 0.000; Study 3B Control Phase 2 – Study 3A Control Phase 2 = –17.61, z = –6.06, p < 0.000; Study 3B Control Phase 3 – Study 3A Control Phase 3 = –17.10, z = –5.27, p < 0.000. ABUNDANCE: Study 3B Abundance Phase 1 – Study 3A Abundance Phase 1 = –9.68, z = –3.43, p = 0.001; Study 3B Abundance Phase 2 – Study 3A Abundance Phase 2 = –13.51, z = –4.59, p < 0.000; Study 3B Abundance Phase 3 – Study 3A Abundance Phase 3 = –13.03, z = –3.97, p < 0.000. SCARCITY: Study 3B Scarcity Phase 1 – Study 3A Scarcity Phase 1 = –9.44, z = –3.35, p = 0.001; Study 3B Scarcity Phase 2 – Study 3A Scarcity Phase 2 = –10.62, z = –3.61, p < 0.000; Study 3B Scarcity Phase 3 – Study 3A Scarcity Phase 3 = –12.21, z = –3.72, p < 0.000.

between Conditions in any Phase of the experiment. Participants in all three Conditions chose to view their peers' results significantly less often in each subsequent Phase.

No change in platform values produced a *decrease* in the number of times participants chose to view their peers. A *decrease* in platform values produced a *decrease* in the number of times participants chose to view their peers. An *increase* in platform values produced a *decrease* in the number of times participants chose to view their peers.

Control participants in Study 3B chose to view their peers significantly less often than Control participants in Study 3A in every Phase of the experiment.[54] Abundance participants in Study 3B chose to view their peers significantly less often than Abundance participants in Study 3A in Phases 2 and 3 (there was no significant difference in Phase 1).[55] There was no significant difference between Scarcity participants in Study 3B and Study 3A in any Phase of the experiment.[56]

Sampling Bias. There were only two peer characteristics found to have a significant effect on the number of times a participant chose to view a given peer. First, participants exhibited the same position-based preference we observed in Studies 2A, 2B, and 3A. Participants chose to view peers more often the closer the peer's Player button was located to the top-left corner of the button tray. Second, participants chose to view peers more often when peers chose to share more often with the participant.

[54] CONTROL: Study 3B Control Phase 1 – Study 3A Control Phase 1 = –5.24, z = –1.95, p = 0.052; Study 3B Control Phase 2 – Study 3A Control Phase 2 =–7.97, z = –2.97, p = 0.003; Study 3B Control Phase 3 – Study 3A Control Phase 3 = –5.77, z = –2.03, p = 0.043.

[55] ABUNDANCE: Study 3B Abundance Phase 1 – Study 3A Abundance Phase 1 = –3.66, z = –1.34, p = 0.180; Study 3B Abundance Phase 2 – Study 3A Abundance Phase 2 = –6.13, z = –2.25, p = 0.024; Study 3B Abundance Phase 3 – Study 3A Abundance Phase 3 = –6.22, z = –2.15, p = 0.032.

[56] SCARCITY: Study 3B Scarcity Phase 1 – Study 3A Scarcity Phase 1 = –1.88, z = –0.69, p = 0.490; Study 3B Scarcity Phase 2 – Study 3A Scarcity Phase 2 = –1.25, z = –0.46, p = 0.645; Study 3B Scarcity Phase 3 – Study 3A Scarcity Phase 3 = –0.36, z = –0.12, p = 0.901.

Peer achievement (realized points earned within a given Phase of the experiment) did not significantly affect participants' decisions. There was no relationship between a peer's relative achievement rank within the group and the number of times the participant chose to view that peer. (Neither was there a relationship between the number of times a participant chose to view a given peer and the peer's *global* achievement across *all* Phases or the peer's achievement in the *previous* Phase.)

In Phase 1, participants with higher achievement (relative to their peers) viewed *all* of their peers more often than participants with lower achievement viewed *any* of their peers. This was also true in Phases 2 and 3 for Abundance and Scarcity participants, but not for Control participants (the relationship between Participant Rank and the number of peer views was not significant for Control participants in Phase 2 or Phase 3).

6.2.5.7 Group Network Structure

Resource shocks did not have a significant effect on the structure of View Networks within each experimental group of participants. The Average Degree and Density of groups in all three Conditions decreases significantly across Phases. This results from an overall decrease in the number of times participants choose to view their peers across Phases.

The Centralization and Out-Degree Variance of participants groups increases significantly between Phases 1 and 2. As the experiment progresses, a greater proportion of the total number of peer views in a given group originates from a single participant.

Group Hierarchy and In-Degree Variance are stable across Phases. No single participant tends to receive a greater proportion of the total number of peer views in a given group.

In Phases 1 and 3, Control groups in Study 3B had similar Average Degree to Control groups in Study 3A. In Phase 2, Control groups in Study 3B had significantly lower Average Degree than Control groups in Study 3A.[57] Abundance and Scarcity groups in Study 3B had similar Average Degree to groups in the corresponding Condition of Study 3A in every Phase of the experiment.[58]

Control groups in Study 3B had significantly lower Density than Control groups in Study 3A in every Phase of the experiment.[59] Abundance groups in Study 3B had similar Density to Abundance groups in Study 3A in Phases 1 and 3, but significantly lower Density in Phase 2.[60] Scarcity groups in Study 3B had similar Density to Scarcity groups in Study 3A in every Phase of the experiment.[61]

Groups in each Condition of Study 3B had similar Centralization to groups in the corresponding Condition of Study 3A in every Phase of the experiment.[62]

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[57] CONTROL: Study 3B Control Phase 1 – Study 3A Control Phase 1 = –3.97, z = –1.50, p = 0.133; Study 3B Control Phase 2 – Study 3A Control Phase 2 = –6.77, z = –2.51, p = 0.012; Study 3B Control Phase 3 – Study 3A Control Phase 3 = –4.80, z = –1.63, p = 0.103.

[58] ABUNDANCE: Study 3B Abundance Phase 1 – Study 3A Abundance Phase 1 = –1.36, z = –0.51, p = 0.608; Study 3B Abundance Phase 2 – Study 3A Abundance Phase 2 = –4.06, z = –1.49, p = 0.136; Study 3B Abundance Phase 3 – Study 3A Abundance Phase 3 = –4.40, z = –1.48, p = 0.139. SCARCITY: Study 3B Scarcity Phase 1 – Study 3A Scarcity Phase 1 = –3.02, z = –1.13, p = 0.257; Study 3B Scarcity Phase 2 – Study 3A Scarcity Phase 2 = –2.38, z = –0.87, p = 0.382; Study 3B Scarcity Phase 3 – Study 3A Scarcity Phase 3 = –1.36, z = –0.46, p = 0.648.

[59] CONTROL: Study 3B Control Phase 1 – Study 3A Control Phase 1 = –1.10, z = –2.04, p = 0.042; Study 3B Control Phase 2 – Study 3A Control Phase 2 = –1.62, z = –2.94, p = 0.003; Study 3B Control Phase 3 – Study 3A Control Phase 3 = –1.20, z = –1.99, p = 0.047.

[60] ABUNDANCE: Study 3B Abundance Phase 1 – Study 3A Abundance Phase 1 = –0.82, z = –1.51, p = 0.130; Study 3B Abundance Phase 2 – Study 3A Abundance Phase 2 = –1.46, z = –2.64, p = 0.008; Study 3B Abundance Phase 3 – Study 3A Abundance Phase 3 = –1.42, z = –2.33, p = 0.020.

[61] SCARCITY: Study 3B Scarcity Phase 1 – Study 3A Scarcity Phase 1 = –0.30, z = –0.55, p = 0.585; Study 3B Scarcity Phase 2 – Study 3A Scarcity Phase 2 = –0.20, z = –0.36, p = 0.716; Study 3B Scarcity Phase 3 – Study 3A Scarcity Phase 3 = –0.02, z = –0.03, p = 0.977.

[62] CONTROL: Study 3B Control Phase 1 – Study 3A Control Phase 1 = 0.06, z = 1.50, p = 0.133; Study 3B Control Phase 2 – Study 3A Control Phase 2 = 0.06, z = 1.47, p = 0.143; Study 3B Control Phase 3 – Study 3A Control Phase 3 = –0.01, z = –0.33, p = 0.741. ABUNDANCE: Study 3B Abundance Phase 1 – Study 3A Abundance Phase 1 = 0.04, z = 1.06, p = 0.290; Study 3B Abundance Phase 2 – Study 3A Abundance Phase 2 = 0.06, z = 1.44, p = 0.151; Study 3B Abundance Phase 3 – Study 3A Abundance Phase 3 = 0.04, z = 1.04, p = 0.297. SCARCITY: Study 3B Scarcity Phase 1 – Study 3A Scarcity Phase 1 = 0.03, z = 0.77, p = 0.441; Study 3B Scarcity Phase 2 – Study 3A Scarcity Phase 2 = 0.02, z = 0.40, p = 0.686; Study 3B Scarcity Phase 3 – Study 3A Scarcity Phase 3 = 0.01, z = 0.15, p = 0.879.

Control groups in Study 3B had similar Out-Degree Variance to Control groups in Study 3A in Phases 1 and 3, but significantly higher Out-Degree Variance in Phase 2.[63] Abundance and Scarcity groups in Study 3B had similar Centralization to groups in the corresponding Condition of Study 3A in every Phase of the experiment.[64]

Groups in each Condition of Study 3B had similar Hierarchy and In-Degree Variance to groups in the corresponding Condition of Study 3A in every Phase of the experiment.[65, 66]

6.2.5.7 Take-Aways from Study 3B

The biggest take-away from Study 3B is that there is no interaction between resource shocks and competition. In the presence of competition, resource shocks still have no effect on participants' willingness to share with peers, or to view peers' results. Competition did have a significant

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[63] CONTROL: Study 3B Control Phase 1 – Study 3A Control Phase 1 = 57.83, z = 1.08, p = 0.280; Study 3B Control Phase 2 – Study 3A Control Phase 2 = 95.78, z = 1.94, p = 0.053; Study 3B Control Phase 3 – Study 3A Control Phase 3 = 36.88, z = 0.72, p = 0.469.

[64] ABUNDANCE: Study 3B Abundance Phase 1 – Study 3A Abundance Phase 1 = –14.28, z = –0.26, p = 0.791; Study 3B Abundance Phase 2 – Study 3A Abundance Phase 2 = 10.14, z = 0.20, p = 0.839; Study 3B Abundance Phase 3 – Study 3A Abundance Phase 3 = 16.04, z = 0.31, p = 0.755. SCARCITY: Study 3B Scarcity Phase 1 – Study 3A Scarcity Phase 1 = 7.62, z = 0.14, p = 0.888; Study 3B Scarcity Phase 2 – Study 3A Scarcity Phase 2 = 10.99, z = 0.22, p = 0.826; Study 3B Scarcity Phase 3 – Study 3A Scarcity Phase 3 = 28.80, z = 0.56, p = 0.575.

[65] CONTROL: Study 3B Control Phase 1 – Study 3A Control Phase 1 = –0.01, z = –0.52, p = 0.603; Study 3B Control Phase 2 – Study 3A Control Phase 2 = 0.00, z = 0.22, p = 0.827; Study 3B Control Phase 3 – Study 3A Control Phase 3 = 0.00, z = 0.21, p = 0.835. ABUNDANCE: Study 3B Abundance Phase 1 – Study 3A Abundance Phase 1 = –0.01, z = –0.94, p = 0.346; Study 3B Abundance Phase 2 – Study 3A Abundance Phase 2 = –0.00, z = –0.19, p = 0.852; Study 3B Abundance Phase 3 – Study 3A Abundance Phase 3 = 0.01, z = 0.51, p = 0.613. SCARCITY: Study 3B Scarcity Phase 1 – Study 3A Scarcity Phase 1 = –0.00, z = –0.36, p = 0.720; Study 3B Scarcity Phase 2 – Study 3A Scarcity Phase 2 = –0.02, z = –1.74, p = 0.083; Study 3B Scarcity Phase 3 – Study 3A Scarcity Phase 3 = 0.00, z = 0.03, p = 0.979.

[66] CONTROL: Study 3B Control Phase 1 – Study 3A Control Phase 1 = –2.45, z = –0.78, p = 0.434; Study 3B Control Phase 2 – Study 3A Control Phase 2 = –0.76, z = –0.23, p = 0.815; Study 3B Control Phase 3 – Study 3A Control Phase 3 = –0.28, z = –0.07, p = 0.944. ABUNDANCE: Study 3B Abundance Phase 1 – Study 3A Abundance Phase 1 = –0.90, z = –0.29, p = 0.775; Study 3B Abundance Phase 2 – Study 3A Abundance Phase 2 = 2.36, z = 0.72, p = 0.472; Study 3B Abundance Phase 3 – Study 3A Abundance Phase 3 = 4.47, z = 1.13, p = 0.259. SCARCITY: Study 3B Scarcity Phase 1 – Study 3A Scarcity Phase 1 = –0.58, z = –0.19, p = 0.853; Study 3B Scarcity Phase 2 – Study 3A Scarcity Phase 2 = –3.65, z = –1.11, p = 0.266; Study 3B Scarcity Phase 3 – Study 3A Scarcity Phase 3 = –0.78, z = –0.20, p = 0.843.

main effect on participants' willingness to share their results with peers. Participants in all three Conditions of Study 3B shared their results less frequently than participants in the corresponding Condition of Study 3A.

Interestingly, Abundance and Control participants in Study 3B chose to view their peers less often than participants in the corresponding Condition of Study 3A. But, there was no significant difference in the frequency with which Scarcity participants in Study 3B chose to view their peers compared with Scarcity participants in Study 3A.

7 CONCLUSION: DISCUSSION, LIMITATIONS, AND FUTURE DIRECTIONS

I'm going to start with a discussion of the most consequential results in the research program, focusing only on those results with significant practical and theoretical implications. Then, I'll describe the limitations of the present studies, and conclude with some suggestions for future directions of research.

7.1 The Non-Effect of Resource Level Shifts on Social Learning Strategies and Communication Network Structure

The primary goal of the present research program was to test whether shifts in resource levels drive changes in the structure of communication networks. My central hypothesis was that downward shifts in resource levels reduce people's appetite for social information. I proposed that this reduction in appetite for social information leads people to initiate and maintain fewer communication ties. The results of present experiments do not support this hypothesis. I observe no effect of resource shocks (positive *or* negative) on experimental participants' appetite for social information (Study 2B). And, I observe no effect of resource shocks on participants' decisions (not) to communicate with their peers, either with or without competition (Studies 3A and 3B, respectively). This *absence* of a resource level effect allows us to make important refinements to theories of communication network emergence and social learning strategies.

The results of the present experiments suggest that a downward shift in resource levels ("having less") is *not* the critical component of scarcity that drives changes in communication network structure or social learning behavior. Rather, it is some *other* element of scarcity that is absent from the present experimental design. It is useful to pause here and review each of the components of scarcity that usually present as confounders in prior research, and verify that none of these components are confounded with downward shifts in resource levels in the present experiments.

Expected Uncertainty. The variance in realized rewards across Trials is identical for each platform, at each resource level (High, Medium, Low). On each Trial, the point value of each platform is drawn from a normal distribution around that platform's average value, with a standard deviation of 20 points. This is true in each Condition, in each Phase of the experiment. Scarcity participants *do not* experience an increase in expected uncertainty across Phases, nor do they experience higher expected uncertainty than participants in the Control or Abundance Conditions.

Ambiguity (Unexpected Uncertainty). Within each Phase, the average value of each platform is constant. The average value of each platform does not change across Trials. At the start of each new Phase, participants in all three Conditions face a new list of platforms, with different names than those they saw in the previous Phase. Scarcity participants do not experience an increase in ambiguity across Trials, nor do they experience higher ambiguity than participants in the Control or Abundance Conditions as they advance across Phases. Participants were also asked to rate how confident they were that their estimates of the platform values accurately represented the rank-order of the platform's values. Confidence ratings were not significantly different across Conditions.

Competition. Competition is directly manipulated in Study 3B through a rank-order tournament. Importantly, this competition manipulation did not increase ambiguity or expected uncertainty (participants' actions had no effect on the points peers earned from each platform, and peers' actions had no effect on the points participants earned from each platform). Scarcity participants did not experience an increased sense of competition across Trials or Phases, nor did they experience more intense competition than Abundance or Control participants.[1]

Emotional Stress. See Section *A.3 Feelings Inventory* in the Supplement for Study 3A and Study 3B participants' self-reported positive and negative emotions during the experiment. Participants reported the extent to which they were currently experiencing each of six emotions (Happy, Successful, Friendly, Hostile, Frustrated, Anxious), on a scale of 0 ("not experiencing that feeling at all right now") to 100 ("experiencing that feeling very much right now"). Ratings were collected before the start of the procedure, in the middle of each Phase, and at the end of each Phase.

Participants' ratings of the extent to which they were feeling "Anxious" were low (around 25/100) at every time point, and relatively stable across Phases (ratings did not increase significantly over the course of the experiment, in any Condition). Participants' ratings of "Frustrated" were also low at every time point, and only increased over the course of the experiment. There were no differences between Conditions. Scarcity participants did not experience increasing stress levels across Phases, nor did they experience more stress than Control and Abundance participants.

Negative (versus Positive) Affect. Refer again to Section *A.3 Feelings Inventory* in the Supplement for Study 3A and Study 3B participants' self-reported positive and negative emotions during the experiment. In Study 3A, Scarcity participants reported slightly lower

[1] Also see Section *A.3 Feelings Inventory* in the Supplement for Study 3B participants' ratings of the extent to which they were feeling "Hostile" during the experiment. Ratings of "Hostile" were low (between 10/100 and 15/100), and only increased slightly compared to the rating taken before the start of the procedure. There are no significant differences between Conditions. Scarcity participants did not experience an increased emotional response to competition (hostility) across Phases, nor did Scarcity participants experience a higher emotional response to competition than participants in the Abundance and Control Conditions. Also note that ratings of "Friendly" are constant across Phases, and there were no differences in participants' feelings of friendliness between Conditions.

ratings of "Happy" and "Successful" than Abundance participants in Phase 3 (but there was no significant difference between Scarcity and Control). There were no differences between Conditions in ratings of the three positive emotions (Happy, Successful, Friendly) in Study 3B. There were no differences between Conditions in ratings of the three negative emotions (Anxious, Hostile, Frustrated) in Study 3A or in Study 3B.

(Unfavorable) Social Comparison. The opportunity for social comparison was present in Study 2B (Exemplar Players), and in Studies 3A and 3B (peers). The likelihood that participants experience unfavorable social comparisons (lower personal performance compared to exemplars or peers) is the same across all three Conditions in each study. Scarcity participants are no more likely to experience unfavorable social comparisons than participants in the Abundance and Control Conditions.

Scarcity participants' ratings of feeling "Successful" were lower than Abundance and Control participants in Phases 2 and 3 of Study 3A (there were no differences between Conditions in Study 3B). But, this doesn't seem to stem from unfavorable social comparison. Participants were asked to rate their *relative* performance compared to other players on a scale of 0 ("Worst Performance") to 100 ("Best Performance").[2] There were no significant differences in performance ratings between Conditions in Study 2B, 3A, or 3B.[3] Participants rated their own performance as above average in all three studies.[4]

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[2] "How do you think your performance in The Sales Game compares with other players? Indicate your response on the scale below. At least 100 people have played The Sales Game so far. Select "Worst Performance" if you think every other person performed better than you did. Select "Best Performance" if you think you performed better than every other person who has played the game."

[3] STUDY 2B: Control – Abundance = 2.71, z = 0.78, p = 0.435; Control – Scarcity = –2.15, z = –0.62, p = 0.538; Abundance – Scarcity = –4.87, z = 1.37, p = 0.170. STUDY 3A: Control – Abundance = 0.22, z = 0.12, p = 0.902; Control – Scarcity = 0.26, z = 0.14, p = 0.887; Abundance – Scarcity = 0.03, z = 0.02, p = 0.984. STUDY 3B: Control – Abundance = –1.52, z = –0.68, p = 0.497; Control – Scarcity = –2.19, z = –0.98, p = 0.326; Abundance – Scarcity = –0.67, z = 0.30, p = 0.765.

[4] STUDY 2B: M = 65.75, SD = 18.15. STUDY 3A: M = 62.95, SD = 16.08. STUDY 3B: M = 61.64, SD = 20.82.

In the absence of these common confounders, we observe no effect of shifts in resource levels on participant's appetite for social information, or on their willingness to share information with their peers. This suggests it is these confounding variables, *and not* downward shifts in resource levels, that drive the structural changes in communication networks observed in past research (e.g. "turtling up" in Kalish et al. 2015; Ramirez-Sanchez & Pinkerton, 2009; Romero, Uzzi, and Kleinberg, 2016, 2019).

We successfully isolated competition in the present studies (without increasing uncertainty or ambiguity), and found that the mere presence of competition decreases willingness to share information with peers, and the frequency of peer views. These results suggest that competition is one of the scarcity components that drives communication network contraction.

Ambiguity is another component of the scarcity construct that drives communication network contraction. Toelch and colleagues (2009) isolated uncertainty and ambiguity in a similar multiarmed bandit paradigm *without* shifting resource levels. The authors found that increasing ambiguity (*unexpected* uncertainty over each resource's average value) decreases the frequency with which participants choose to view decisions made by their peers. Toelch and colleagues' explanation for this result is that unexpected uncertainty is a signal that the resource environment is in flux, which means that peers' information about the true state of the environment is outdated. As a result, participants choose to explore the environment independently to obtain updated information.

Emotional stress is another strong candidate as a driver of communication network contraction. In Kalish and colleagues' (2015) quasi-experimental study of military recruits during a multi-day training exercise, there were no treatment groups. All recruits completed the same series of exercises. Recruits were matched up into groups, and self-reports of stress levels and communication partners were collected at three points in time over the course of the exercises. Self-reported stress levels varied across members of each group. Those reporting increased stress levels subsequently decreased their number of communication partners.

Finally, there is converging directional evidence that identity threat and negative affect cause people to contract their personal communication networks. Menon and Smith (2014) found that inducing identity threat through an identity disconfirming prime led participants to report fewer close contacts. Smith, Menon, and Thompson (2012) found that people with low (but not high) socioeconomic status reported fewer contacts after being told to imagine being laid off. Shea, Menon, Smith, and Emich (2015) found that people primed with negative affect reported smaller, more redundant social networks. In their observational study of a large engineering consulting firm, Parker, Halgin, and Borgatti (2016) found that employees reduced contact with weak ties and increased contact with strong ties following a negative performance review.

7.2 The Effect of Resource Level Shifts on Explore-Exploit Strategies

We do observe a clear effect of resource level shifts on *solo* participants' explore-exploit strategies when participants *do not* have an opportunity to take side observations of the platform values. In Study 1, a *downward* shift in resource levels *increased* exploration and *decreased* exploitation. Increased exploration is concentrated over the first few Trials, and decreased exploitation is observed across all Trials. An *upward* shift in resource levels produced a slight (non-significant) *decrease* in exploration, and a slight (significant) *increase* in exploitation. Both effects of an upward shift are concentrated over the first few Trials. The effect of a shift in resource levels was more pronounced following *downward* shifts than *upward* shifts. This is consistent with patterns observed in recent experimental studies examining choice behavior in prey selection (Garrett & Daw, 2020) and bidding tasks (Huijmans et al., 2019; Khaw, Glimcher, & Louie, 2017).

Garrett and Daw (2020) investigated choice adaptation in a prey selection game with solo (human) participants. At each time step, participants chose whether to accept the currently available prey, or to wait for higher quality prey to show up later. Participants played the game twice across two different environments (blocks). High quality prey appeared less frequently in the Poor environment than in the Rich environment. Participants either played the game in the Poor environment first (PoorRich) or in the Rich environment first (RichPoor). PoorRich participants adapted their choice behavior to the Rich environment faster than RichPoor participants adapted their choice behavior to the Poor environment.

Garrett and Daw propose an asymmetric learning rule to account for this pattern: *positive* prediction errors (receiving higher rewards than anticipated) have a larger effect on participants' posterior estimates of the average reward level in a given environment than *negative* prediction errors (receiving lower rewards than anticipated. When RichPoor participants were exposed to repeated observations of the low-quality prey before advancing to the Poor environment (Experiment 3), their choice behavior was consistent with PoorRich participants. In other words, when participants were given additional opportunities to sample the environment, those who experienced a downward shift in average resource values behaved similarly to those who experienced an upward shift. Increasing opportunities to sample the environment resolved the asymmetry.

This is similar to what we observe in the present experiments. In Studies 2A, 2B, 3A, and 3B, the effect of resource shifts on explore-exploit strategies are muted by participants' access to side observations. We see brief hints of increased (decreased) exploration and decreased (increased) exploitation among Scarcity (Abundance) participants on the first few Trials of Phase 2 (following the first shift in resource values). These effects are much smaller than what we observed in Study 1, and quickly dissipate (converge toward the exploration/exploitation rates exhibited by Control participants). And, the temporary increase in exploration among Scarcity participants is more pronounced than the decrease in exploration among Abundance participants.

7.3 The Effect of Sampling Process on Use of Side Observations

In past experimental studies of social learning strategies, participants were *either* given the opportunity to view contemporaneous peers *or* the opportunity to view decisions made by past participants. In some cases, researchers used deception and told participants that samples generated by a random (or guided) algorithm were decisions made by past participants. But, to my knowledge, no experiment has *explicitly* offered participants the option to view samples generated by a random algorithm. The present studies are the first to compare participants' propensity to use side observations generated by each of these processes (contemporaneous peers, past participants, random sampling algorithm).

This distinction probably sounds a little too "inside baseball," but it has important implications for the way we interpret the results of past research. The goal of social learning experiments is to identify characteristics of fundamental cognitive and social processes that generalize from the experimental environment to human behavior in the real world. Social learning researchers take an evolutionary perspective, and make claims about the way human and non-human animal brains developed specialized processes for social interaction. Studies that focus on non-human animals emphasize the role of conspecifics. Heterospecifics are treated as a special case. Artificial or virtual agents *are not considered at all*.

We need to include an *explicitly* artificial (preferably random) sampling device in the design of social learning experiments if we want to extrapolate from participants' behavior in an anonymous virtual environment to human behavior in everyday life. It would be inappropriate to conclude that participants' propensity to use information generated by an artificial device generalizes to their propensity to learn from their peers in the real world. If we find that participants treat information generated by an artificial device the same way they do social information it calls into question whether participants actually believed the cover story (they might assume the experimenter is lying about the origins of the information presented).

In Study 2A, participants were (truthfully) told that Random Pitches each contained three randomly selected platforms. In Study 2B, participants were (truthfully) told that Exemplar Player pitches each contained the platforms selected by a real participant on each Trial of Study 1. On average, participants in Study 2B chose to view Exemplar Players about the same number of times in each Phase as Study 2A participants chose to view Random Pitches. However, there was a lot of heterogeneity across individual participants' propensities to view side observations (Random Pitches, Exemplar Players) in each Study. Figures 7.1 and 7.2 present the distributions of Random Pitch and Exemplar Player view frequencies for Studies 2A and 2B, respectively.

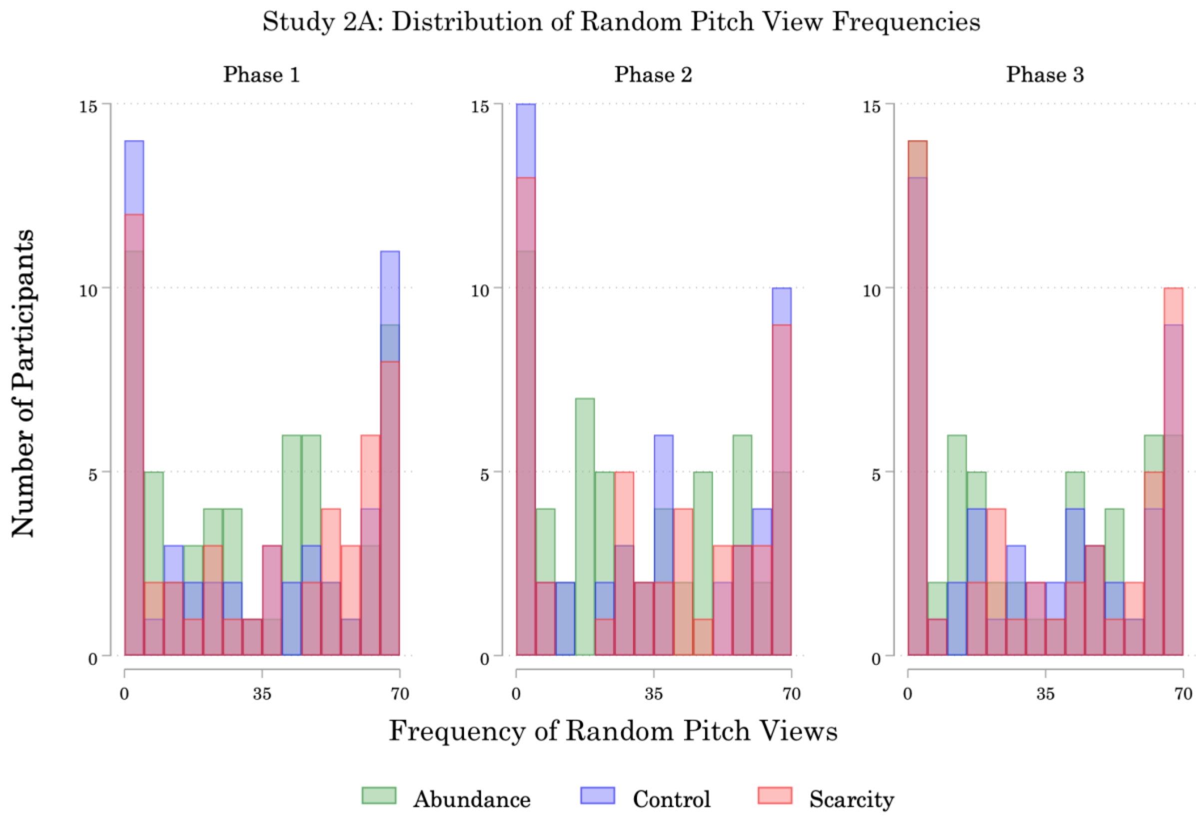

Figure 7.1. Study 2A: Distribution of Random Pitch View Frequencies, by Phase and Condition. N = 157. Green = Abundance (N = 58); Blue = Control (N = 51); Red = Scarcity (N = 48). The x-axis shows the cumulative number of times participants chose to view Random Pitches across Trials 2–15 in a given Phase. The y-axis shows the number of participants at each Random Pitch view frequency. The distributions are close to bimodal in each Phase, with a large group of participants choosing to view Random Pitches *less than five times*, and another large group choosing to view Random Pitches *more than 65 times*.

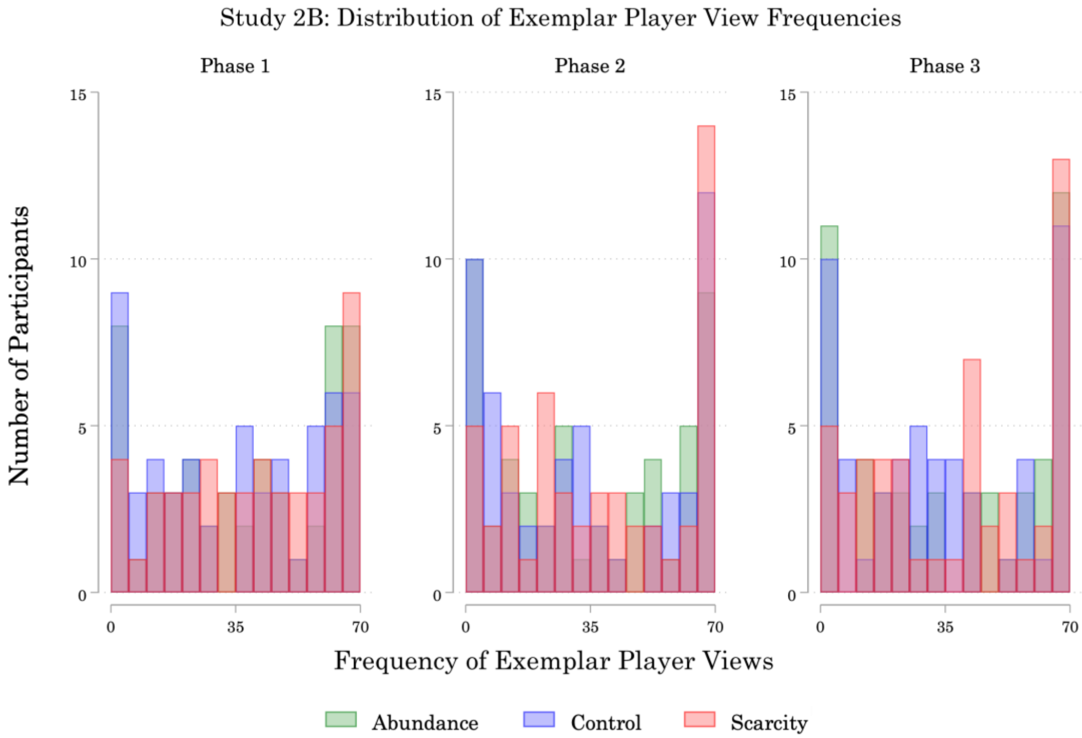

Figure 7.2. Study 2B: Distribution of Exemplar Player View Frequencies, by Phase and Condition. N = 158. Green = Abundance (N = 52); Blue = Control (N = 55); Red = Scarcity (N = 51). The x-axis shows the cumulative number of times participants chose to view Exemplar Players across Trials 2–15 in a given Phase. The y-axis shows the number of participants at each Exemplar Player view frequency. The distributions are somewhat uniform in each Phase, except for a large group of participants choosing to view Exemplar Players *less than five times*, and another large group of participants choosing to view Exemplar Players *more than 65 times*.

The distributions of Random Pitch view frequencies are close to bimodal, with a large group of participants choosing to view Random Pitches *less than five times*, and another large group of participants choosing to view Random Pitches *more than 65 times*. The distributions of Exemplar Player view frequencies are a bit more uniform, but we still observe two large clusters of participants, one choosing to view Exemplar Players less than five times, and the other choosing to view Exemplar Players more than 65 times. It seems like a larger proportion of participants is in the left-tail of the Random Pitches distributions (rarely view) than there is in the left-tail of the Exemplar Player distributions. And, in Phases 2 and 3, there seems to be a larger proportion of participants in the right-tail of the Exemplar Player distributions (always view) than in the right-tail of the Random Pitches distributions.

A means-comparison test is probably not appropriate for identifying differences in the distributions of Random Pitch view frequencies versus Exemplar Player view frequencies. It is possible for these distributions to have the same mean and standard deviation, while the proportion of participants in different ranges of view frequencies (e.g. less than 5, 5-10, 55-60) differs between distributions. Given the shape of these distributions, a Kolmogorov-Smirnov (K-S) test for equality of the distributions is not going to work, because the K-S test is not sensitive to differences in the tails of the distributions (and that's where most of the action is). Instead, I'm going to use the procedure proposed by Goldman and Kaplan (2018), which allows me to test whether the two distributions differ at each possible frequency value while controlling for the family-wise error rate (FWER).[5] The Goldman-Kaplan test walks through the CDF of each distribution and identifies regions where we can reject the null hypothesis that the two samples of response values are drawn from the same distribution.

If we compare Studies 2A and 2B within each Phase, the Goldman-Kaplan test fails to reject the null at any point along the two CDFs. But, when we pool Phases 1–3, the Goldman-Kaplan test rejects the null hypothesis at $p = 0.040$ along the following ranges: 4–4, 6–7, 8–8. To see what's going on here, it's easiest to look at the CDFs of the pooled distributions for each Study (Figure 7.3). The green bars mark the approximate rejection regions. The number of

[5] This procedure is implemented in Stata 16 using the `distcomp` package. Briefly, Goldman-Kaplan "walks through" through each point along the CDF of the two distributions of guesses, and identifies the points along those CDFs where the two distributions are significantly different. As we move from the left to the right-hand side of the distribution of response values (moving from view frequencies close to 0 to view frequencies closer to 70), the CDF at point r is the cumulative probability of an observation from sample F or G falling at or below r. Goldman-Kaplan identifies specific ranges between values of r where can reject the null hypothesis that the two samples of response values are drawn from the same distribution. For a more detailed description of the procedure, see Goldman-Kaplan (2018).

participants in Study 2A who chose to view Random Pitches at very low frequencies (between 4 and 8 times in a given Phase) is larger than the number of participants in Study 2B who chose to view Exemplar Players at these frequencies.

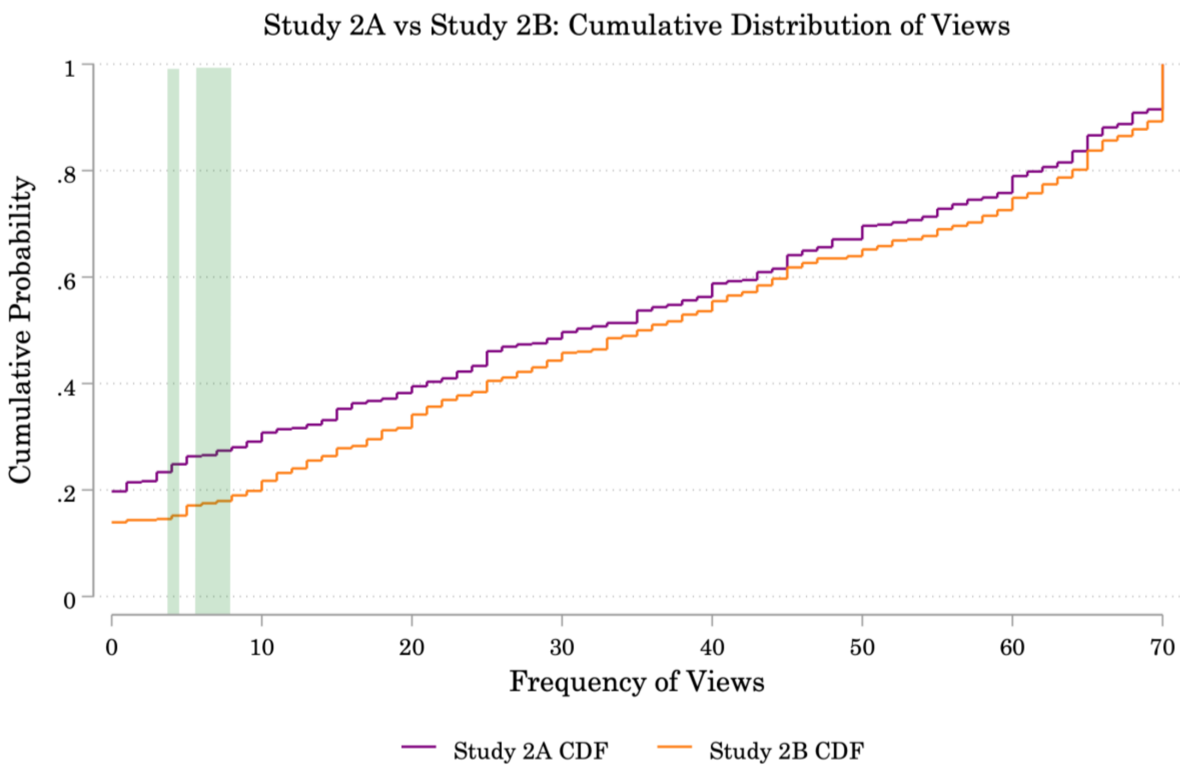

Figure 7.3. Studies 2A and 2B: Cumulative Distributions of View Frequencies, by Study. Frequencies are pooled across Phases 1–3 for each Study. Purple = Study 2A; Orange = Study 2B. Green bars indicate approximate regions of rejection: 4–4, 6–7, 8–8.

Figures 7.4 and 7.5 present the distributions of peer view frequencies for each Phase in Studies 3A and 3B. The distributions are all right-skewed. We don't see large clusters of participants choosing to view peer results at very low frequencies like we did in Studies 2A and 2B. Instead, the distributions of peer views in each Phase are all right-skewed in Study 3A. In Study 3B, the distribution in Phase 1 is right-skewed. The distributions in Phases 2 and 3 are more uniform, but there are still large clusters of participants at very high view frequencies (65+ views).

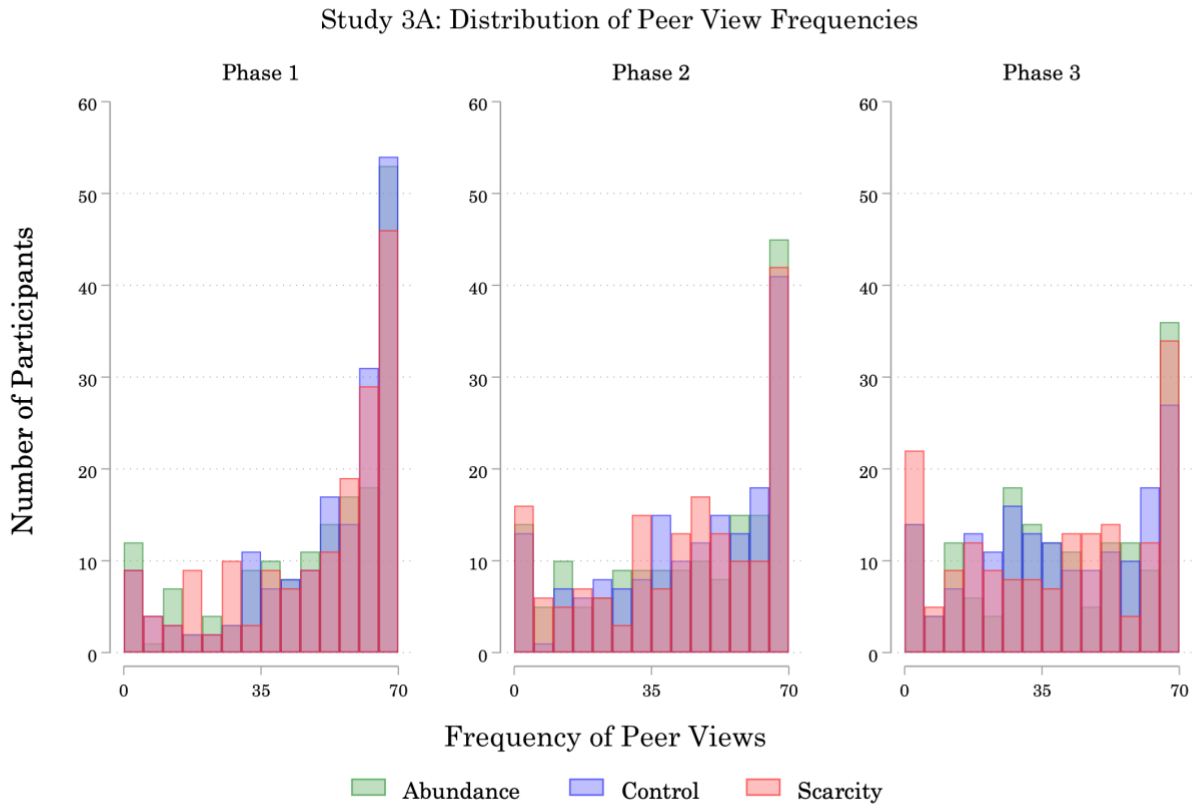

Figure 7.4. Study 3A: Distribution of Peer View Frequencies, by Phase and Condition. N = 513. Green = Abundance (169 participants, 30 groups); Blue = Control (174 participants, 30 groups); Red = Scarcity (170 participants, 29 groups). The x-axis shows the cumulative number of times participants chose to view their peers' results across Trials 2–15 in a given Phase. The y-axis shows the number of participants at each peer view frequency. The distributions in Phases 1 and 2 are right-skewed. The distribution in Phase 3 is more uniform, with a large cluster of participants at very high view frequency (65+ views).

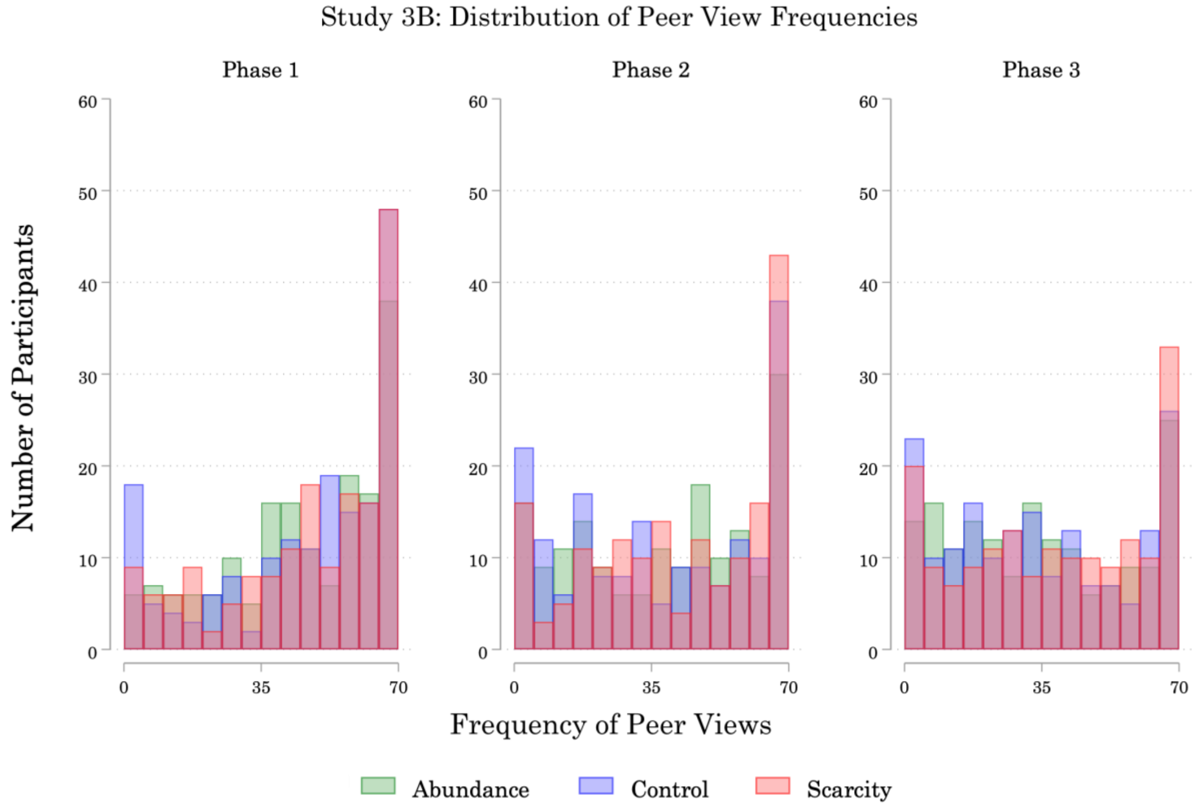

Figure 7.5. Study 3B: Distribution of Peer View Frequencies, by Phase and Condition. N = 519. Green = Abundance (170 participants, 29 groups); Blue = Control (177 participants, 30 groups); Red = Scarcity (172 participants, 30 groups). The x-axis shows the cumulative number of times participants chose to view their peers' results across Trials 2–15 in a given Phase. The y-axis shows the number of participants at each peer view frequency. The distribution in Phase 1 is right-skewed. The distributions in Phases 2 and 3 are more uniform, with a large cluster of participants at very high view frequency (65+ views).

Figure 7.6 presents the *unpooled* CDFs of the view frequency distributions in each Phase of each Study (2A, 2B, 3A, 3B). There are some clear differences in the left tails of the distributions. In every Phase of the experiment, a larger proportion of participants chose to view side observations at low to moderate frequencies when the observations were drawn by a random sampling algorithm (Random Pitches, Study 2A) than when they were drawn by contemporaneous peers (peer results, Studies 3A and 3B). In Phases 1 and 2, a larger proportion of participants chose to view side observations at low to moderate frequencies when the observations were drawn by past participants (Exemplar Players, Study 2B) than when they were drawn by contemporaneous peers (peer results, Studies 3A and 3B).

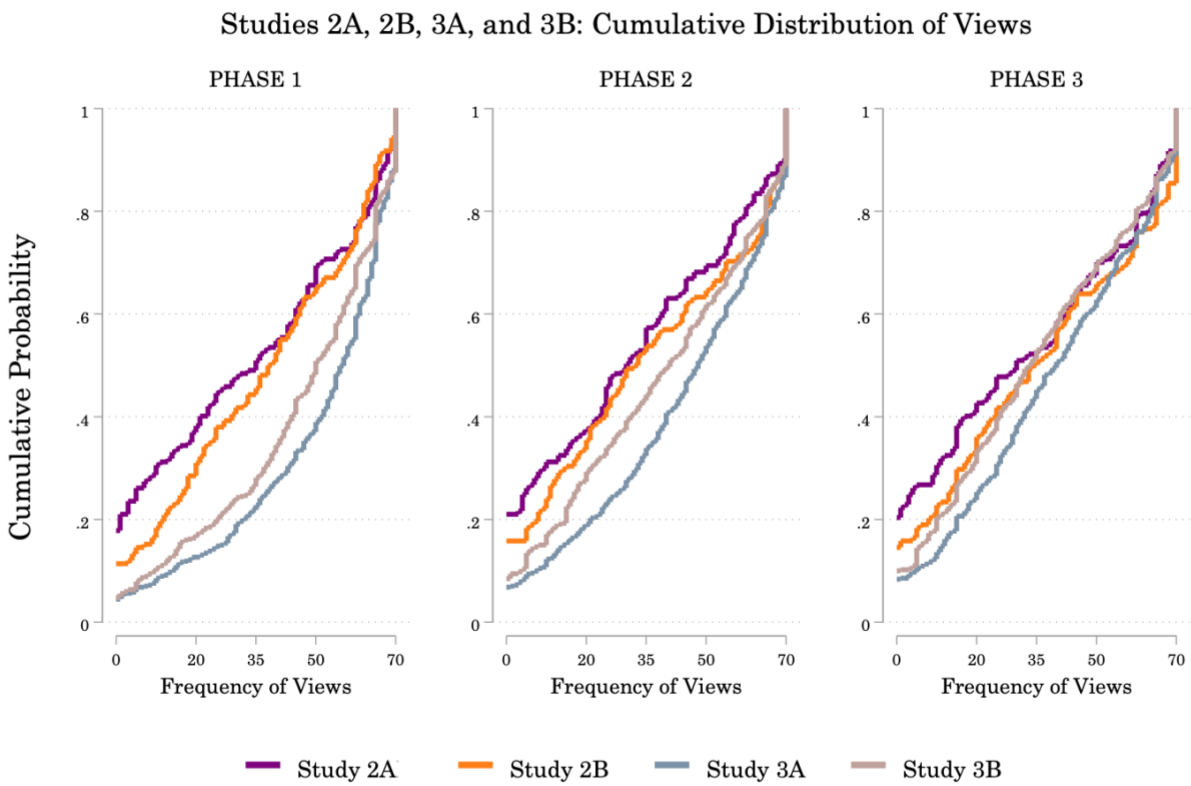

Figure 7.6. Studies 2A, 2B, 3A, and 3B. Cumulative distributions of view frequencies, by Phase and Study. Purple = Study 2A; Orange = Study 2B; Steel Blue = Study 3A, Rose = Study 3B.

In every Phase of the experiment, the proportion of participants in Study 3A who chose to view their peers at low to moderate frequencies was significantly smaller than the proportion of participants in Study 2A who chose to view Random Pitches at low to moderate frequencies.[6] In Phase 1, the proportion of participants in Study 3B who chose to view their peers at low to

[6] In Phase 1, the Goldman-Kaplan test rejects the null hypothesis of equality along the following regions ($p < 0.000$): 1–60, 61–62, 63–63. In Phase 2, the Goldman-Kaplan test rejects the null hypothesis of equality along the following regions ($p < 0.000$): 3–51, 58–58. In Phase 3, the Goldman-Kaplan test rejects the null hypothesis of equality along the following regions ($p < 0.000$): 1–25, 28–28.

moderate frequencies was significantly smaller than the proportion of participants in Study 2A who chose to view Random Pitches at low to moderate frequencies. In Phases 2 and 3, the proportion of participants in Study 3B who chose to view their peers at low frequencies was significantly smaller than the proportion of participants in Study 2A who chose to view their peers at low frequencies.[7]

In Phases 1 and 2, the proportion of participants in Study 3A who chose to view their peers at low to moderate frequencies was significantly smaller than the proportion of participants in Study 2B who chose to view Exemplar Players at low to moderate frequencies.[8] In Phase 1, the proportion of participants in Study 3B who chose to view their peers at low to moderate frequencies was significantly smaller than the proportion of participants in Study 2A who chose to view Random Pitches at low to moderate frequencies. In Phases 2 and 3, the proportion of participants in Study 3B who chose to view their peers at low frequencies was significantly smaller than the proportion of participants in Study 2A who chose to view their peers at low frequencies.[9]

While we still see a lot of heterogeneity in view frequency, a smaller proportion of participants tend to view side observations at low to moderate frequency when these observations are generated by contemporaneous peers than when they are generated by past participants or by a random sampling algorithm.

[7] In Phase 1, the Goldman-Kaplan test rejects the null hypothesis of equality along the following regions ($p < 0.000$): 1–49, 50–54. In Phase 2, the Goldman-Kaplan test rejects the null hypothesis of equality along the following regions ($p = 0.007$): 3–4, 5–8, 9–12, 11–14. In Phase 3, the Goldman-Kaplan test rejects the null hypothesis of equality along the following regions ($p = 0.005$): 1–6.
[8] In Phase 1, the Goldman-Kaplan test rejects the null hypothesis of equality along the following regions ($p < 0.000$): 11-59, 60–60, 61–62, 63–64. In Phase 2, the Goldman-Kaplan test rejects the null hypothesis of equality along the following regions ($p < 0.000$): 7–7, 9–9, 10–10, 11–43, 44–44, 46–46, 47–47. The Goldman-Kaplan test does not reject the null hypothesis of equality in Phase 3.
[9] In Phase 1, the Goldman-Kaplan test rejects the null hypothesis of equality along the following regions ($p = 0.001$): 20–44, 45–49, 51–51. In Phases 2 and 3, the Goldman-Kaplan test does not reject the null hypothesis of equality.

These results suggest that the generating process matters. Participants do not treat side observations generated by different processes as equivalent. A small proportion of participants choose to view side observations at low frequencies when they generated by contemporaneous peers than when they are generated by past participants or by a random sampling algorithm. Fewer participants choose to view side observations at low frequencies when they are generated by past participant than when they are generated by a random sampling algorithm.

Extrapolating from this pattern to "real world" workplace behavior suggests that employees are less likely to ignore information about the environment (e.g. market demand) when that information concerns the experience of their peers in the present than when that information concerns the experience of their peers in the past.

Part of the reason companies use customer relationship management software like that offered by Salesforce is so they can maintain detailed historical records of their sales teams' experience with customers. Sales personnel are supposed to use historical information about past customer engagements to craft their sales strategies. The results of the present experiments might explain why this doesn't always happen in practice.

7.4 Limitations of the Present Research Program

There are four major limitations of the present research program. First, the novel experimental paradigm used across the five studies has never been tested outside of this program. Certain features of this paradigm might have undermined or obfuscated the effect of shifts in resource levels on participants' search and communication behavior. Second, these experiments were all conducted during an unprecedented global economic and health crisis. The "laboratory" is not insulated from the real world, and participants' experience of *real* scarcity in everyday life may have overwhelmed the subtle resource shift manipulation in the present experiments, resulting in all participants behaving as if they were in the Scarcity Condition. Third, there were significant behavioral differences between the MTurk and CDR samples in Studies 3A and 3B. Pronounced differences in response to the experimental treatments makes it difficult to draw strong conclusions from the results of these studies. Finally, online crowdsourcing platforms are beset by a tidal wave of fraud that has grown exponentially since the start of the Covid-19 pandemic. The crowdsourced research bubble may have finally burst.

7.4.1 Potential Design Flaws

The most glaring flaw in the design of the group experiments is that participants' experience in Phase 1 may be sufficient to induce minimal ingroups. In open responses collected during the debrief, and in public reviews participants posted about the experiment online, participants mentioned how happy and pleased they were to find that their peers frequently chose to share their results. This experience of reciprocity in Phase 1 may bond participants together, inducing "strong ties" among members of a given experimental group. As a result, there are no "weak ties" for participants to shed in subsequent Phases. If this is the case, there would be no opportunity for us to observe network contraction in subsequent Phases of the experiment.

Along this same line, it is possible that the group size (6 participants) was too small to allow for variation in communication network structure across Conditions. There may be some minimum number of peers whom participants wish to sample, and we might only observe differences in the rates of peer views when the size of the group exceeds this minimum. (But see examples of observable differences in similarly sized groups in McElreath et al., 2008; Mesoudi & O'Brien, 2008; Mesoudi, 2011).

The second most glaring flaw in the experimental design is that participants in each Condition start the procedure at different resource levels (Scarcity = High; Control = Medium; Abundance = Low). This is consistent with related experiments (e.g. the PoorRich versus RichPoor design in Garrett and Daw, 2020), but the fact of the matter is that participants enter the experiment with goals or expectations for the amount of compensation they will receive. Most MTurk participants use browser plugins or tools in their Worker dashboard to set and track hourly earnings goals. As time ticks by, these participants have a persistent visual reminder of how well they are tracking their goal. These goals may interact with differences in the size of the bonuses earned in Phase 1, resulting in unanticipated effects on behavior. For example, Scarcity participants, who accumulate high bonuses very quickly in Phase 1, may experience a "house money" effect, making them less risk averse and more prone to explore in Phase 2.

Third, shifts in reward levels may have occurred too gradually. In the SNC experiments with non-human animals, behavioral differences are less pronounced (or absent) when the reward levels are too close together or transition slowly over time (Flaherty, 1982). It is possible that there was not enough space between the ranges of platform values to really induce a resource "shock," and instead participants experienced something more like a slow realization. We also did not use any negative values, which undermines the ecological validity of the design. Following a negative resource shock, resources that used to be reliable may no longer produce rewards. If an agent spends energy foraging that resource, and gets nothing in return, the result is a negative balance (e.g. a salesperson incurs an opportunity cost when she spends time calling on clients who are now bankrupt and can no longer yield any sales).

Related to the above, the fact that the distributions of platform values were uniform may have reduced ecological validity (high value resources don't tend to occur with equal frequency to medium and low value resources in real life). A skewed distribution (many low values, very few high values) may have promoted increased search, or increased hoarding behavior under competition. Alternate shapes of the platform value distributions were used in pretests of the experimental task. In these pretests, participant behavior was consistent across normal, uniform, and right-skewed distributions of platform values. However, participants played solo in all of these pretests, so I was unable to observe any effects on behavior in experimental groups.

The duration of the experiment may have been too long. In Studies 3A and 3B, groups of participants took between 60 and 75 minutes to complete the procedure, on average. In their open responses during the debrief, a handful of participants mentioned that they needed a bathroom break, and were unable to maintain focus on the task. Participants' behavior in Phase 3 may have been more influenced by boredom or fatigue than belief-updating or social learning strategies. One hour is not an uncommon duration for group experiments, but longer experiments are more often run with participants who are physically present in the same location. The online environment introduces technical and coordination challenges that make it more difficult to run experiments over longer periods of time.

Alternatively, participants may not have had *enough* time. Many noted in their open responses during the debrief that they felt rushed and would have preferred less restrictive time limits. While the time constraints did not increase levels of anxiety or frustration, it's possible that participants engaged a "cheaper" heuristic decision-making strategy in lieu of one more costly in terms of time and cognitive load.

Finally, the task may have been too complicated. Choosing three platforms on each Trial (instead of one) from a list of 20 platforms (instead of fewer) may have increased the level of difficulty to a point where participants did not have sufficient cognitive resources to think strategically about the best sampling or social learning strategy. However, we do see significant improvement (in terms of rewards and discovery) across Trials within each Phase, suggesting that participants are not behaving randomly and do have some command over the task. The most frequent open response received during the debrief (and in public reviews of the experiment on Worker forums) was that the task was difficult or challenging, but a lot of fun. The number of times participants mentioned how much fun they had was quite surprising (especially because participants are not required to enter anything into the open response box at the end of the debrief).

7.4.2 The Laboratory Is Not Insulated from the Real World

The "laboratory" (physical or virtual) is not insulated from the outside world. The present experiments were conducted during a time of unprecedented global crisis. Never before has the United States experienced *concurrent* health, economic, and political crises of similar magnitude to those that occurred over the course of the present experimental studies. A number of studies have investigated the effect of traumatic events and crises on economic and social preferences. Some of these studies have used well-established, consistently replicated experimental games. The results of these studies are mixed, likely due to significant differences in the composition of the participant pools and the nature of the crises affecting the participants in each study.

The specific behaviors or preferences affected (e.g. risk-tolerance, trust, prosociality) and the direction of the effects are difficult to predict due to differences in results across participant pools (e.g. US college students versus rural farmers), types of crises (e.g. recession versus hurricane), and types of participants (e.g. men versus women). But, what is clear is that experimental participants' environment outside of the lab can and does affect their behavior inside the lab.

Such behavioral differences have been observed in experiments conducted during the Great Recession (e.g. Fisman, Jakiela, & Kariv, 2015), and following natural disasters (e.g. Charness, Dupuy, & Joxhe, 2020; Eckel, El-Gamal, & Wilson, 2009; Fleming, Chong, & Bejarano, 2014). Intertemporal behavioral differences have also been observed in the same participants across periods of scarcity or abundance, even when these periods are anticipated and cyclical (Aksoy et. al, 2019; Bartos, 2018; Boonmanunt, 2019). Early experiments conducted over the course of the Covid-19 crisis also reveal similar behavioral differences across time within the same participants (e.g. Lohmann et al., 2020; Schachat, Walker, & Wei, 2020). I will selectively highlight two examples relevant to the present studies to underscore the importance of this concern – the first from a study conducted before and during the Great Recession, and the second from a study conducted before and during the Covid-19 pandemic.

Fisman, Jakiela, and Kariv (2015) conducted identical experiments before and shortly after the "Great Recession" of 2008. The researchers used modified versions of the dictator game (Andreoni and Miller, 2002; Fisman, Kariv, & Markovits, 2007) to capture participants' selfishness (measured as the weight the participant placed on her own payoffs) and equality-efficiency tradeoffs (measured as the level of concern the participant exhibited for reducing differences in payoffs versus increasing total payoffs). Compared with participants in the pre-recession sample, participants in the recession sample were more selfish and were more concerned with efficiency than with equality.[10]

[10] Participants in both the pre-recession and recession periods were undergraduate students at Berkeley. The majority of participants were female (65% pre-recession, 60% recession), and a minority of the participants were economics or business majors (26% pre-recession, 11% recession). These details are relevant to a discussion we

Fisman and colleagues conducted two versions of their dictator game during the recession period. The first version was identical to the pre-recession version. All potential payoffs to the participant and her counterpart were positive (neither was subject to a loss). The second version exposed the participant (and the counterpart) to losses. Recession participants exhibited similar levels of selfishness and similar prioritization of efficiency in both the no-loss and in the loss versions of the experiment. The loss treatment employed by Fisman and colleagues is arguably a stronger scarcity manipulation than the one employed in the present experiments (participants in the present experiments were never exposed to losses). Despite the fact that Fisman and colleagues introduced a stronger scarcity manipulation, the effect of this manipulation was still quite modest compared to the effect of the recession. In other words, the effect of the economic recession on participant behavior dwarfed the effect of the scarcity manipulation.

In a longitudinal panel study, Lohmann and colleagues (2020) conducted experiments with university students in China[11] over several waves starting in October 2019. On each wave, students participated in several well-established experimental games designed to measure economic and social preferences (e.g. Joy of Destruction, Abbink & Herrmann, 2011; Lottery Choice Task, Eckel & Grossman, 2002). The researchers found that greater exposure to Covid-19 (number of confirmed cases in the student's home town) increased anti-social behavior. The increase in anti-social behavior was greater for male students than for female students. Male students also exhibited a significant increase in risk aversion, but no change in risk aversion was observed among female students.

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will have later around differences between the behavior of the CDR sample and the MTurk sample in the present experiments.

[11] Students were initially recruited at Beijing universities, but were dispersed across China on subsequent waves. Students traveled to their home cities for Spring Festival in January, 2020, and most were unable to return to their universities due to state-imposed travel restrictions.

In my view, there is a very low probability that we would observe the exact same behavioral patterns if we ran the present experiments in 2019, or at some point far in the future when daily life approaches something close to what it was like in 2019. We must be cautious about generalizing from the behavior observed in the present experiments to samples beyond gig workers and college students *during the Covid-19 pandemic*. Because I used a novel experimental paradigm in the present studies, I have no baseline for participant behavior outside of the context of the current global crisis.

One important methodological and cultural issue that this situation highlights is that it is *critical* for researchers to provide explicit information about the precise time periods during which experiments were run. And, journals should feature this information prominently with the study abstract. It should not be hidden in an online supplement or appendix. The belief that experimenters can create a self-contained world inside of the lab is a counterproductive illusion. Experiments must be situated in the temporal and cultural context in which they were run.

7.4.3 Behavioral Differences between Participant Pools

There were significant behavioral differences between the MTurk and CDR participants samples in Studies 3A and 3B. Section *A.2 Participants Pools* in the Supplement presents a summary of these differences with separate figures for each participant pool illustrating the patterns in response values for each focal dependent variable.

I do not think these differences are due to the prevalence of fraud on MTurk (discussed in the next section). For the most part, the MTurk sample provided high-quality data. Between the two populations, I would not select the CDR participants as more representative of the "average" person's behavior. At least, not the average computer literate person's behavior. My phone number and email address were posted with the study information on the CDR recruiting platform. Based on the content of (frequent) phone calls and emails I received from the CDR participants, there was a much higher rate of computer illiteracy in the CDR pool than in the MTurk pool. Discomfort performing basic tasks like navigating the internet and interacting with web forms interferes with a participant's ability to engage with the present experimental task. I have no way to estimate what proportion of the CDR sample was significantly impaired in this way.

Aside from apparent differences in technical proficiency, there were also significant differences in the distributions of demographic characteristics across the two participant pools. Section *A.4 Demographics* in the Supplement presents summary statistics for participants' responses to the demographics, social networks, and Covid-19 questionnaires. Of the variables whose distributions differ significantly across pools, the following four have the highest potential to produce the observed behavioral differences: age, gender, personal impact of Covid-19, and living under an active stay-at-home order.[12]

The age distribution of the CDR sample was highly right-skewed, with a large cluster of participants in their early 20s, while the MTurk sample exhibited a flatter, more normal distribution around the mean age of 35. Men slightly outnumbered women in the MTurk Sample, but women outnumbered men by a margin of 2:1 in the CDR sample. A larger proportion of participants in the CDR sample (around 70%) reported that they were "severely" personally impacted by Covid-19 than in the MTurk sample (closer to 55%). Over 20% of the

[12] There is also a *much* larger proportion of participants from the South in the MTurk sample than in the CDR sample. But, I don't think it's productive to conjecture about cultural differences between US regions without any concrete evidence that these differences exist *and* are relevant in the context of the present experimental task. Also, it was painful enough to have to trudge through the gender differences literature.

MTurk sample reported that they were only “slightly impacted” by Covid-19, which was a rare response among the CDR sample. Finally, around 80% of the CDR sample reported that they were currently living under a stay-at-home order, compared to only 60% of participants in the MTurk sample.

I will just quickly highlight a few behaviors associated with each of these variables that I think could be relevant in the context of the present experimental task. But, to be very clear, for the age and gender effects I am cherry-picking from among those studies that demonstrate significant results. It is important to keep in mind that for any significant effects of age and gender identified in the literature, *especially* for gender, there exists at least one study exhibiting no effect, and at least one other study exhibiting an effect in the opposite direction. It is important for the reader to keep that in mind.

In the context of economic and social games, younger age (specifically, college student status) has been associated with less generosity, lower reciprocity motivation, and lower prosociality compared with representative samples from the adult population (Cappelen et al., 2015; Carpenter, Burks, & Verhoogen, 2005). This is inconsistent with what we observe in the CDR sample (versus MTurk). CDR participants were *more* likely to share results, implying higher prosociality and reciprocity motivation.

What is difficult with the CDR sample is that they are not really a “student” sample. There are a good number of community members in the CDR pool. So the relatively younger age of the CDR sample does not necessarily imply a higher proportion of students *per se*. If anything, looking more closely at their explore-exploit strategies, the CDR sample seems very inconsistent with the stereotype of a “college student.” For example, it seems like the CDR participants might be having a harder time updating their beliefs over the platform value distributions. Just looking at the Control Condition, where participants have an advantage because they are repeatedly sampling from the same range of values, CDR participants are having a tougher time finding the True Top Three platforms in each Phase than participants in the MTurk sample.

We also don't see the same improvement in Discovery *across* Phases among the CDR Control participants that we do among the MTurk participants. CDR participants also exploiting their Personal-Best platforms less often, and their Standardized Achievement Acores are lower. Given these "anomalies," I don't think focusing on the age difference between samples is going to give us much traction.

Evidence of gender effects in economic and social games has been inconsistent and often contradictory. I just want to mention that one more time before I highlight a few very selective examples of gender differences that *might* exist. Female gender has been associated with higher reciprocity motivation, higher prosociality, and lower competitiveness compared with representative samples of adult men (Boschini et al., 2014; Brañas-Garza, Capraro, and Rascón-Ramírex, 2018; Gneezy, Niederle, & Rustichini, 2003), but the evidence for gender differences among college students is mixed (Cappelen et al., 2015). Higher reciprocity and lower response to competitive environments is consistent with the higher rates of sharing we observe among CDR participants in Study 3B.

Women have also been found to make more positive assessments of prospective team members' abilities (Kuhn & Villeval, 2015), and all-women teams have been found to be better at collaborating than mixed-gender or all-male teams in some cases (Berge, Juniwaty, & Sekei, 2016). Higher expectations over peers' abilities could increase participants' interest in viewing peers' results. And, a propensity toward collaboration could incline participants toward coordinating search for the highest-valued platforms in each Phase.

The heightened perception of being personally impacted by Covid-19, and the higher frequency of living under a stay-at-home order, could also be the source of behavioral differences between the two pools. In their longitudinal study of university students in Wuhan, Schachat, Walker, and Wei (2020) found that trust, cooperation, altruism, and risk tolerance increased following the onset of the pandemic. However, this only occurred among those students who *left* Wuhan to stay with their families during lockdown. Students who *remained* in Wuhan exhibited lower trust, lower cooperation, and ambiguity aversion. This is consistent with the literature on near misses (Eckel, El-Gamal, & Wilson, 2009; Madsen, Dillon, & Tinsley, 2016), where an "almost disaster" is sometimes processed as a "success" and increases a person's perception of their own luck, skill, or resilience. While the full experience of a disaster and its consequences has the opposite effect.

Unfortunately, this doesn't get us very far. Whether participants who report severe personal impact from Covid-19 follow one path (increased altruism, cooperation, risk tolerance) or the other (lower trust, ambiguity aversion) really depends on how the participant defines "severe." There is a difference between being hospitalized, or losing a loved one, and being upset that you can't attend class in-person or hang out at crowded bars. Some people would reserve the rating "severely impacted" only for the former case, others would freely use it in the latter. Judging by the CDR participants' behavior in the experiment, it seems more like they are experiencing the "severe impact" of Covid-19 as a near miss than as a debilitating catastrophe.

I think the only way to really figure out what's going on here is to use a method like inverse probability of treatment weighting (IPTW) or marginal mean weighting through stratification (MMWS, see Hong, 2012) to homogenize the two participant pools across as many observables as are available at time zero (the Enrollment Questionnaire and the Feelings Inventory collected before the start of the experiment). The problem is that you need to define the propensity score model on a control group (or, at least within Conditions, you'd need to choose one the participant pools to use as your base), and it's not clear which group that should be in this case.

Control participants in the MTurk and CDR pools behave quite differently, and have quite different joint distributions over observable individual difference measures. Without having some idea which group really represents the "ground truth" for behavior in the present experimental paradigm, it doesn't make sense to try and weight participant observations based on the "representativeness" of a given participant as a function of whichever group you used to define the propensity score model.

7.4.4 Emerging Challenges for Online Experiments

Between December 2019 and June 2020, suspected fraudulent Worker accounts appearing in experiments I ran on MTurk increased from approximately 5% to more than 50%. I currently use state-of-the-art automated methods for preventing and detecting fraud. And, I restrict access to only Workers living in the United States who have completed at least 1000 HITs and have an approval rating of more than 98%. None of my automated measures (which worked well prior to 2020) were sufficient to protect my experiments from bad actors. I resorted to building my own panel of pre-screened Worker accounts using a specially designed screening questionnaire. I reviewed every single response by hand, and only Workers who passed the screening criteria were allowed to participate in the present experiments (see Section *A.1 MTurk Screening*

Criteria in the Supplement). Despite my best efforts, I am sure some bad actors made their way into the present experiments.

It seems that fraudulent accounts are entering the MTurk platform at an increasing rate. Many of these accounts are run by groups of coordinated actors, who share information about screening questionnaires, and experimental tasks, to maximize the amount of money they can extract from researchers. Worker accounts with US mailing addresses are currently being bought and sold on web forums. There are owners of US Worker accounts renting those accounts out like taxi medallions. I've seen evidence that fraudulent accounts can remain active on MTurk for months before they are detected (and some may never be detected).

Due to the relatively high pay rate I offered for the present experiments, I was specifically targeted by these groups. In addition to attacking my experiments, they also attacked me personally, and repeatedly. I received daily emails from Workers threatening to slander me on online forums, or to report me to the IRB and get me "kicked out of school," unless I paid them. Most of these emails came from Worker accounts for which I had no record of the Worker ever interacting with the experimental task. It seems that certain criminal groups believe researchers will cave easily to threats, and are using aggressive harassment campaigns as an alternative method for extracting money when they are unable to pass through screening mechanisms.

Even honest Workers can sometimes undermine an entire research program. Workers post detailed information about HITs on community forums and on Reddit. Sometimes these posts reveal experimental manipulations. The focal manipulation of the present research program was revealed in a post to TurkerView on October 20, 2020. This was right in the middle of the most critical period of data collection, while Studies 3A and 3B were being run daily. It took me two days to get the post removed (the author and site moderator were both very kind and responsive, and the author did not intend to reveal the manipulation, but it took a couple days to get in touch and explain the situation). These posts are automatically displayed to the thousands of Workers who use TurkerView. It is impossible to know how many participants were exposed to this information.

My experimental manipulation was also revealed in a Reddit post at some point between October and November, 2020. I was not actively monitoring Reddit for reviews of my HITs, so I did not realize this occurred until after the forum moderators removed the post. I have no idea how long the post was visible before the moderators removed it, or how many Workers were exposed to the post content.

These problems are not unique to MTurk. The same criminal actors hold accounts on other crowdsourcing platforms, such as Prolific. In my view, products offered by third-party service firms do not provide sufficient protection against this mass of increasingly sophisticated fraudsters. (And, it should be cause for concern whenever third-party providers refuse to reveal the details of their own screening methods.)

All this is to say that the research community needs to strongly consider shifting away from crowdsourcing platforms unless it is possible to implement validated approaches for maintaining thoroughly vetted panels of crowdsourced participants. I recommend introducing significant hurdles to the screening process, such as requiring each new participant to interview with the research team or an *in-house* representative over video conference before they are cleared to join the panel. I strongly advise against "outsourcing" *any* aspect of this process to third party service firms.

7.5 Future Directions

It seems necessary at this point to construct a research program around a unified experimental paradigm in which it is possible to manipulate each component of scarcity in isolation to better understand their individual effects on behavior. Then, within the same paradigm, we can begin to combine components to understand the effect of their interactions. One problem with the social learning and behavioral ecology literature is that each research team comes up with its own experimental paradigm, and the idiosyncrasies of these interactive tasks are such that it is difficult to compare their results with one another.

I have great admiration for the clever tasks designed by behavioral ecologists (e.g. Toelch, Mesoudi, and their colleagues), but I struggle to understand how one might extrapolate their results to other experimental contexts. By choosing to use my own novel experimental paradigm in the present experiments, I have contributed to this problem. In retrospect, I'm not sure whether it was a good choice to pursue "mundane realism" over paradigmatic cohesion. In future research, experimentalists should first investigate their research question using established paradigms before transitioning to novel contexts. This would help us build a more coherent set of empirical results from which it will be easier to extract consistent behavioral patterns that can help us refine theory.

We've started to accumulate really rich, exciting observational studies that demonstrate how groups respond to crisis, but it doesn't seem like we have the theoretical or experimental tools to disentangle the underlying mechanisms present in each context. Can we compare the experience of a middle manager at Enron in December, 2001, to that of a hedge fund analyst following a stock price shock in 2014? If we observe both people respond similarly to their respective crises, does that mean the same mechanisms are driving their behavior? I don't think we have any way to know right now. But, things sure aren't getting better anytime soon. So, we should probably start trying to figure it out.

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9 SUPPLEMENT

A.1 MTurk Screening Criteria

MTurk participants' responses to the Enrollment Questionnaire were evaluated based on the following criteria. If the participant failed more than one of the below criteria, they were not allowed to participate in the focal experiments.

1. *Location:* The participant was asked to report their home state twice, on two separate pages (participants had the option to select "Prefer not to disclose"). If the participant reported a different home state the second time this question was asked, the participant failed this criterion.
2. *Home State Open Response:* Participants were asked, "What is your favorite thing about living in your home state? (Please respond with one complete, grammatically correct sentence)." If the participant provided a one-word answer, they failed this criterion. If the participant pasted content from a website such as the state tourism websites, they failed this criterion. If the participant's response was non-sequitur, or incoherent, they failed this criterion.
3. *Non-Existent News Providers:* Participants were presented with a list of news providers (e.g. CNN, Fox, MSNBC) and asked to select all of the news providers they regularly consulted and trusted. Two of the provider names were fabricated ("American Post" and NWTC"). If the participant selected either of these fabricated provider names, they failed this criterion.
4. *Close Contacts:* Participants were asked to provide *only a first name* or a *nickname* for each of their closest contacts. If participants provided first and last names, they failed this criterion. If participants provided something other than names, such as email addresses and phone numbers, they failed this criterion. If participants provided a non-sequitur (e.g. copy pasting a portion of a novel), they failed this criterion.
5. *CDR + MTurk*: Participants were asked 1) if they ever participant in experiments through the Center for Decision Research at the University of Chicago Booth School of Business, and 2) to report whether they recall participating in The Sales Game only if they regularly participate in experiments through the CDR. If the participants' responses to these two questions contradicted one another (e.g. the participant answered "No" to the first question, and "Yes" to the second question), they failed this criterion.

A.2 Studies 3A & 3B: Participant Pools

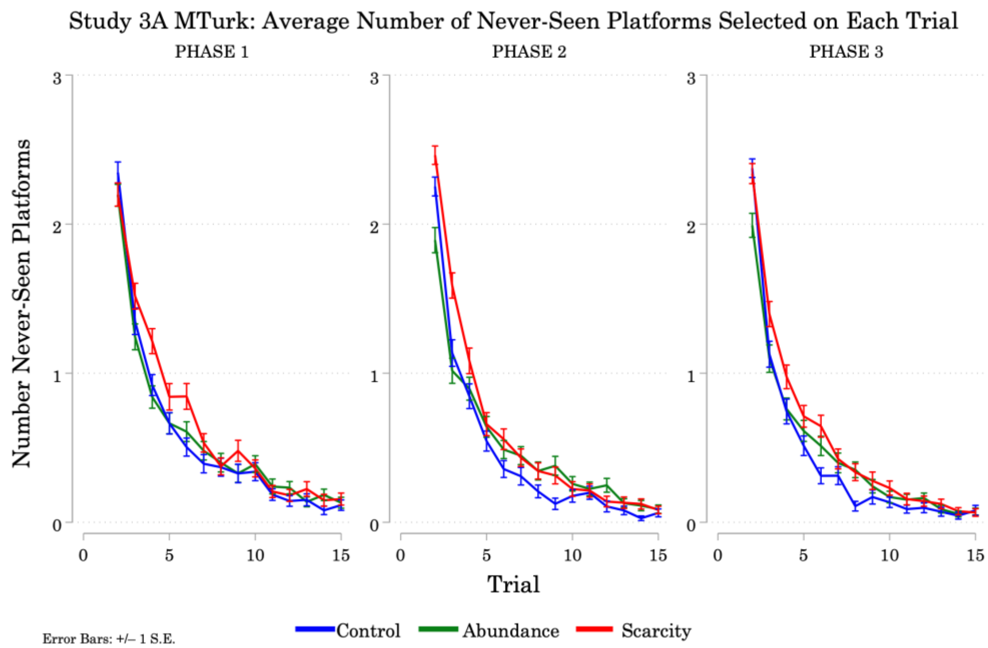
Each section of this Appendix is organized as follows: 1) brief summary of differences between participant pools, 2) pool-specific figures for each dependent variable.

A.2.1 Study 3A: Differences between Participant Pools

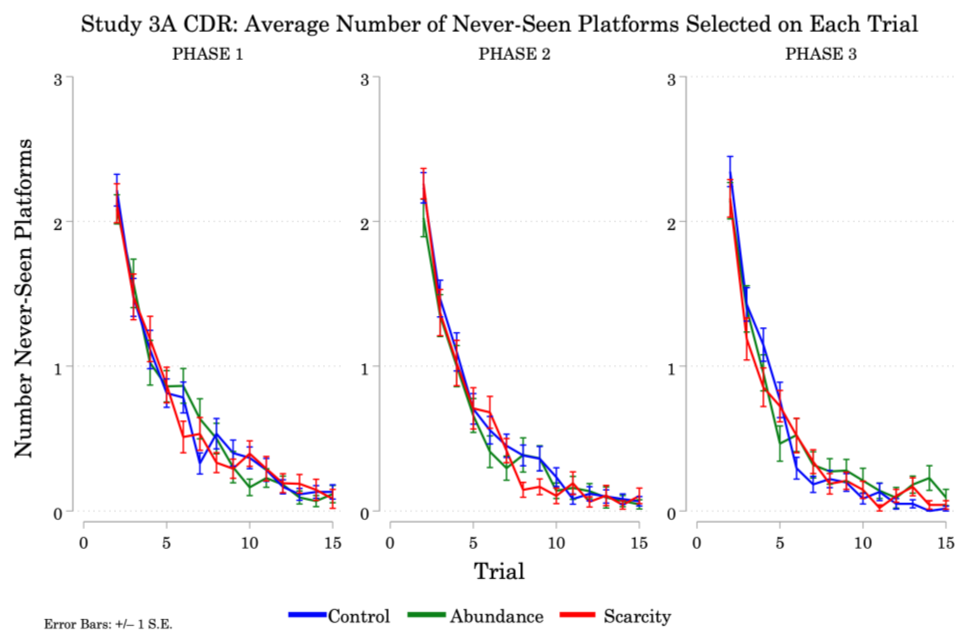
See Table 6.1 in Section 6.1 for the count of groups (and participants) in each experimental Condition, by recruiting source (CDR versus MTurk).

Summary of differences between participant pools:

1. Exploration
   - MTurk: Scarcity explores ***more*** in every Phase
   - CDR: ***No differences*** in any Phase
2. Exploitation
   - MTurk: Scarcity exploits ***less*** in every Phase
   - CDR: ***No differences*** in any Phase
3. Discovery
   - MTurk: Scarcity selects top-three highest valued ***less*** often in Phases 1, 2, 3
   - CDR: Scarcity selects top-three highest valued ***more*** often in Phases 1 & 2
4. Rewards
   - MTurk: Control ***higher*** than Scarcity / Abundance in Phase 2
   - CDR: Control ***lower*** than Scarcity / Abundance in Phase 2
5. Shares to peers
   - MTurk: Scarcity shares to ***fewer*** peers in Phases 2 & 3
   - MTurk: Scarcity shares to ***more*** peers in Phases 1, 2, 3
6. Peer views
   - MTurk: Control views ***more*** peers on early Trials of Phases 2 & 3,
     no difference on later Trials of Phases 2& 3
   - CDR: ***No difference*** on early Trials of Phases 2 & 3,
     Abundance views ***more*** peers on later Trials of Phases 2 & 3

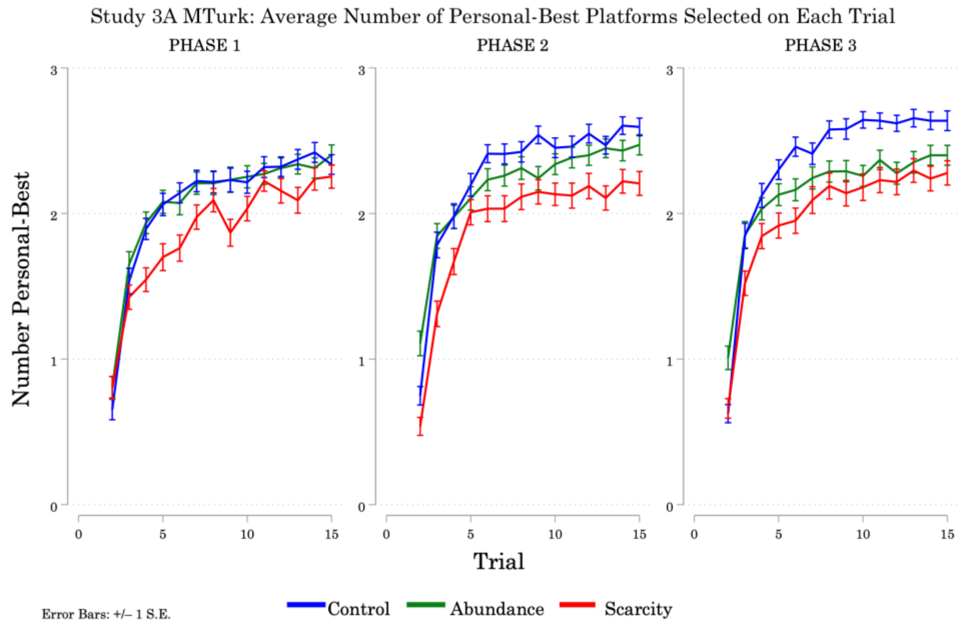


(a)

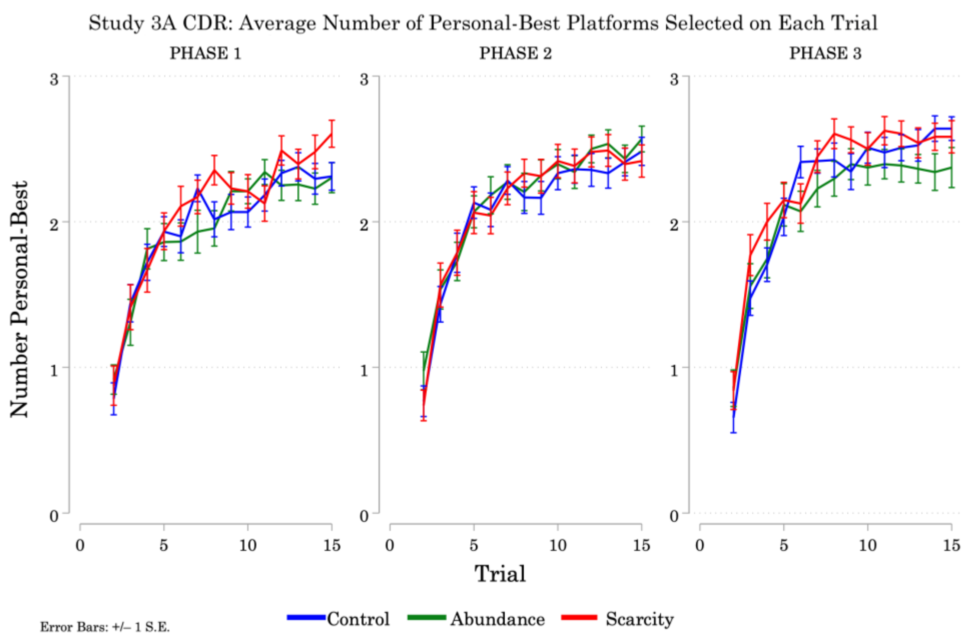


(b)

Figure A.2.1. Study 3A: Exploration – MTurk versus CDR. Average number of Never-Seen platforms selected on each Trial by participants recruited through MTurk (a) and by participants recruited through the CDR (b).

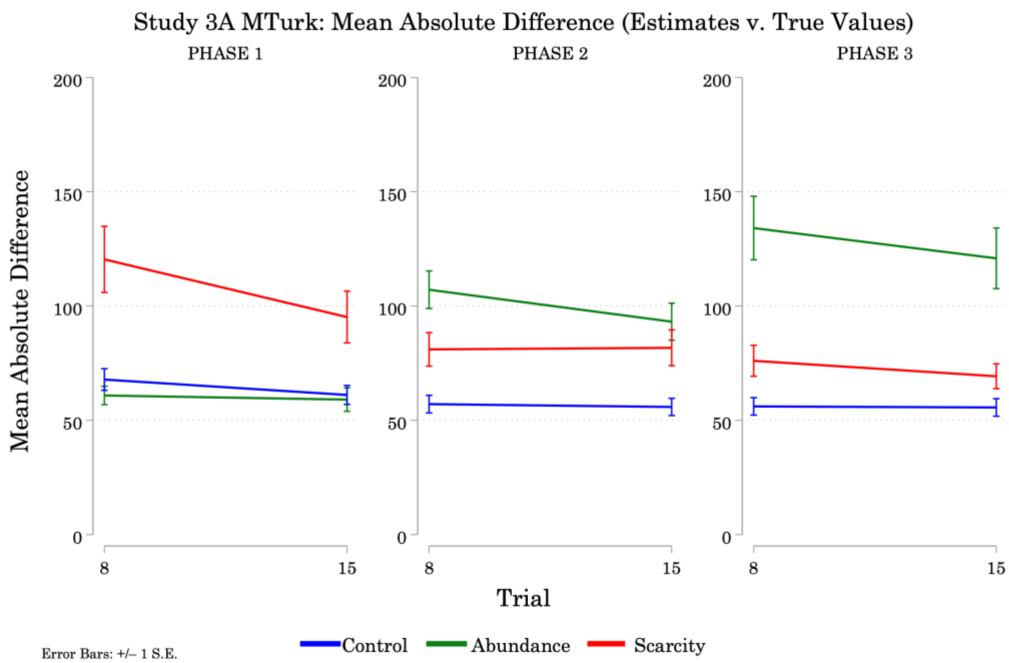


(a)

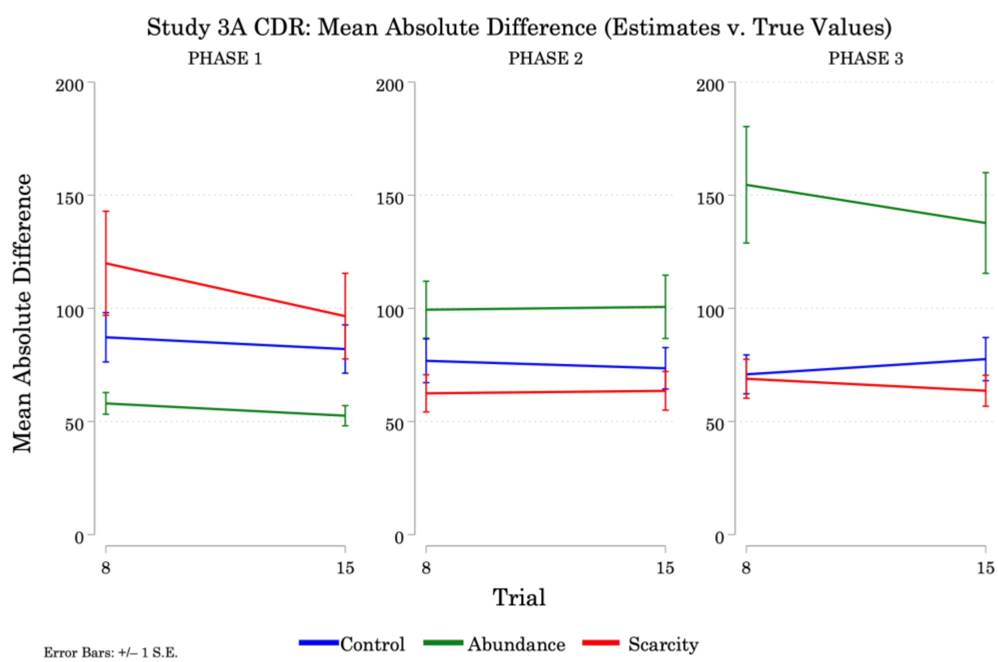


(b)

Figure A.2.2. Study 3A: Exploitation – MTurk versus CDR. Average number of Personal-Best platforms selected on each Trial by participants recruited through MTurk (a) and by participants recruited through the CDR (b).

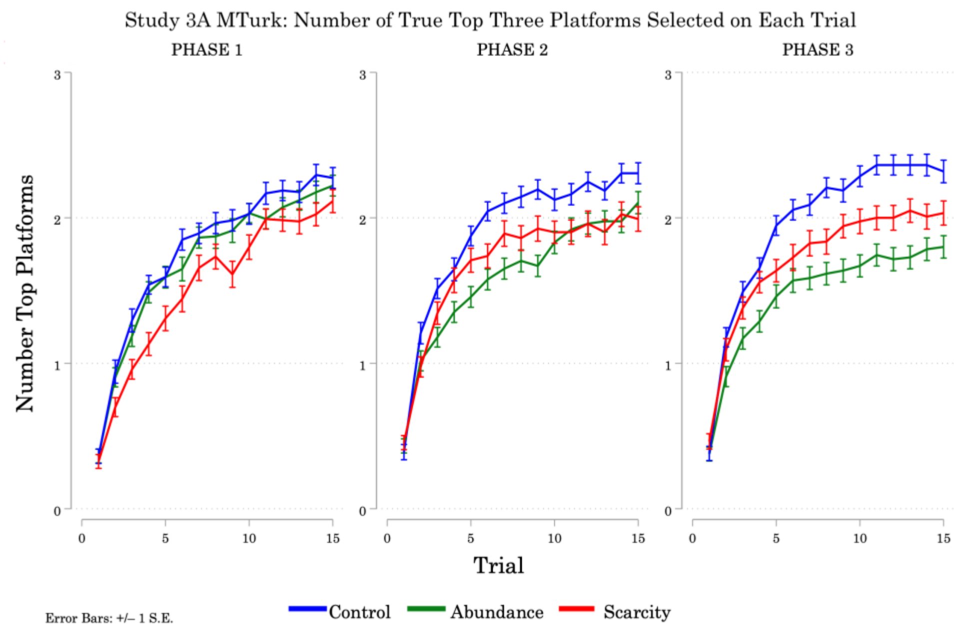


(a)

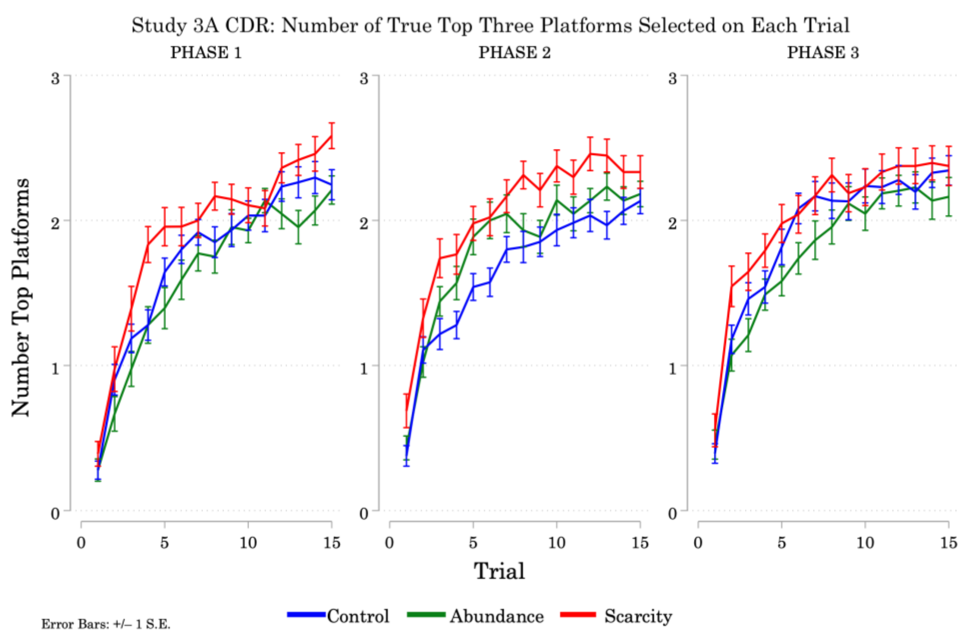


(b)

Figure A.2.3. Study 3A: Mental Models – MTurk versus CDR. Mean absolute difference between true platform values and estimates submitted by participants recruited through MTurk (a) and by participants recruited through the CDR (b).

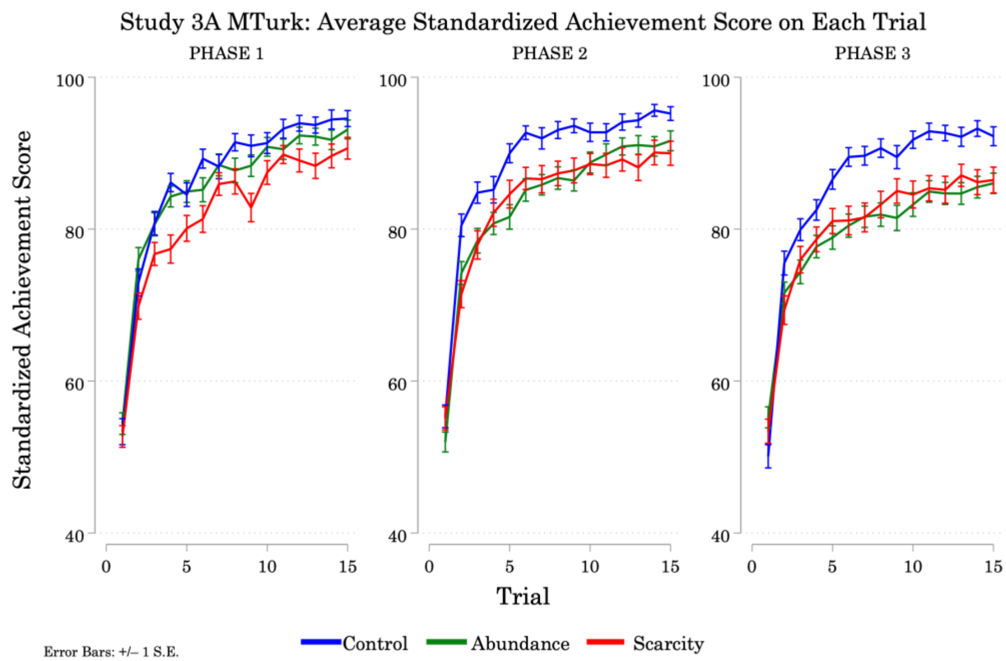


(a)

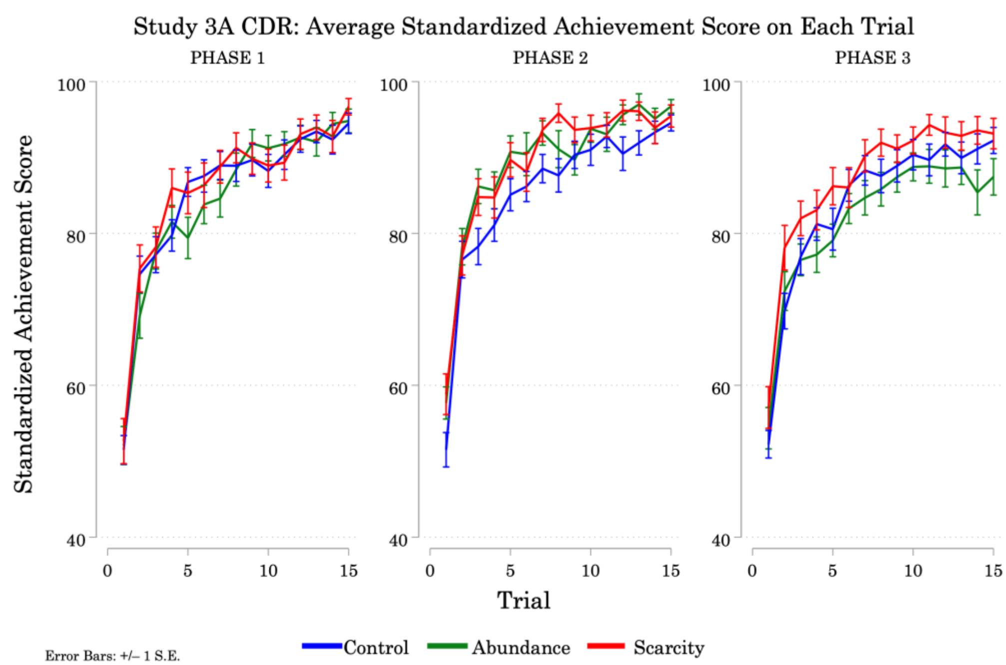


(b)

Figure A.2.4. Study 3A: Discovery– MTurk versus CDR. Number of True Top Three platforms selected on each Trial by participants recruited through MTurk (a) and by participants recruited through the CDR (b).

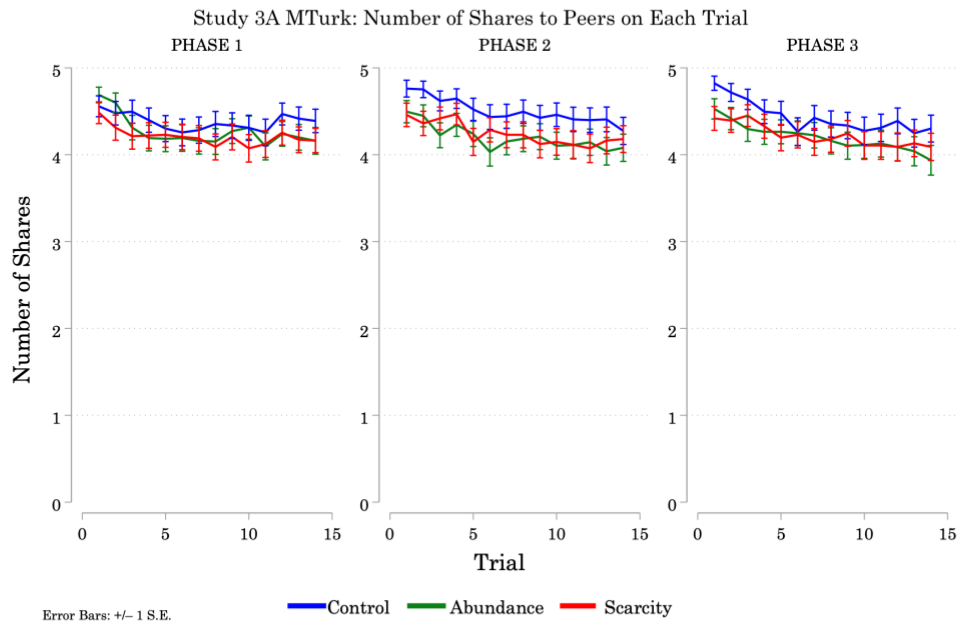


(a)

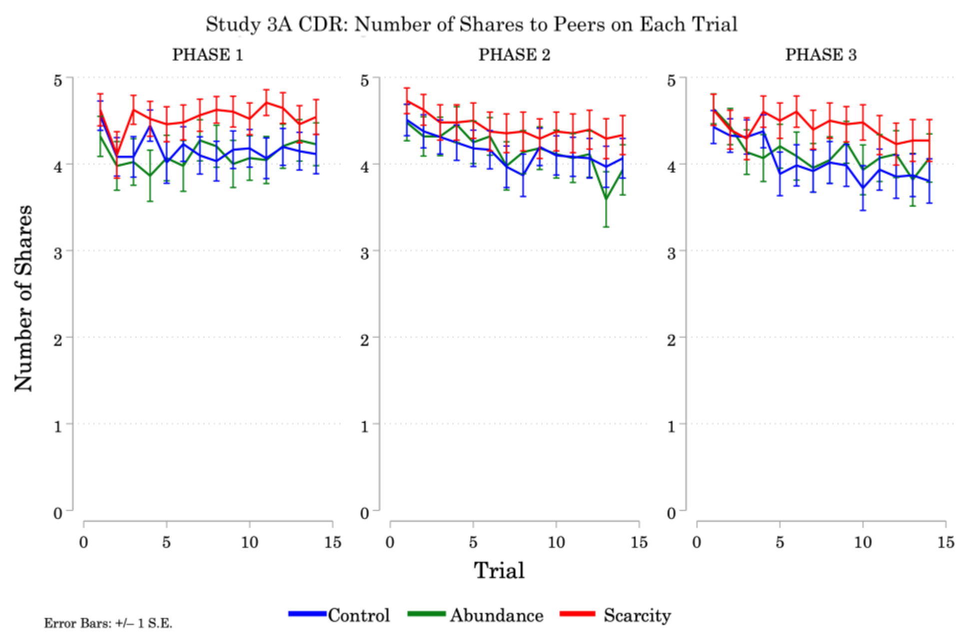


(b)

Figure A.2.5. Study 3A: Rewards– MTurk versus CDR. Average standardized achievement score earned on each Trial by participants recruited through MTurk (a) and by participants recruited through the CDR (b).

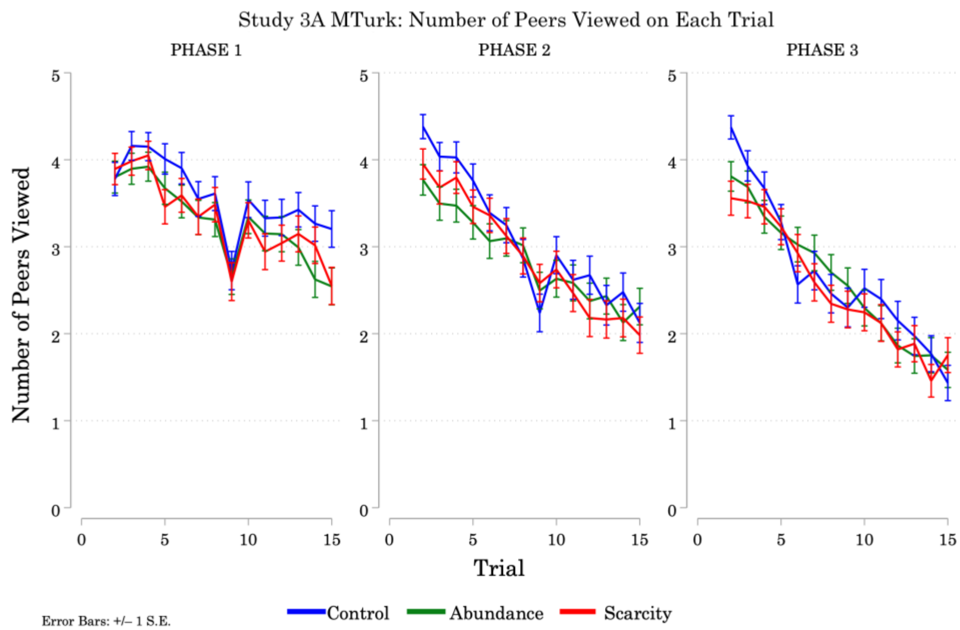


(a)

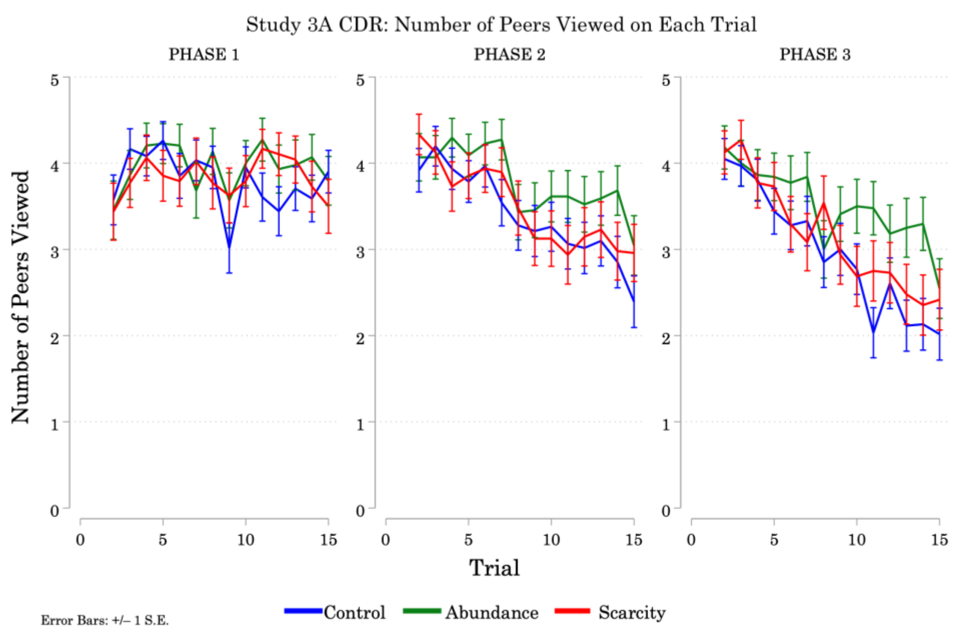


(b)

Figure A.2.6. Study 3A: Shares to Peers – MTurk versus CDR. Average number of peers with whom results were shared on each Trial by participants recruited through MTurk (a) and by participants recruited through the CDR (b).



(a)



(b)

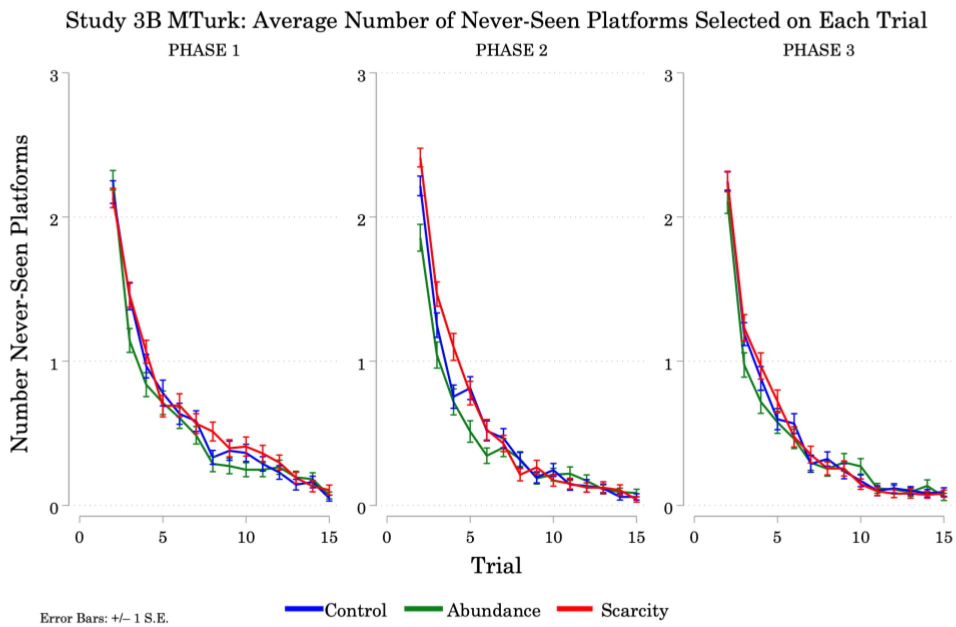
Figure A.2.7. Study 3A: Peer Views– MTurk versus CDR. Average number of peers whose results were viewed on each Trial by participants recruited through MTurk (a) and by participants recruited through the CDR (b).

A.2.2 **Study 3B**: Differences between Participant Pools

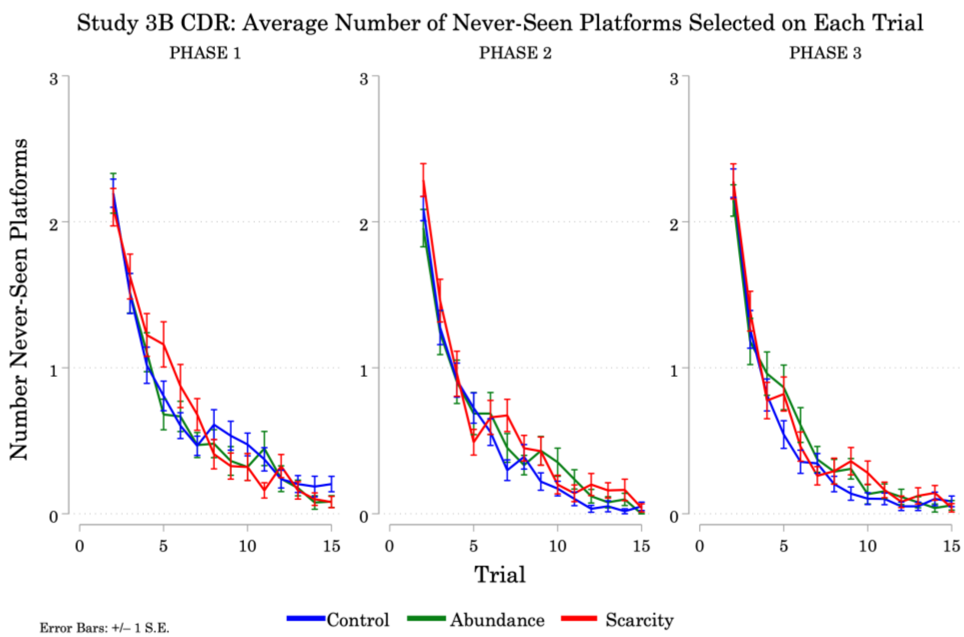
See Table 6.20 in Section 6.2 for the count of groups (and participants) in each experimental Condition, by recruiting source (CDR versus MTurk).

Summary of differences between participant pools:

1. Exploration
   - MTurk: ***No difference*** between Control and Scarcity in any Phase, Abundance explores ***less*** than Control and Scarcity in every Phase
   - CDR: Scarcity explores more than Control in Phases 2 & 3, Abundance ***same as*** Control in Phase 2, ***same as*** Scarcity in Phase 3
2. Exploitation
   - MTurk: ***No differences*** in any Phase
   - CDR: Abundance exploits ***more*** than Control and Scarcity in Phase 1, Abundance and Control exploit ***more*** than Scarcity in Phases 2 & 3
3. Discovery
   - MTurk: Abundance selects top-three ***less*** often than others in Phases 2, 3
   - CDR: Abundance selects top-three ***more*** often than others in Phase 3
4. Rewards
   - MTurk: Control ***higher*** than Scarcity / Abundance in Phases 2 & 3
   - CDR: ***No differences*** in Phases 2 & 3
5. Shares to peers
   - MTurk: Abundance and Scarcity share ***more*** than Control in Phases 2 & 3
   - MTurk: Scarcity shares ***more*** than Abundance and Control in Phases 1, 2, 3
6. Peer views
   - MTurk: ***No differences*** in any Phase
   - CDR: Scarcity shares ***more*** in Phase 2 (maybe in Phase 3)

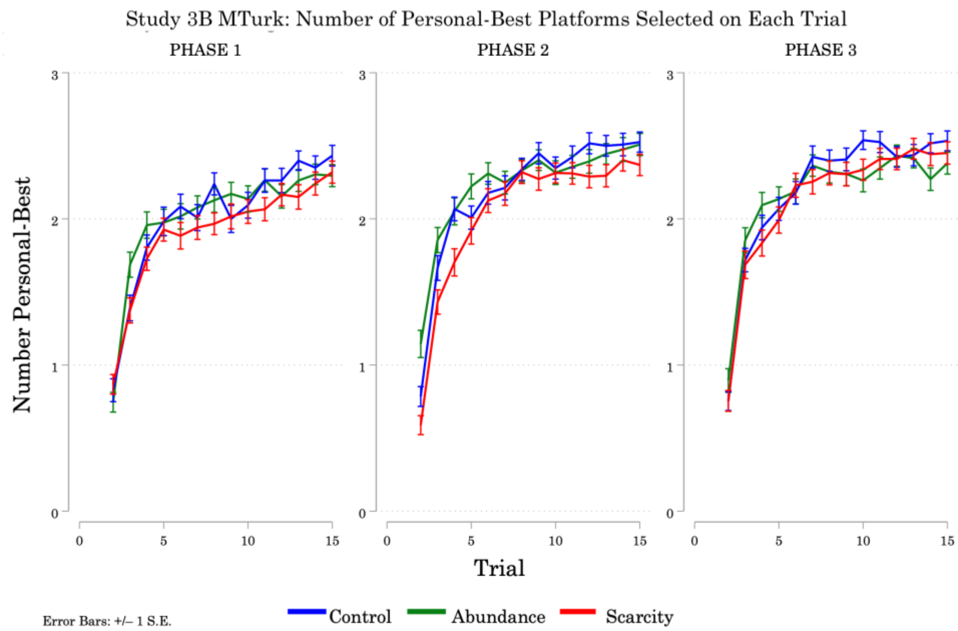


(a)

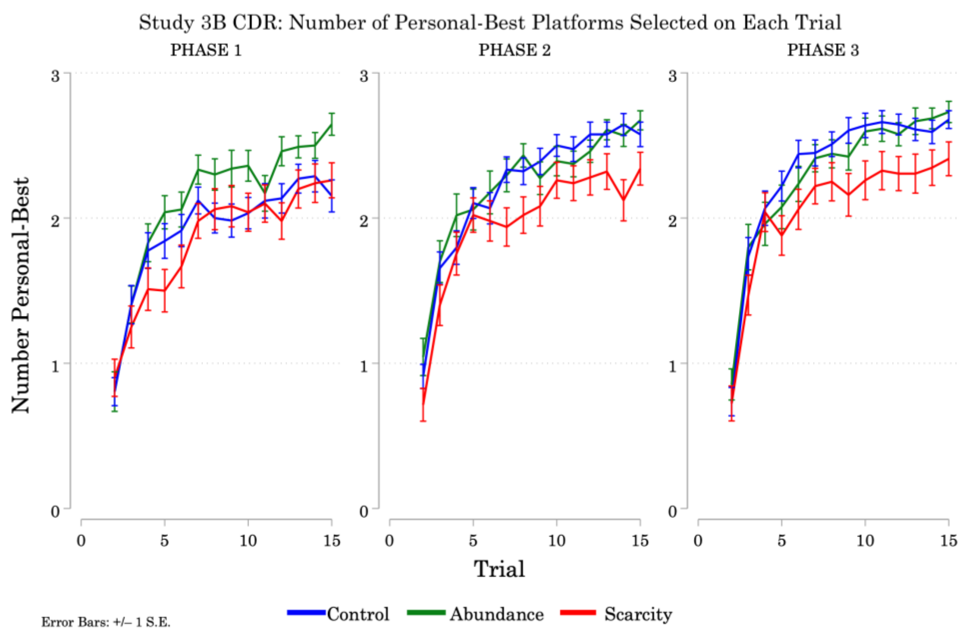


(b)

Figure A.2.8. Study 3B: Exploration – MTurk versus CDR. Average number of Never-Seen platforms selected on each Trial by participants recruited through MTurk (a) and by participants recruited through the CDR (b).

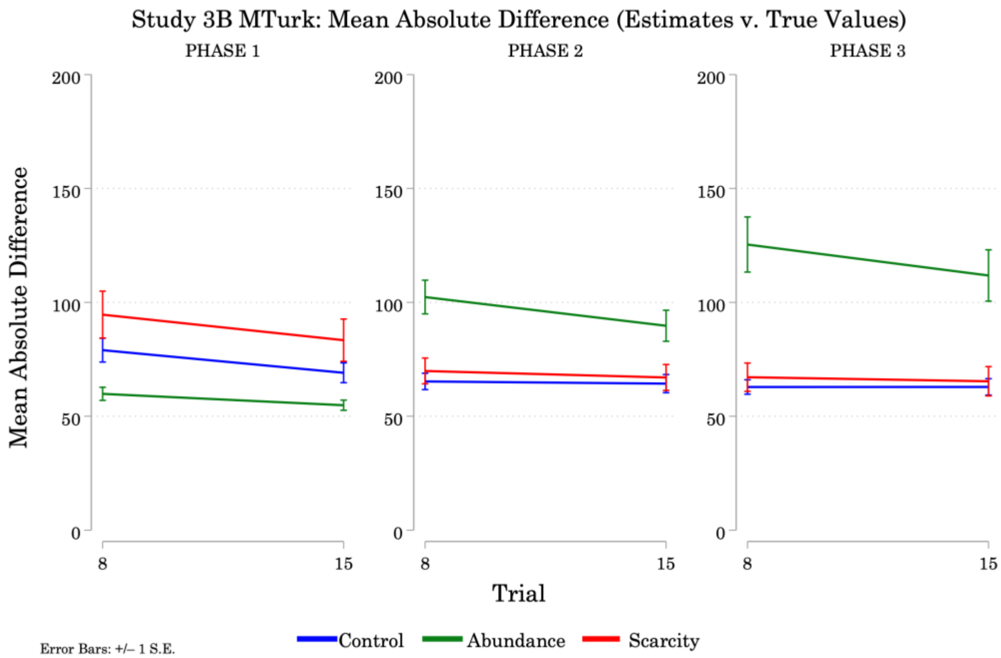


(a)

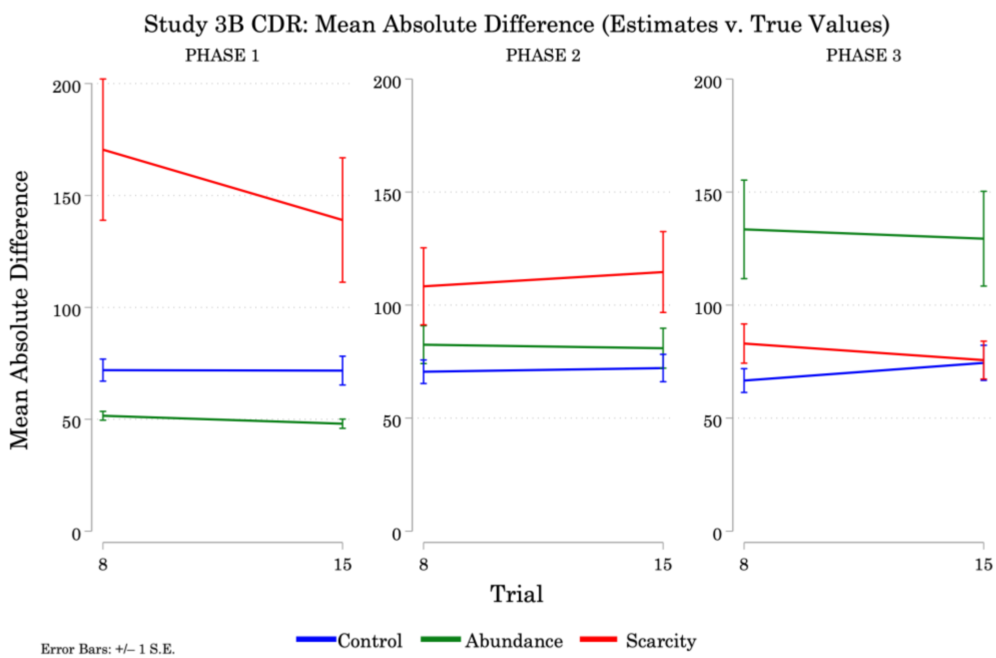


(b)

Figure A.2.9. Study 3B: Exploitation – MTurk versus CDR. Average number of Personal-Best platforms selected on each Trial by participants recruited through MTurk (a) and by participants recruited through the CDR (b).

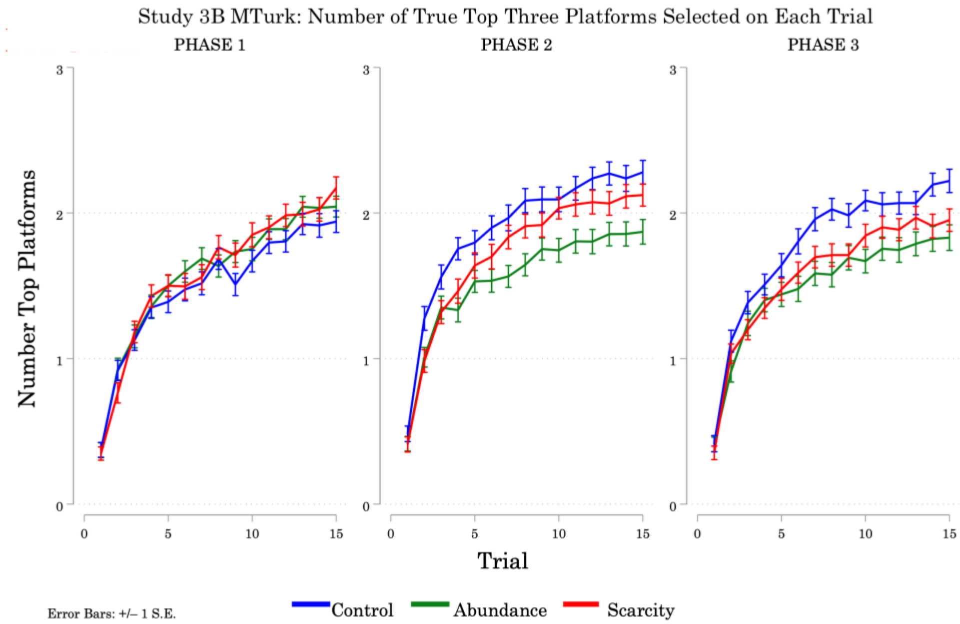


(a)

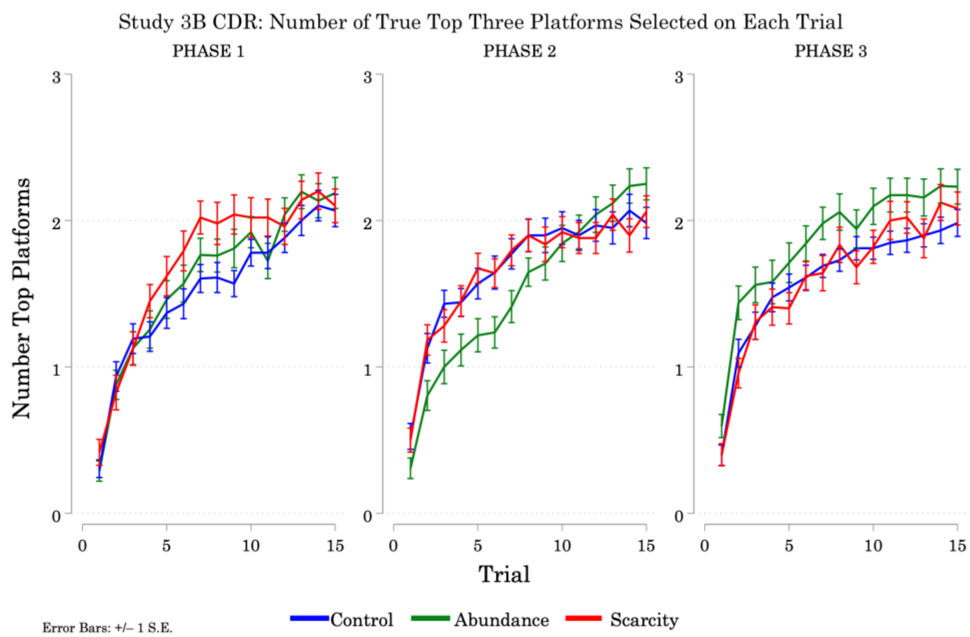


(b)

Figure A.2.10. Study 3B: Mental Models – MTurk versus CDR. Mean absolute difference between true platform values and estimates submitted by participants recruited through MTurk (a) and by participants recruited through the CDR (b).

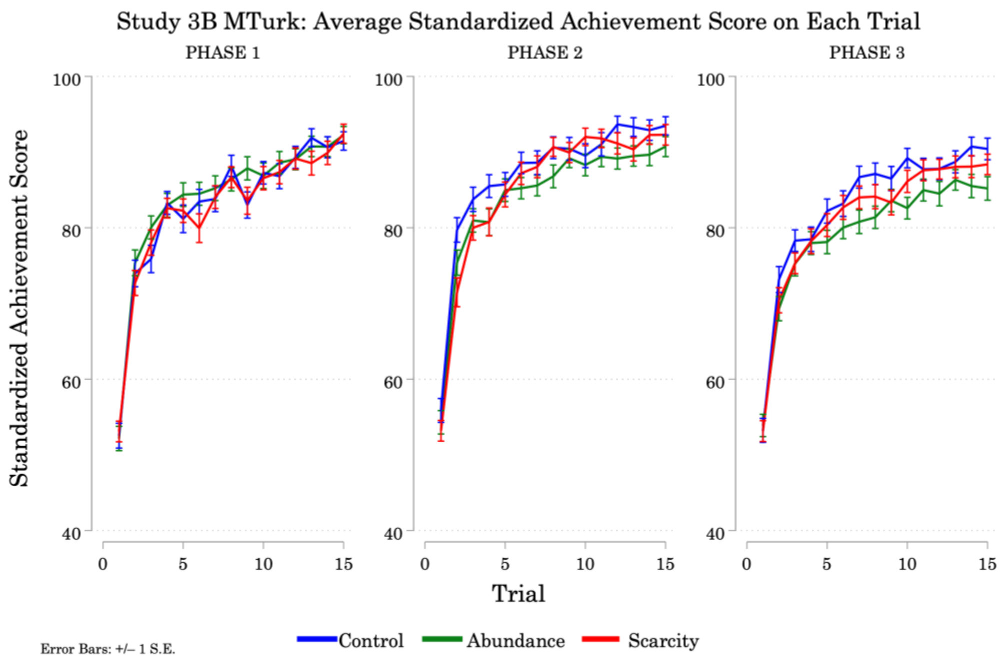


(a)

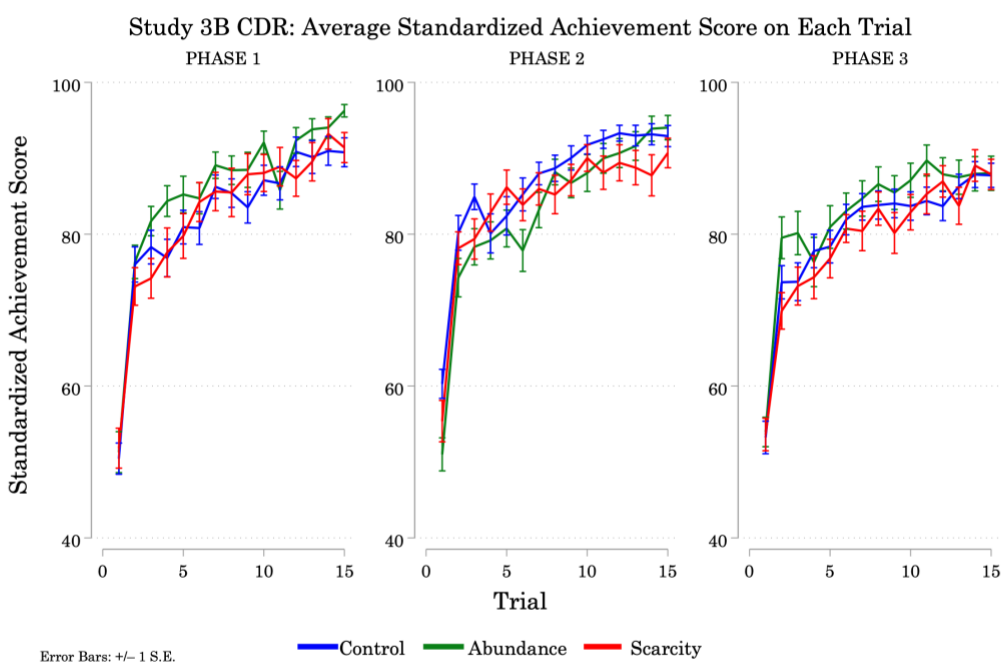


(b)

Figure A.2.11. Study 3B: Discovery– MTurk versus CDR. Number of True Top Three platforms selected on each Trial by participants recruited through MTurk (a) and by participants recruited through the CDR (b).

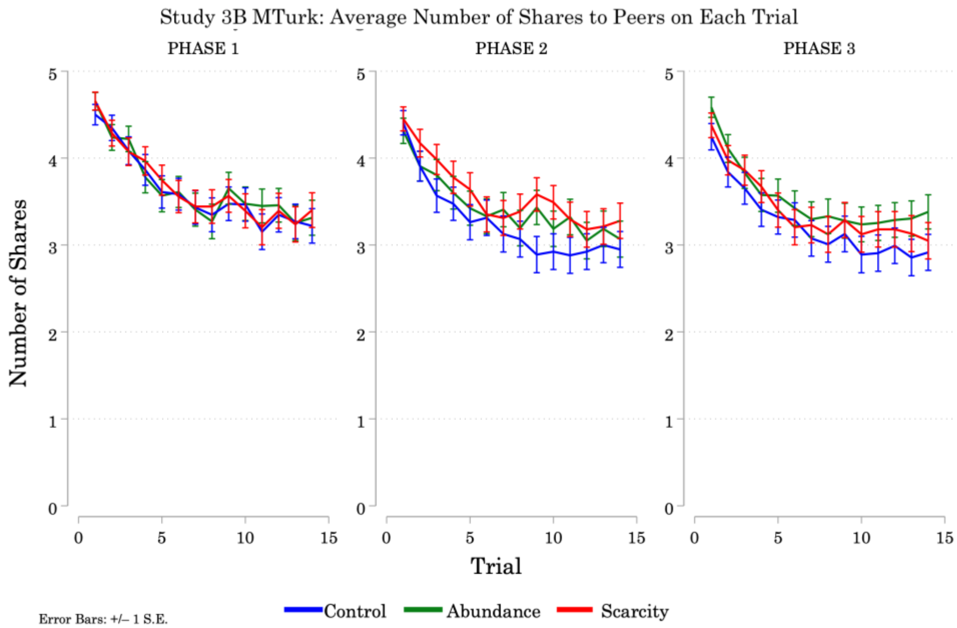


(a)

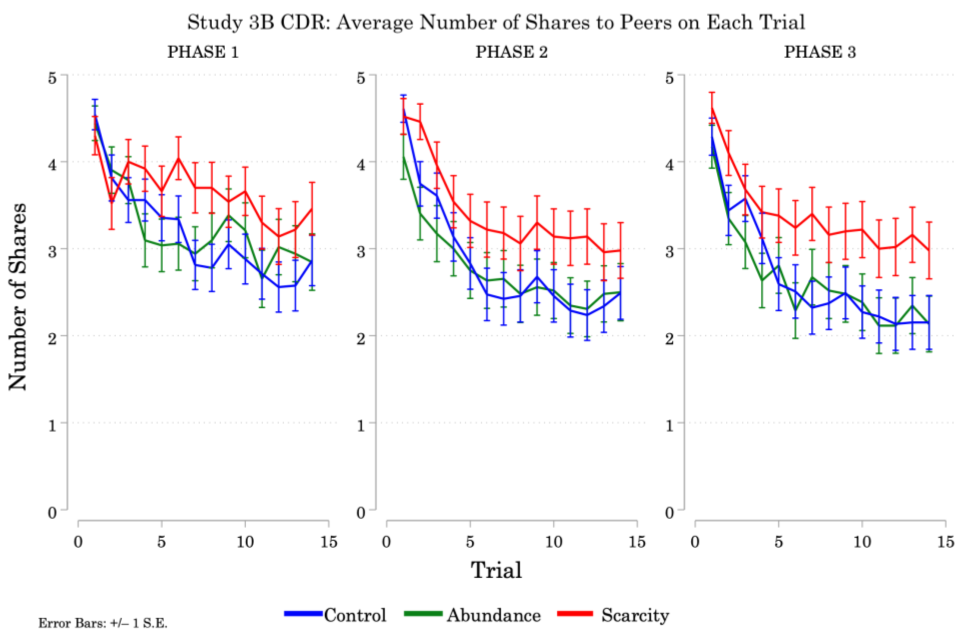


(b)

Figure A.2.12. Study 3B: Rewards– MTurk versus CDR. Average standardized achievement score earned on each Trial by participants recruited through MTurk (a) and by participants recruited through the CDR (b).

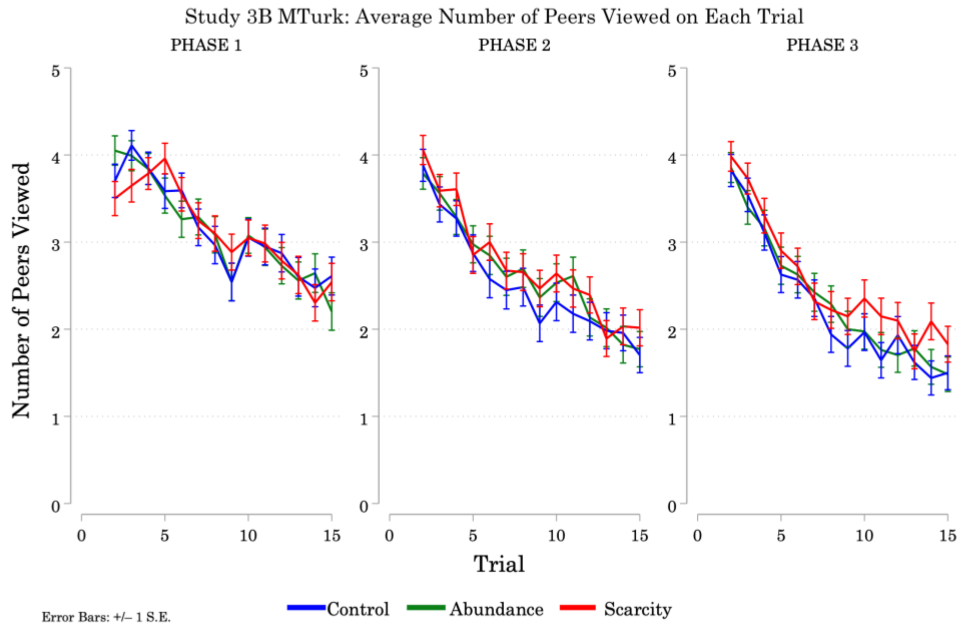


(a)

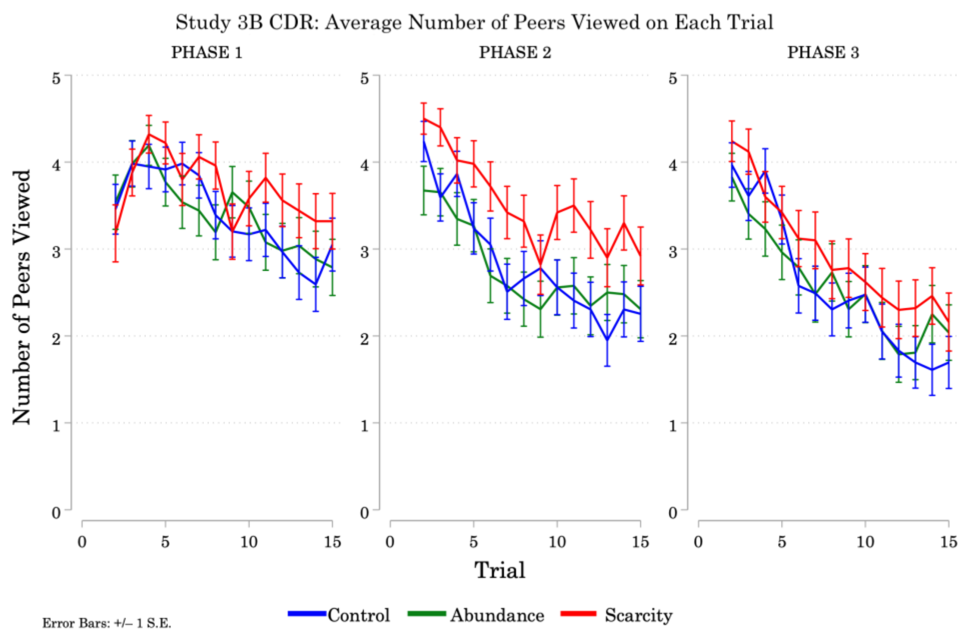


(b)

Figure A.2.13. Study 3B: Shares to Peers – MTurk versus CDR. Average number of peers with whom results were shared on each Trial by participants recruited through MTurk (a) and by participants recruited through the CDR (b).



(a)



(b)

Figure A.2.14. Study 3B: Peer Views– MTurk versus CDR. Average number of peers whose results were viewed on each Trial by participants recruited through MTurk (a) and by participants recruited through the CDR (b).

A.3 Studies 3A & 3B: Feelings Inventory

Participants were asked to rate the extent to which they were currently feeling each of six emotions (Happy, Friendly, Successful, Hostile, Anxious, Frustrated) prior to the start of the procedure (Trial 0), and on Trials 8 and 15 of each Phase.

> How are you feeling right now? Please rate each feeling below on the scale given. A rating of 0 means that you are not experiencing that feeling at all right now. A rating of 100 means you are experiencing that feeling very much right now.

The feelings were presented in random order each time they appeared. Participants indicated their ratings using a continuous sliding scale below the name of each feeling.

In each of the figures below, Trials are numbered from 0–45 so that it's easier to see how emotional states progressed across each Phase of the experiment. Phase 1 = Trials 8 & 15; Phase 2 = Trials 23 & 30; Phase 3 = Trials 38 & 45.

A.3.1 Study 3A: Feelings Inventory

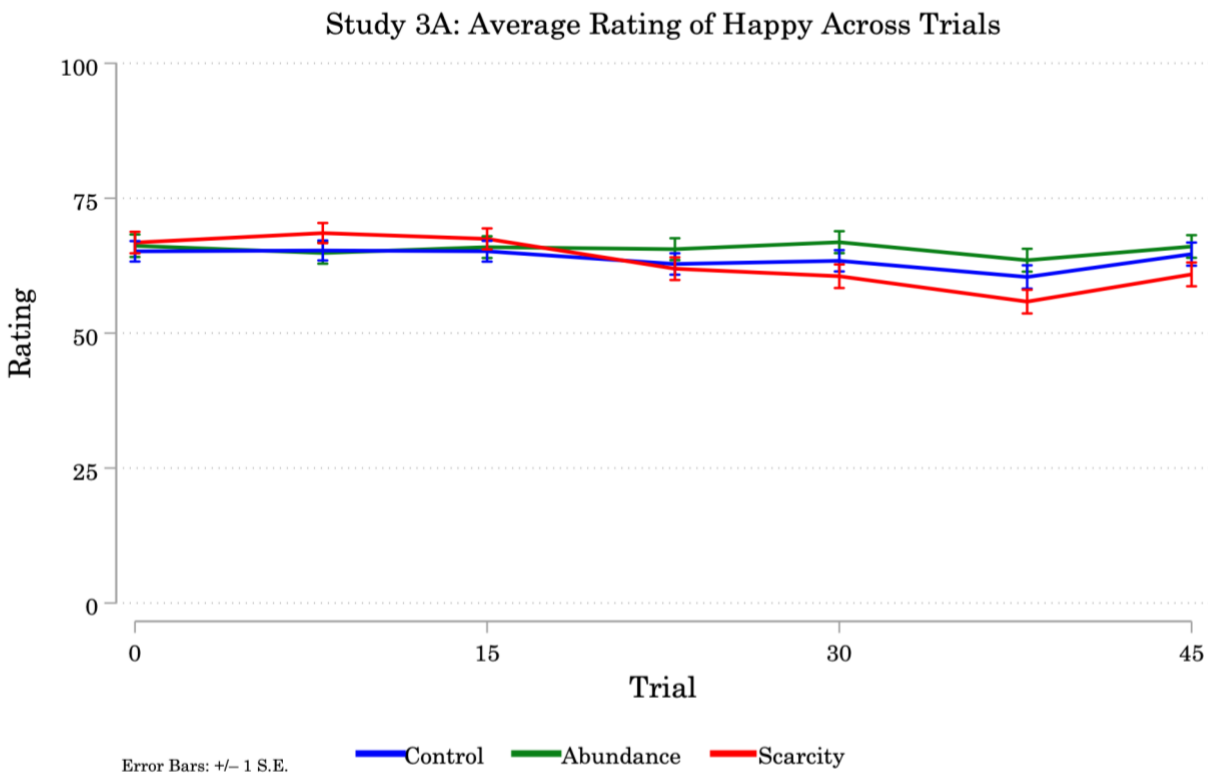


Figure A.3.1. Study 3A: Happy Ratings. Participant ratings of "Happy" before the procedure started (Trial 0), during Phase 1 (Trials 8 & 15), during Phase 2 (23, 30), and during Phase 3 (38 & 45). N = 513. Green = Abundance (169 participants, 30 groups); Blue = Control (174 participants, 30 groups); Red = Scarcity (170 participants, 29 groups). There are no significant differences between Control and Scarcity, or between Control and Abundance, on any Trial. Abundance participants' ratings are significantly higher than Scarcity participants' on Trials 30 (end of Phase 2), 38 (middle of Phase 3), and 45 (end of Phase 3).

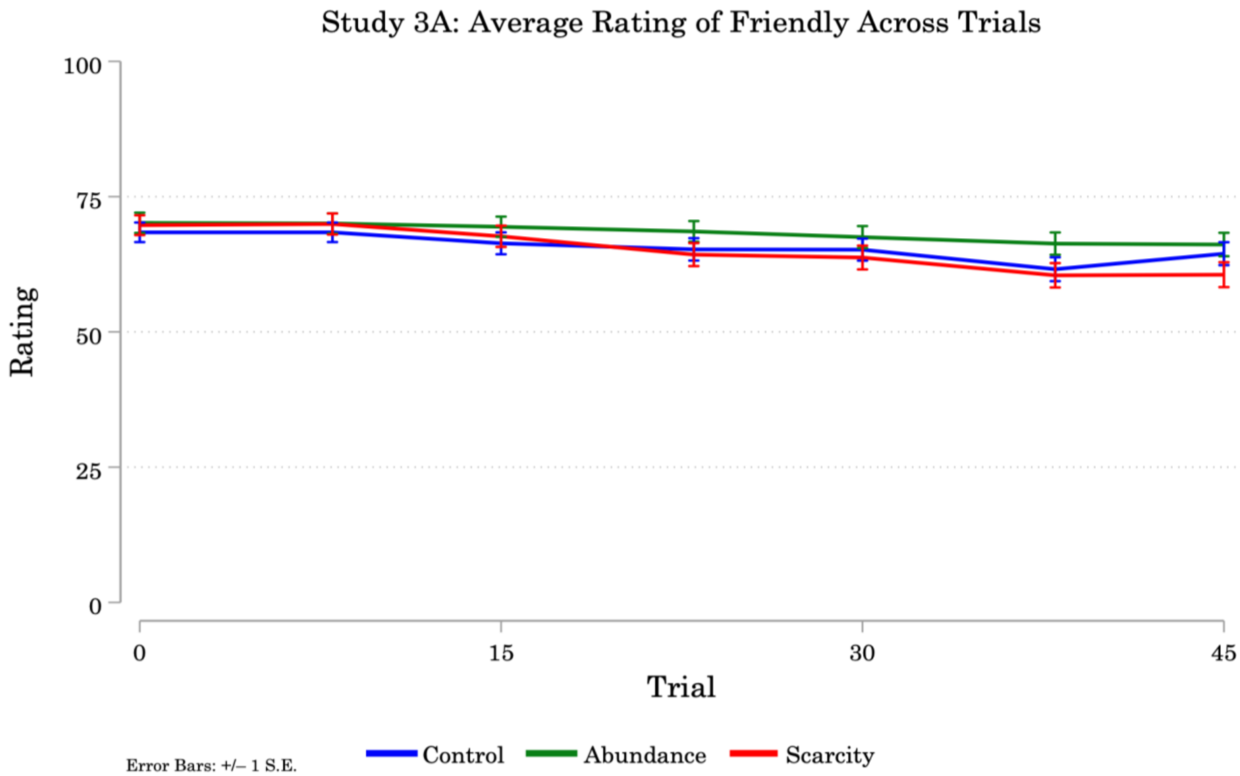


Figure A.3.2. Study 3A: Friendly Ratings. Participant ratings of "Friendly" before the procedure started (Trial 0), during Phase 1 (Trials 8 & 15), during Phase 2 (23, 30), and during Phase 3 (38 & 45). N = 513. Green = Abundance (169 participants, 30 groups); Blue = Control (174 participants, 30 groups); Red = Scarcity (170 participants, 29 groups). There are no significant differences between Control and Scarcity, or between Control and Abundance, on any Trial. Abundance participants' ratings are significantly higher than Scarcity participants' on Trials 38 and 45 (middle and end of Phase 3).

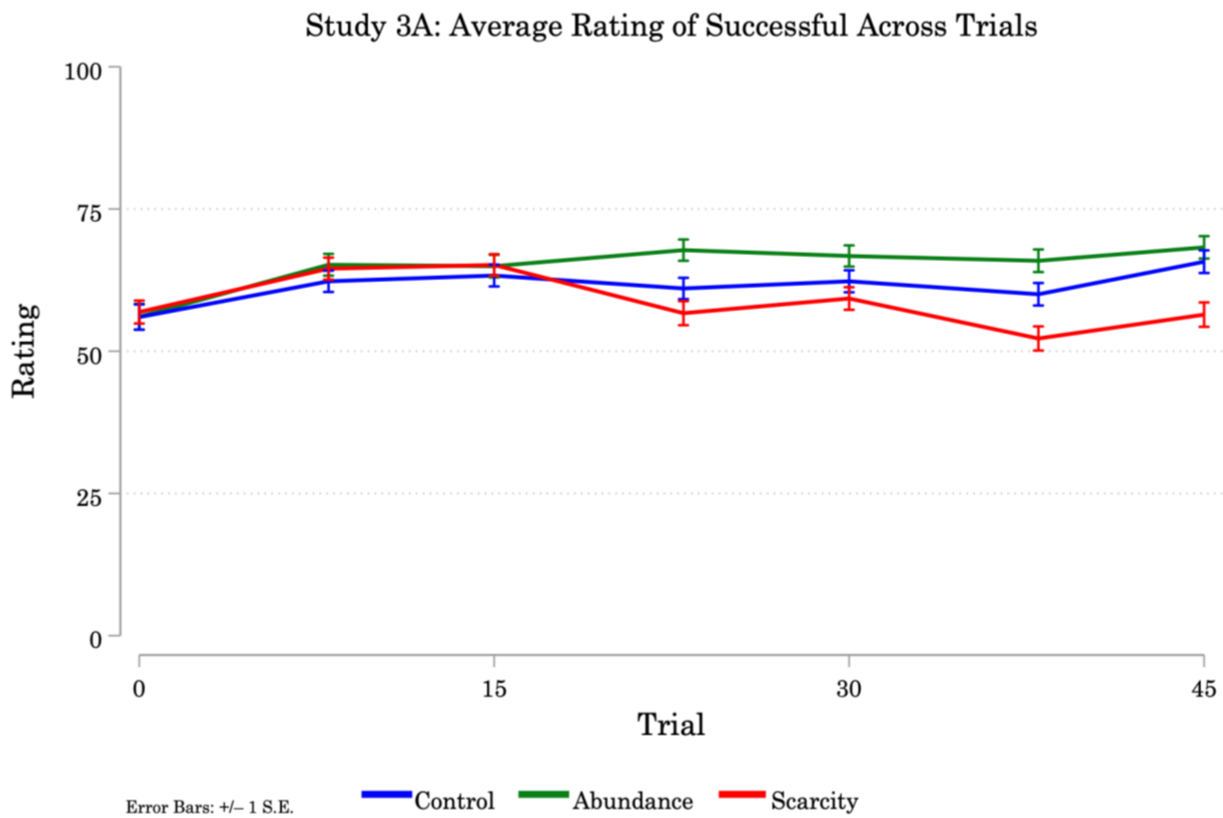


Figure A.3.3. Study 3A: Successful Ratings. Participant ratings of "Successful" before the procedure started (Trial 0), during Phase 1 (Trials 8 & 15), during Phase 2 (23, 30), and during Phase 3 (38 & 45). N = 513. Green = Abundance (169 participants, 30 groups); Blue = Control (174 participants, 30 groups); Red = Scarcity (170 participants, 29 groups). Abundance participants' ratings are significantly higher than Controls on Trials 23 and 38 (middle/end of Phase 3). Scarcity participants' ratings are significantly lower than Controls on Trials 38 and 45 (middle/end of Phase 3). Abundance participants' ratings are significantly higher than Scarcity participants' on Trials 23 and 30 (middle /end of Phase 2) and on Trials 38 and 45 (middle/end of Phase 3).

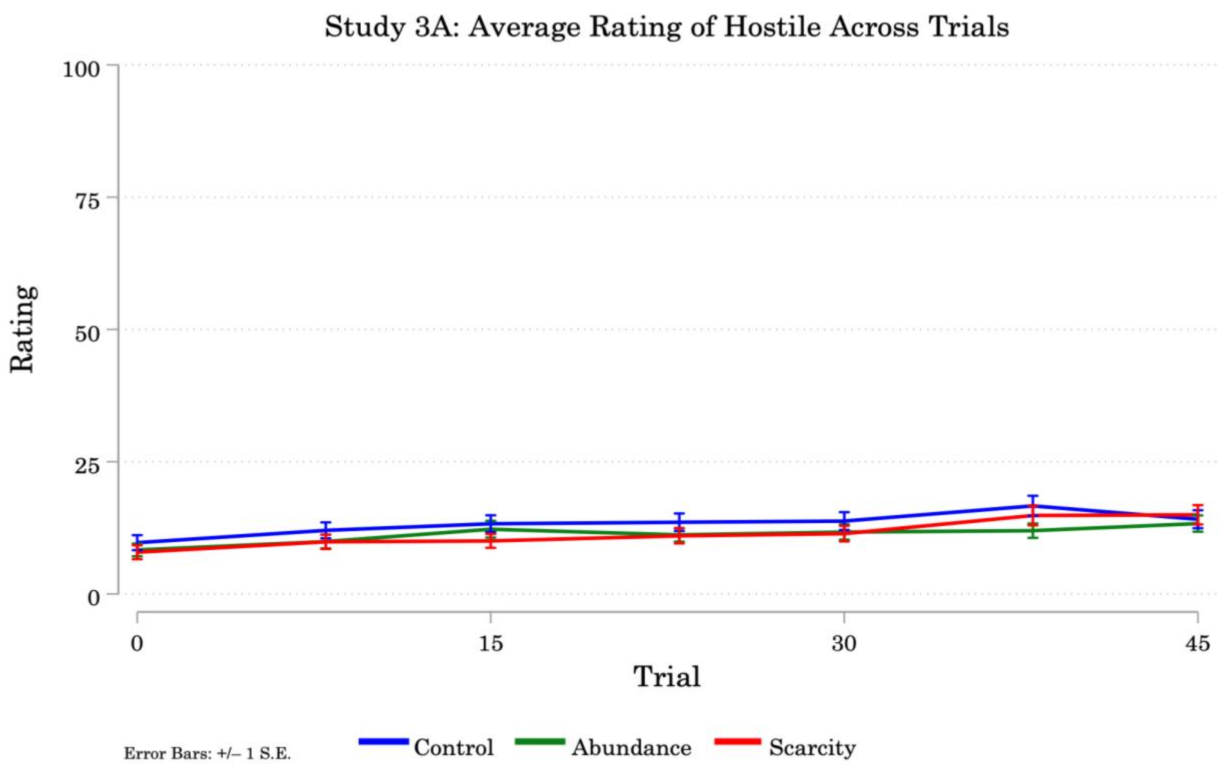


Figure A.3.4. Study 3A: Hostile Ratings. Participant ratings of "Hostile" before the procedure started (Trial 0), during Phase 1 (Trials 8 & 15), during Phase 2 (23, 30), and during Phase 3 (38 & 45). N = 513. Green = Abundance (169 participants, 30 groups); Blue = Control (174 participants, 30 groups); Red = Scarcity (170 participants, 29 groups). There are no significant differences between Conditions on any Trial. Note that ratings of Hostile are flat across Phases.

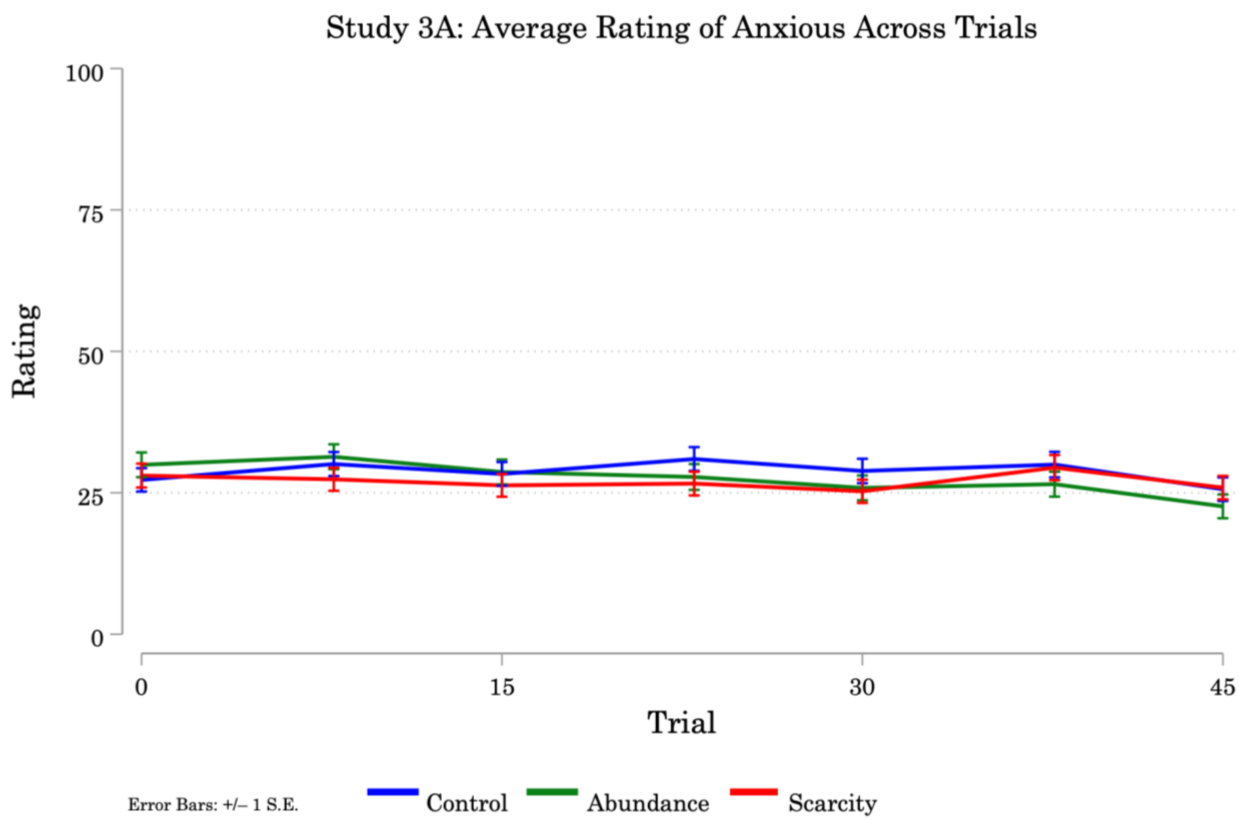


Figure A.3.5. Study 3A: Anxious Ratings. Participant ratings of "Anxious" before the procedure started (Trial 0), during Phase 1 (Trials 8 & 15), during Phase 2 (23, 30), and during Phase 3 (38 & 45). N = 513. Green = Abundance (169 participants, 30 groups); Blue = Control (174 participants, 30 groups); Red = Scarcity (170 participants, 29 groups). There are no significant differences between Conditions on any Trial. Note that ratings of Anxious are flat across Trials.

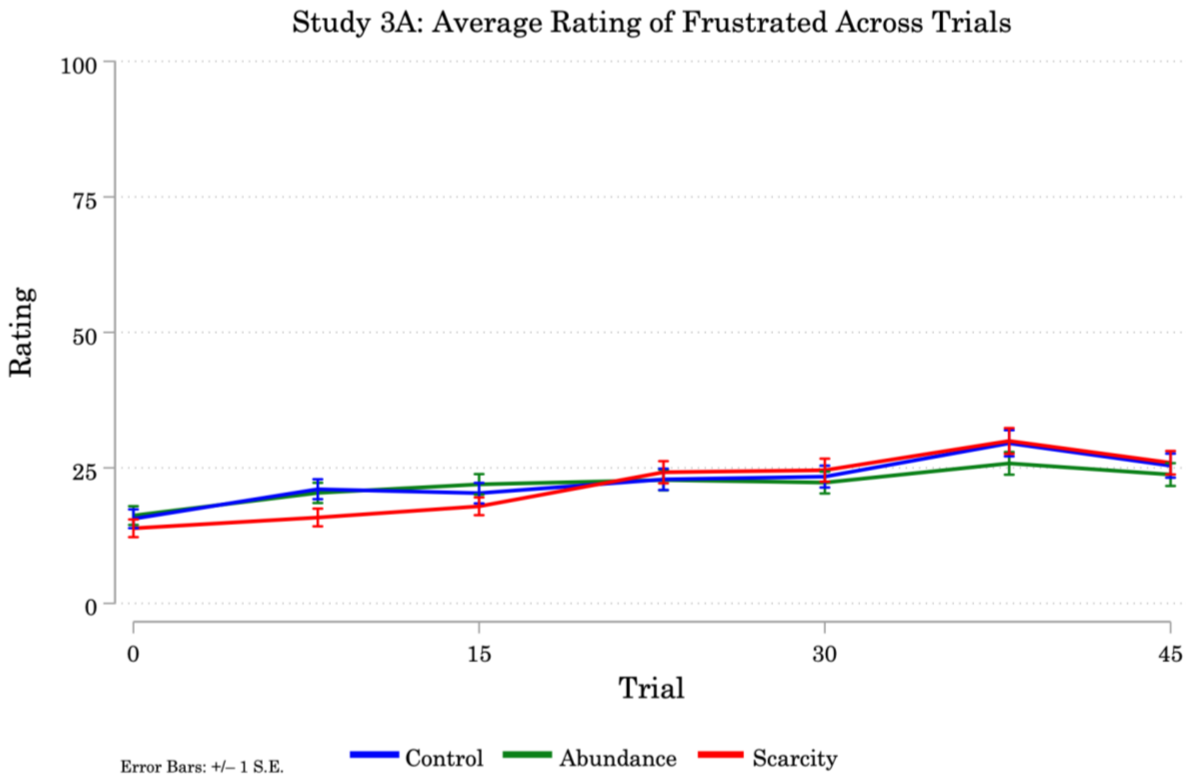


Figure A.3.6. Study 3A: Frustrated Ratings. Participant ratings of "Frustrated" before the procedure started (Trial 0), during Phase 1 (Trials 8 & 15), during Phase 2 (23, 30), and during Phase 3 (38 & 45). N = 513. Green = Abundance (169 participants, 30 groups); Blue = Control (174 participants, 30 groups); Red = Scarcity (170 participants, 29 groups). There are no significant differences between Conditions on any Trial. Ratings of Frustrated increase slightly in the middle of Phase 3, but are otherwise relatively flat across Trials.

A.3.2 Study 3B: Feelings Inventory

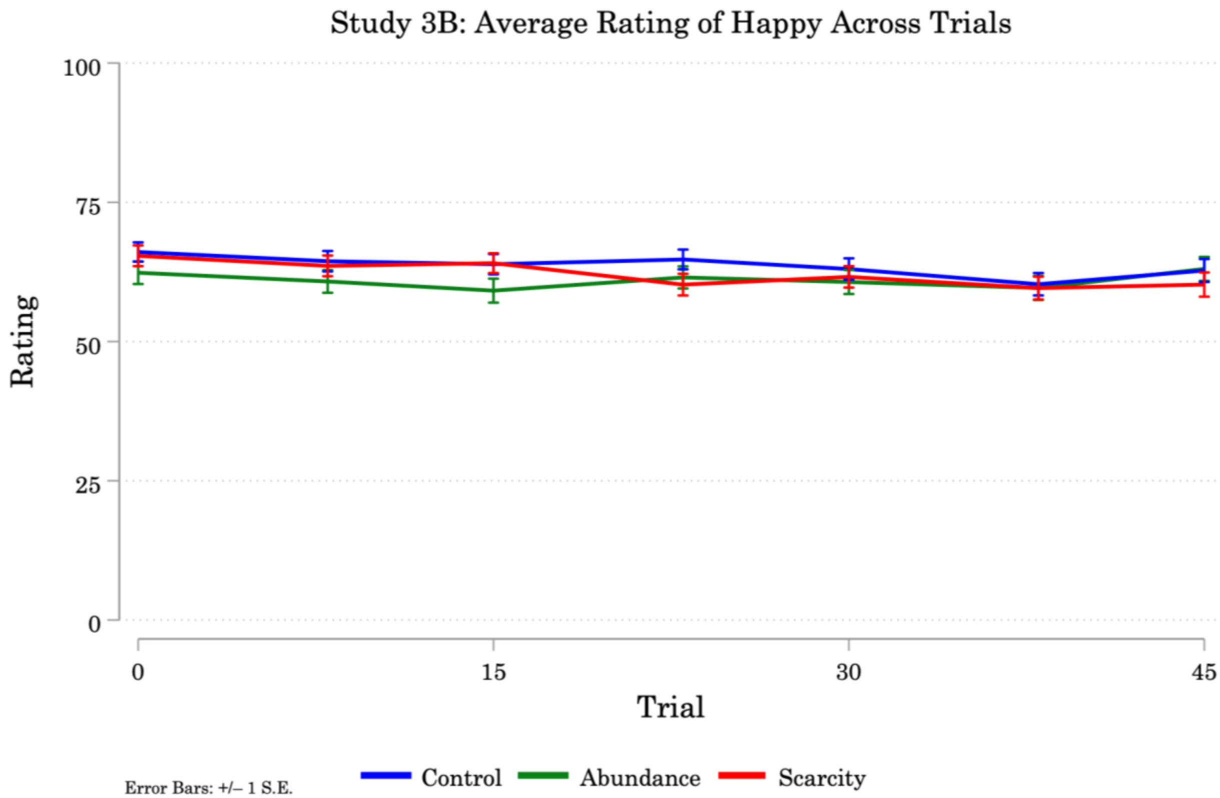


Figure A.3.7. Study 3B: Happy Ratings. Participant ratings of "Happy" before the procedure started (Trial 0), during Phase 1 (Trials 8 & 15), during Phase 2 (23, 30), and during Phase 3 (38 & 45). N = 519. Green = Abundance (170 participants, 29 groups); Blue = Control (177 participants, 30 groups); Red = Scarcity (172 participants, 30 groups). There are no significant differences between Conditions on any Trial.

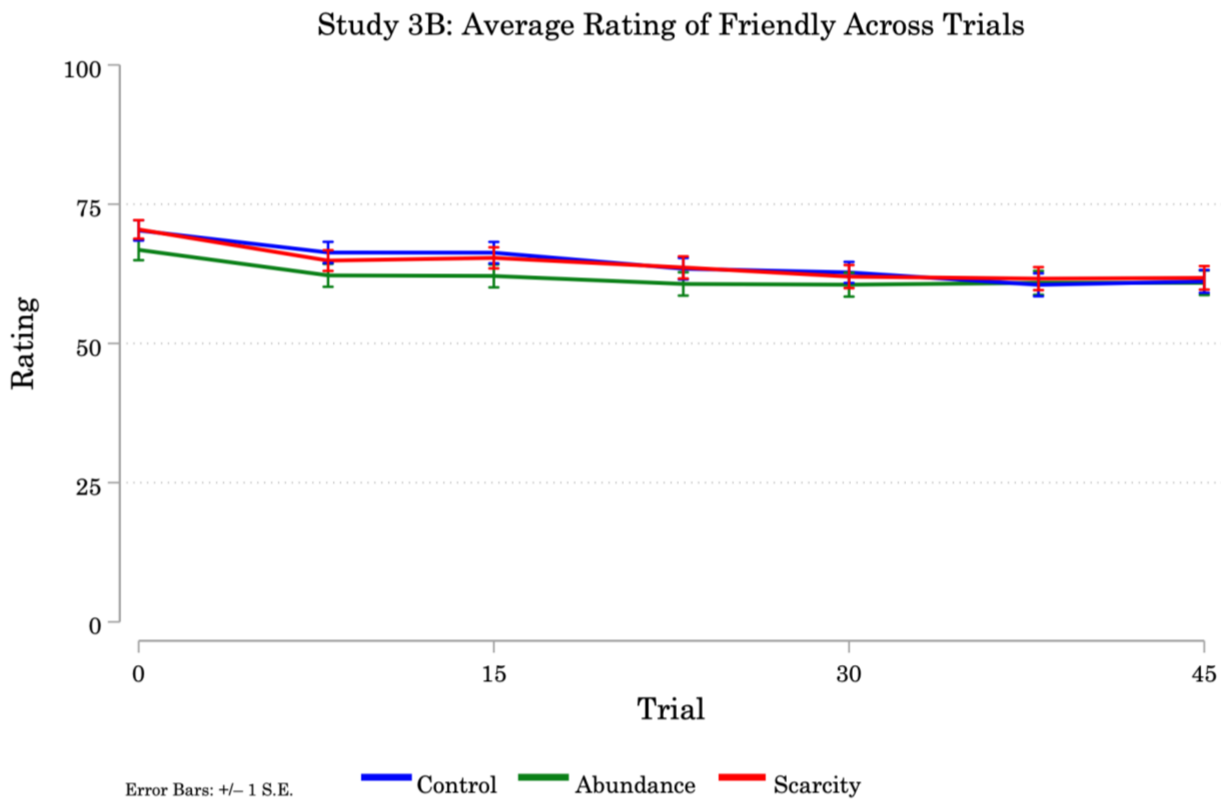


Figure A.3.8. Study 3B: Friendly Ratings. Participant ratings of "Friendly" before the procedure started (Trial 0), during Phase 1 (Trials 8 & 15), during Phase 2 (23, 30), and during Phase 3 (38 & 45). N = 519. Green = Abundance (170 participants, 29 groups); Blue = Control (177 participants, 30 groups); Red = Scarcity (172 participants, 30 groups). There are no significant differences between Conditions on any Trial.

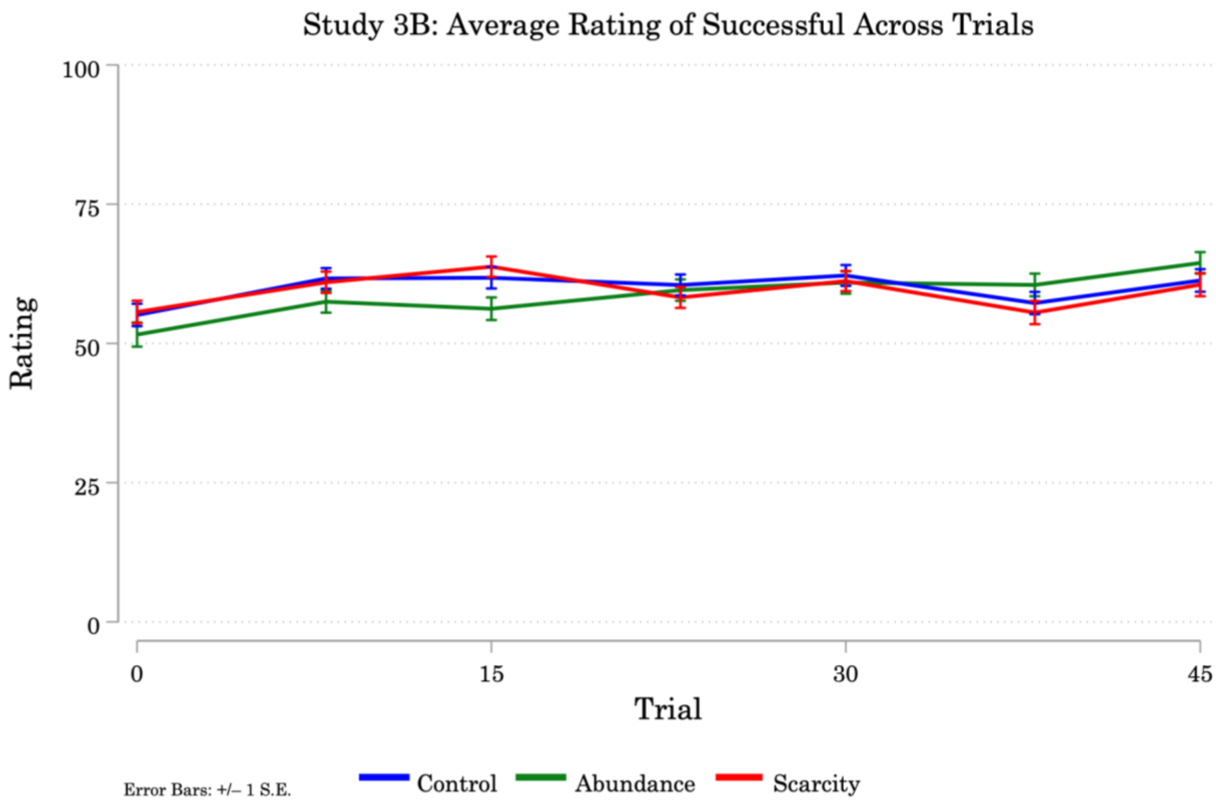


Figure A.3.9. Study 3A: Successful Ratings. Participant ratings of "Successful" before the procedure started (Trial 0), during Phase 1 (Trials 8 & 15), during Phase 2 (23, 30), and during Phase 3 (38 & 45). N = 519. Green = Abundance (170 participants, 29 groups); Blue = Control (177 participants, 30 groups); Red = Scarcity (172 participants, 30 groups). There are no differences between Scarcity and Control on any Trial. Abundance participants' ratings are significantly lower than Control and Scarcity participants on Trials 15 (end of Phase 1).

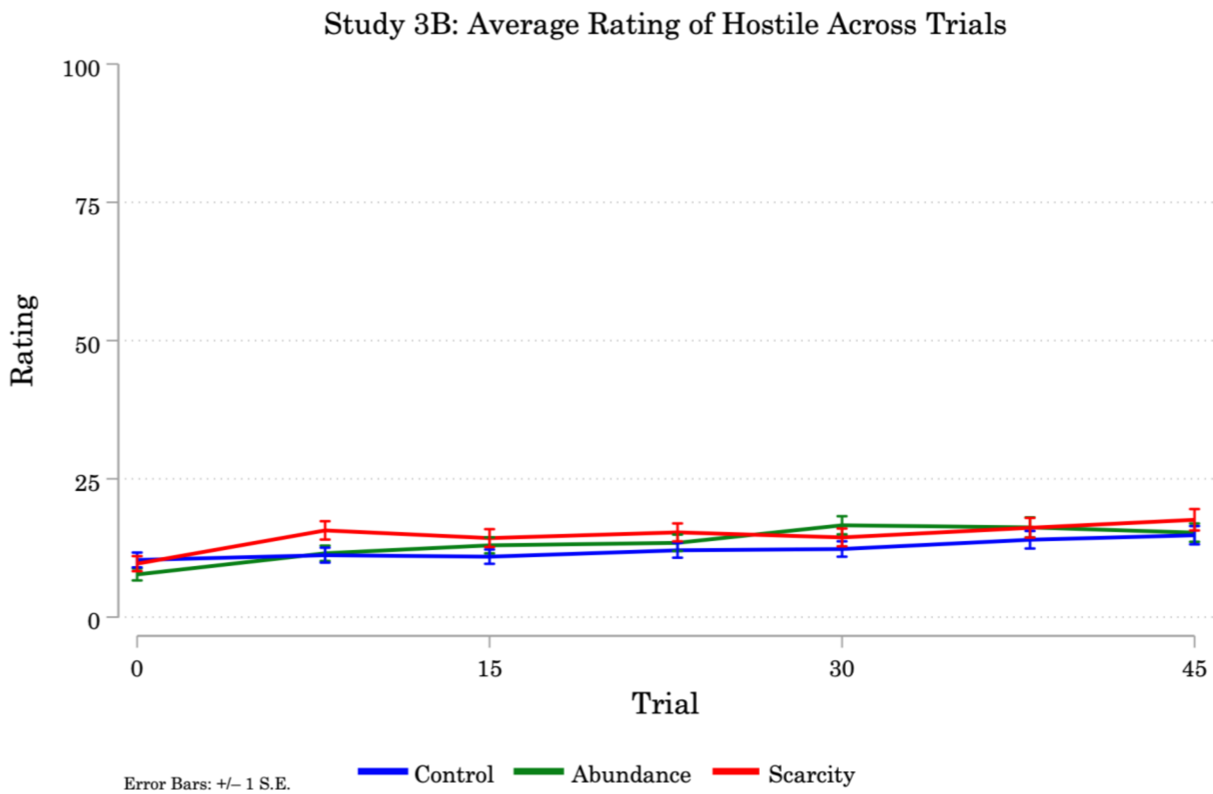


Figure A.3.10. Study 3B: Hostile Ratings. Participant ratings of "Hostile" before the procedure started (Trial 0), during Phase 1 (Trials 8 & 15), during Phase 2 (23, 30), and during Phase 3 (38 & 45). N = 519. Green = Abundance (170 participants, 29 groups); Blue = Control (177 participants, 30 groups); Red = Scarcity (172 participants, 30 groups). There are no significant differences between Conditions on any Trial. Note that ratings of Hostile are relatively flat across Phases. Ratings in Phase 3 are slightly higher than Ratings at time zero (before the procedure), but otherwise there are no significant differences across Trials.

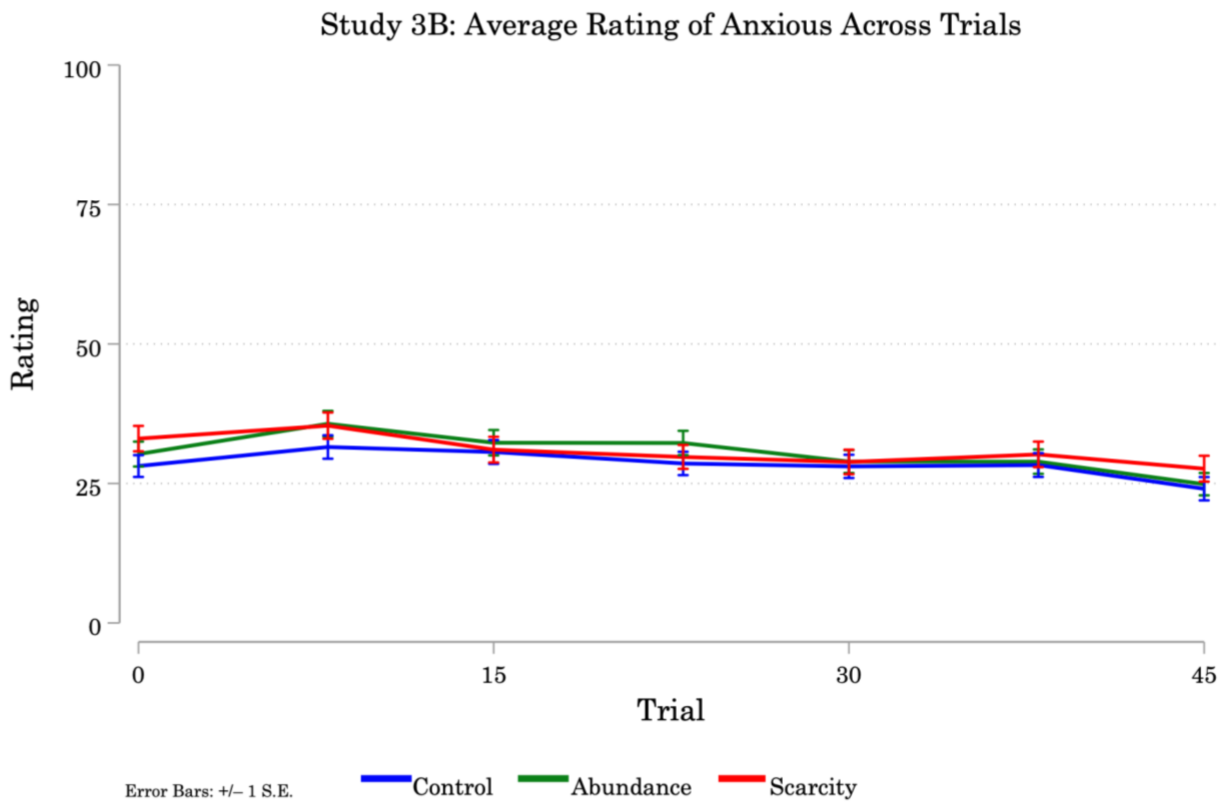


Figure A.3.11. Study 3B: Anxious Ratings. Participant ratings of "Anxious" before the procedure started (Trial 0), during Phase 1 (Trials 8 & 15), during Phase 2 (23, 30), and during Phase 3 (38 & 45). N = 519. Green = Abundance (170 participants, 29 groups); Blue = Control (177 participants, 30 groups); Red = Scarcity (172 participants, 30 groups). There are no significant differences between Conditions on any Trial. Note that ratings of Anxious increase slightly between time zero (before the start of the procedure) and Trial 8 (middle of Phase 1), but are otherwise flat across Phases before declining on Trial 45 (end of Phase 3).

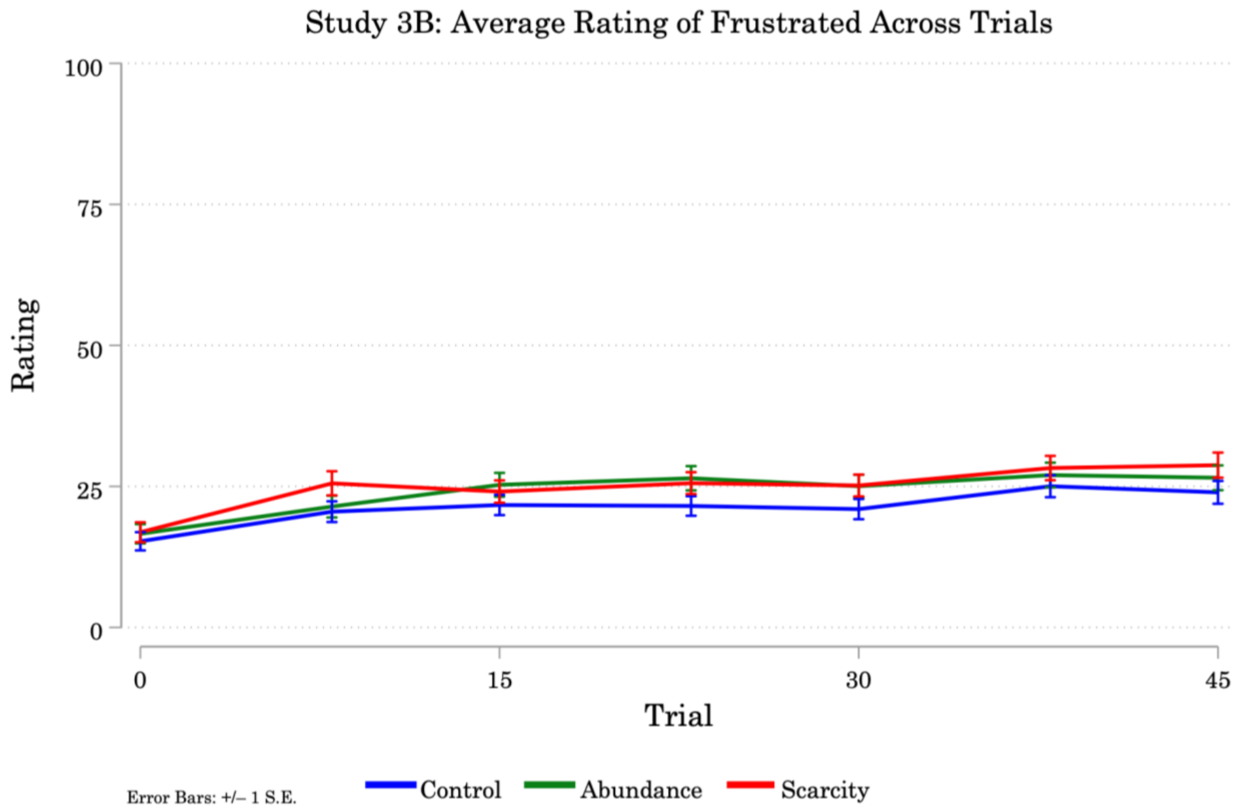


Figure A.3.12. Study 3B: Frustrated Ratings. Participant ratings of "Frustrated" before the procedure started (Trial 0), during Phase 1 (Trials 8 & 15), during Phase 2 (23, 30), and during Phase 3 (38 & 45). N = 519. Green = Abundance (170 participants, 29 groups); Blue = Control (177 participants, 30 groups); Red = Scarcity (172 participants, 30 groups). There are no significant differences between Conditions on any Trial. Note that ratings of Anxious increase slightly between time zero (before the start of the procedure) and Trial 8 (middle of Phase 1), but are otherwise flat across Phases.

A.4 Studies 3A & 3B: Demographics

Continuous variables (and categorical scales treated as continuous):

- Age
- Work Experience (number of years)
- Number of Contacts (close communication partners named)
- Average Closeness (average reported closeness to each named contact)
    - 0 = Very Distant ----------------100 = Very Close
- Covid-19: Familiarity
    - 1 = "Never heard of it"
    - 2 = "Not very informed"
    - 3 = "Somewhat informed"
    - 4 = "Well-informed"
    - 5 = "Extremely well-informed"
- Covid-19: Personal impact
    - 1 = "No impact at all"
    - 2 = "Slightly impacted"
    - 3 = "Moderately impacted"
    - 4 = "Significantly impacted"
    - 5 = "Severely impacted"

Categorical variables:

- Female
- Highest Degree: No Degree, High School, 2-Year / Trade, 4-Year College, Masters +
- Region: West, Midwest, South, Northeast, US Territory (can choose not to disclose)
- Industry Division (can choose not to disclose)
    - Division A: Agriculture, Forestry, Fishing
    - Divisions B, C, D: Mining, Construction, Manufacturing
    - Division E: Transportation, Communication, Electric, Gas, Sanitation
    - Divisions F, G: Wholesale & Retail Trade
    - Division H: Finance, Insurance, and Real Estate
    - Division I: Professional, Health, Social, and Entertainment Services
    - Division J: Public Administration
- Professional Role (can choose not to disclose)
    - Self-Employed, Partner
    - Trained Professional
    - Skilled Laborer
    - Consultant
    - Inside or Outside Sales Staff
    - Research and Development
    - Administrative or Support Staff
    - Management (Product, Project, People, or Executive)
- Stay-at-Home ("State or employer issued stay at home directive")
    - 0 = No; 1 = Yes
- Laid Off ("Laid off, fired, or furloughed in the past few months")
    - 0 = No; 1 = Yes

A.4.1 Study 3A: Demographic Differences between CDR and MTurk Pools

The biggest differences between the CDR and MTurk pools are: age, gender, personal impact of Covid-19, and living under a stay-at-home order.

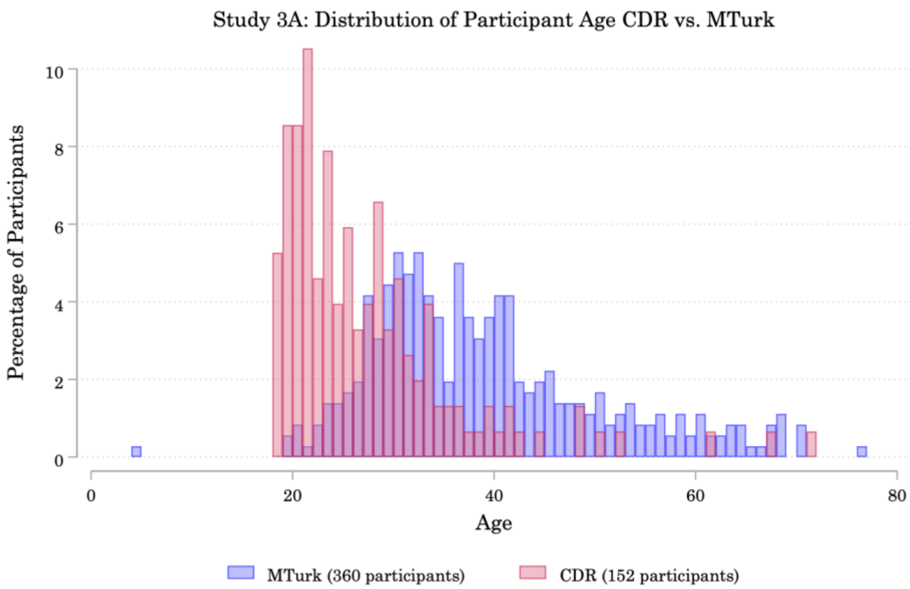


Figure A.4.1. Study 3A: Age – CDR versus MTurk. There are significantly more participants in their early 20s in the CDR pool than in the MTurk Pool.

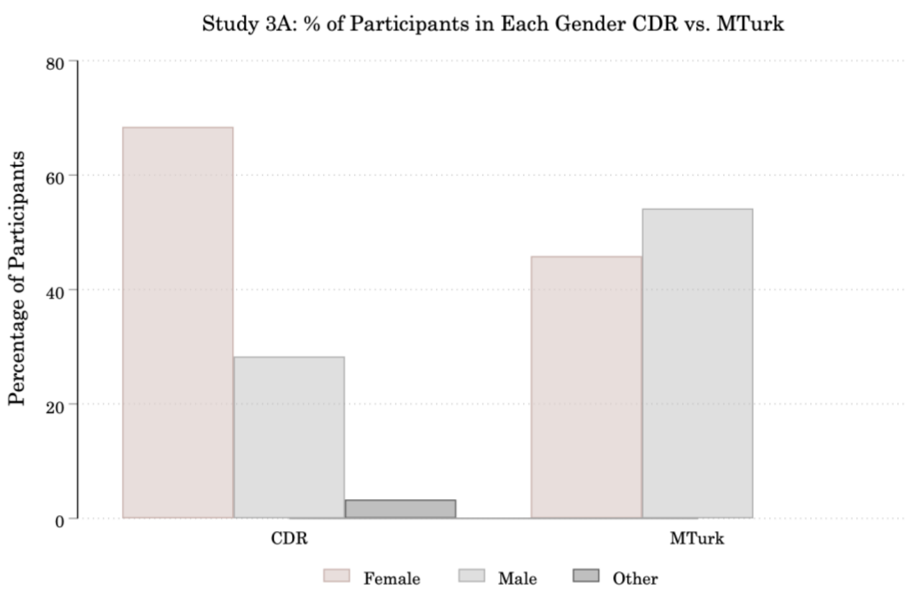


Figure A.4.2. Study 3A: Gender – CDR versus MTurk. Close to 70% of CDR participants identified as female. Less than 50% of MTurk participants identified as female.

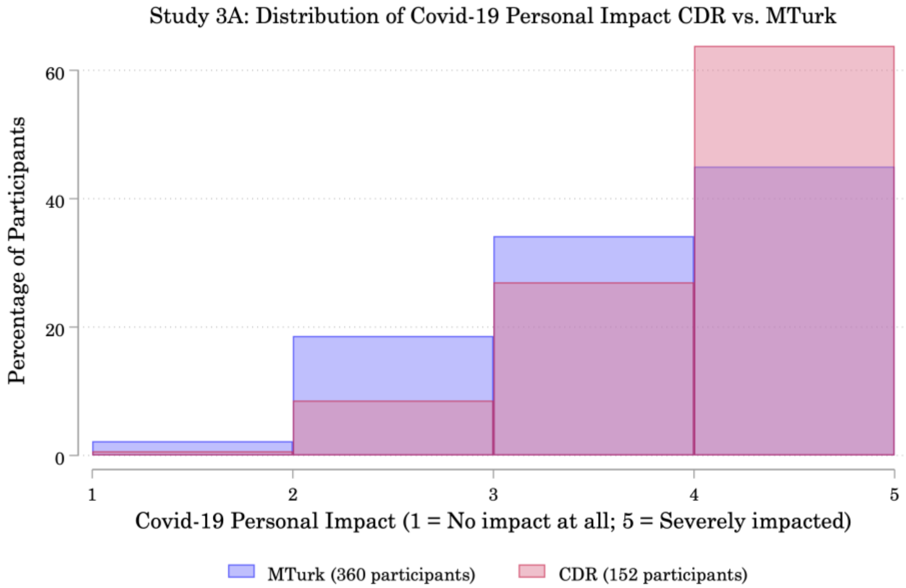


Figure A.4.3. Study 3A: Covid-19 Impact – CDR versus MTurk. The percentage of CDR participants who reported that they were severely personally impacted by Covid-19 was larger than the percentage of MTurk participants who reported severe personal impact.

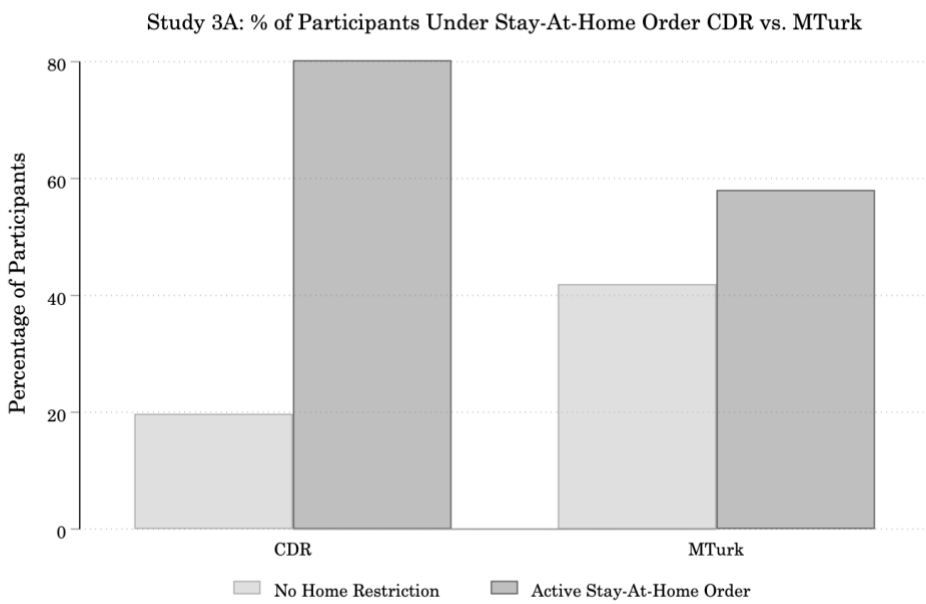


Figure A.4.4. Study 3A: Stay-At-Home Order – CDR versus MTurk. The percentage of CDR participants who reported that they were currently living under a stay-at-home order was larger than the percentage of MTurk participants who reported living under a stay-at-home order.

Table A.4.1. Study 3A: Individual Differences – CDR and MTurk. Summary of individual differences, by Condition. N = 513 (Abundance = 169; Control = 173† ; Scarcity = 170). Excludes dropouts. Continuous variables reported as means (standard deviations in parentheses). Categorical variables reported as percentage of participant sample.

	Abundance	Control	Scarcity	*All Conditions*
Continuous Variables				
Age	36.21 (12.21)	34.49 (12.18)	34.84 (11.96)	35.19 (12.12)
Work Experience	14.41 (11.39)	13.63 (10.91)	14.05 (11.75)	14.02 (11.33)
Number of Contacts	3.30 (0.93)	3.31 (0.89)	3.16 (0.73)	3.26 (0.85)
Average Closeness	82.03 (13.88)	81.22 (15.03)	84.58 (13.14)	82.61 (14.09)
Cov19: Familiarity	4.15 (0.68)	4.14 (0.70)	4.12 (0.76)	4.14 (0.71)
Cov19: Impact	3.50 (0.98)	3.42 (1.01)	3.51 (1.00)	3.48 (1.00)
Categorical Variables				
Female	50.89%	46.82%	60.00%	52.54%
Highest Degree				
No Degree	1.18%	1.16%	0.00%	0.78%
HS Degree	21.30%	24.28%	26.47%	24.02%
2-Year / Skilled Trade	11.24%	11.56%	12.94%	11.91%
4-Year College	42.01%	43.93%	44.12%	43.36%
Masters +	24.26%	19.08%	16.47%	19.92%
Region				
West	19.53%	16.76%	18.42%	18.16%
Midwest	34.91%	21.39%	24.71%	26.95%
South	30.18%	34.10%	32.94%	32.42%
Northeast	13.61%	22.54%	19.41%	18.55%
US Territory	0.59%	0.58%	0.00%	0.39%
Not Disclosed	1.18%	4.62%	4.71%	3.52%
Industry Division				
Division A	1.78%	1.16%	0.59%	1.17%
Division B,C,D	8.88%	9.83%	4.71%	7.81%
Division E	13.02%	13.87%	12.94%	13.28%
Division F,G	8.28%	10.98%	10.59%	9.96%
Division H	5.92%	7.51%	11.76%	8.40%
Division I	55.62%	46.24%	52.94%	51.56%
Division J	1.18%	4.05%	1.76%	2.34%
No Experience	5.33%	6.36%	4.71%	5.47%

† Data are missing for one CDR participant in the Control Condition

Table A.4.1. Study 3A: Individual Differences – CDR and MTurk. (*Continued.*) Summary of individual differences, by Condition. N = 513 (Abundance = 169; Control = 173† ; Scarcity = 170). Excludes dropouts. Continuous variables reported as means (standard deviations in parentheses). Categorical variables reported as percentage of participant sample.

	Abundance	Control	Scarcity	*All Conditions*
Professional Role				
Self-Employed, Partner	12.43%	8.09%	9.41%	9.96%
Trained Professional	23.67%	23.12%	24.12%	23.63%
Skilled Laborer	10.65%	11.56%	9.41%	10.55%
Consultant	2.96%	3.47%	4.71%	3.71%
Sales Staff	4.14%	4.05%	4.12%	4.10%
R&D	6.51%	8.09%	4.71%	6.45%
Admin, Support Staff	19.53%	18.50%	21.76%	19.92%
Management	13.61%	16.18%	16.47%	15.43%
No Experience	5.92%	6.36%	4.71%	5.66%
Not Disclosed	0.59%	0.58%	0.59%	0.59%
Stay-At-Home Order	59.17%	66.47%	68.24%	64.65%
Laid Off	8.28%	12.72%	9.41%	10.16%

† Data are missing for one CDR participant in the Control Condition

Table A.4.2. Study 3A: Individual Differences – CDR. Summary of individual differences, by Condition. N = 162 (Abundance = 44; Control = 60† ; Scarcity = 48). Excludes 9 dropouts (Abundance = 4; Control = 5; Scarcity = 0). Continuous variables reported as means (standard deviations in parentheses). Categorical variables reported as percentage of participant sample.

	Abundance	Control	Scarcity	*All Conditions*
Continuous Variables				
Age	28.57 (9.88)	27.60 (10.50)	24.73 (5.28)	26.97 (9.06)
Work Experience	6.48 (6.73)	7.00 (8.54)	4.35 (4.57)	6.01 (7.02)
Number of Contacts	3.43 (0.95)	3.37 (1.13)	3.23 (0.69)	3.34 (0.96)
Average Closeness	82.28 (13.21)	82.05 (13.06)	85.37 (12.23)	83.16 (12.85)
Cov19: Familiarity	4.14 (0.68)	4.12 (0.72)	3.92 (0.96)	4.06 (0.79)
Cov19: Impact	3.70 (0.98)	3.80 (0.97)	3.71 (0.82)	3.74 (0.90)
Categorical Variables				
Female	65.91%	65.00%	75.00%	68.42%
Highest Degree				
No Degree	2.27%	3.33%	0.00%	1.97%
HS Degree	22.73%	31.67%	29.17%	28.29%
2-Year / Skilled Trade	4.55%	6.67%	4.17%	5.26%
4-Year College	36.36%	36.67%	50.00%	38.16%
Masters +	34.09%	28.33%	16.47%	26.32%
Region				
West	9.09%	13.33%	6.25%	9.87%
Midwest	45.45%	30.00%	33.33%	35.53%
South	22.73%	21.67%	18.75%	21.05%
Northeast	15.91%	20.00%	27.08%	21.05%
US Territory	2.27%	1.67%	0.00%	1.32%
Not Disclosed	4.55%	13.33%	14.58%	11.18%
Industry Division				
Division A	0.00%	0.00%	0.00%	0.00%
Division B,C,D	4.55%	5.00%	0.00%	3.29%
Division E	4.55%	10.00%	8.33%	7.89%
Division F,G	2.27%	8.33%	4.17%	5.26%
Division H	4.55%	6.67%	10.42%	7.24%
Division I	72.73%	55.00%	66.67%	63.82%
Division J	0.00%	3.33%	0.00%	1.32%
No Experience	11.36%	11.67%	10.42%	11.18%

† Demographics are missing for one CDR participant in the Control Condition

Table A.4.2. Study 3A: Individual Differences – CDR. (*Continued*.) Summary of individual differences, by Condition. N = 162 (Abundance = 44; Control = 60† ; Scarcity = 48). Excludes 9 dropouts (Abundance = 4; Control = 5; Scarcity = 0). Continuous variables reported as means (standard deviations in parentheses). Categorical variables reported as percentage of participant sample.

	Abundance	Control	Scarcity	*All Conditions*
Professional Role				
Self-Employed, Partner	2.27%	0.00%	8.33%	3.29%
Trained Professional	18.18%	18.33%	18.75%	18.42%
Skilled Laborer	9.09%	6.67%	6.25%	7.24%
Consultant	6.82%	1.67%	6.25%	4.61%
Sales Staff	0.00%	5.00%	4.17%	3.29%
R&D	13.64%	13.33%	10.42%	12.50%
Admin, Support Staff	27.27%	23.33%	22.92%	24.34%
Management	9.09%	18.33%	10.42%	13.16%
No Experience	11.36%	11.67%	10.42%	11.18%
Not Disclosed	2.27%	1.67%	2.08%	1.97%
Stay-At-Home Order	72.73%	83.33%	83.33%	80.26%
Laid Off	6.82%	16.67%	4.17%	9.87%

† Demographics are missing for one CDR participant in the Control Condition

Table A.4.3. Study 3A: Individual Differences – MTurk. Summary of individual differences, by Condition. N = 360 (Abundance = 125; Control = 113; Scarcity = 122). Excludes 12 dropouts (Abundance = 7; Control = 1; Scarcity = 4). Continuous variables reported as means (standard deviations in parentheses). Categorical variables reported as percentage of participant sample.

	Abundance	Control	Scarcity	*All Conditions*
Continuous Variables				
Age	38.90 (11.83)	38.15 (11.44)	38.81 (11.51)	38.64 (11.57)
Work Experience	17.07 (11.41)	17.15 (10.41)	17.86 (11.52)	17.36 (11.12)
Number of Contacts	3.26 (0.92)	3.27 (0.72)	3.13 (0.75)	3.22 (0.81)
Average Closeness	81.94 (14.16)	80.79 (16.02)	84.27 (13.51)	82.37 (14.59)
Cov19: Familiarity	4.15 (0.68)	4.15 (0.70)	4.20 (0.64)	4.17 (0.67)
Cov19: Impact	3.42 (1.00)	3.22 (0.97)	3.43 (1.06)	3.36 (1.01)
Categorical Variables				
Female	45.60%	37.17%	54.10%	45.83%
Highest Degree				
No Degree	0.80%	0.00%	0.00%	0.28%
HS Degree	20.80%	20.35%	25.41%	22.22%
2-Year / Skilled Trade	13.60%	14.16%	16.39%	14.72%
4-Year College	44.00%	51.33%	41.80%	45.56%
Masters +	20.80%	14.16%	16.39%	17.22%
Region				
West	23.20%	18.58%	22.95%	21.67%
Midwest	31.20%	16.81%	21.31%	23.33%
South	32.80%	40.71%	38.52%	37.22%
Northeast	12.80%	23.89%	16.39%	17.50%
US Territory	0.00%	0.00%	0.00%	0.00%
Not Disclosed	0.00%	0.00%	0.82%	0.28%
Industry Division				
Division A	2.40%	1.77%	0.82%	1.67%
Division B,C,D	10.40%	12.39%	6.56%	9.72%
Division E	16.00%	15.93%	14.75%	15.56%
Division F,G	10.40%	12.39%	13.11%	11.94%
Division H	6.40%	7.96%	12.30%	8.89%
Division I	49.60%	41.59%	47.54%	46.39%
Division J	1.60%	4.42%	2.46%	2.78%
No Experience	3.20%	3.54%	2.46%	3.06%

Table A.4.3. Study 3A: Individual Differences – MTurk. (*Continued*.) Summary of individual differences, by Condition. N = 360 (Abundance = 125; Control = 113; Scarcity = 122). Excludes 12 dropouts (Abundance = 7; Control = 1; Scarcity = 4). Continuous variables reported as means (standard deviations in parentheses). Categorical variables reported as percentage of participant sample.

	Abundance	Control	Scarcity	*All Conditions*
Professional Role				
Self-Employed, Partner	16.00%	12.39%	9.84%	12.78%
Trained Professional	25.60%	25.66%	26.23%	25.83%
Skilled Laborer	11.20%	14.16%	10.66%	11.94%
Consultant	1.60%	4.42%	4.10%	3.33%
Sales Staff	5.60%	3.54%	4.10%	4.44%
R&D	4.00%	5.31%	2.46%	3.89%
Admin, Support Staff	16.80%	15.93%	21.31%	18.06%
Management	15.20%	15.04%	18.85%	16.39%
No Experience	4.00%	3.54%	2.46%	3.33%
Not Disclosed	0.00%	0.00%	0.00%	0.00%
Stay-At-Home Order	54.40%	57.52%	62.30%	58.06%
Laid Off	8.80%	10.62%	11.48%	10.28%

A.4.2 Study 3B: Demographic Differences between CDR and MTurk Pools

The biggest differences between the CDR and MTurk pools are: age, gender, personal impact of Covid-19, and living under a stay-at-home order.

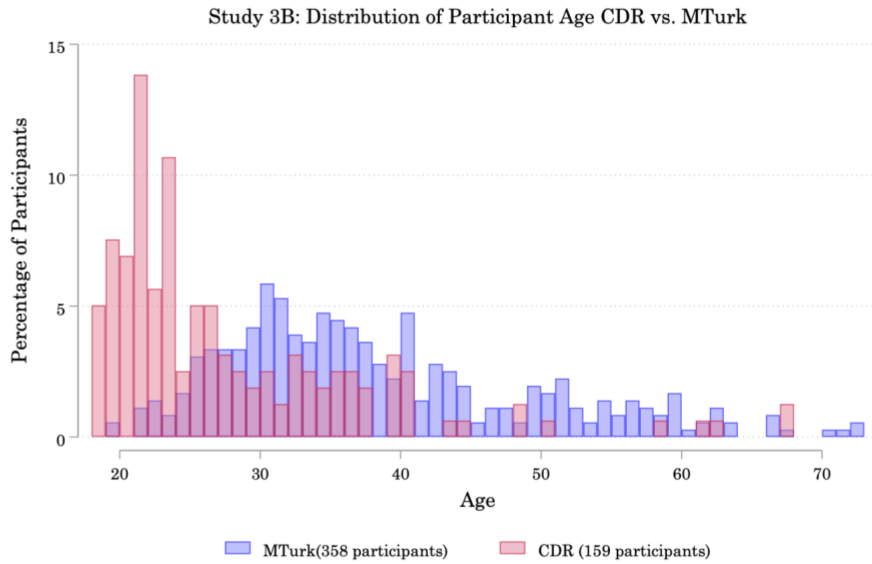


Figure A.4.5. Study 3B: Age – CDR versus MTurk. There are significantly more participants in their early 20s in the CDR pool than in the MTurk Pool.

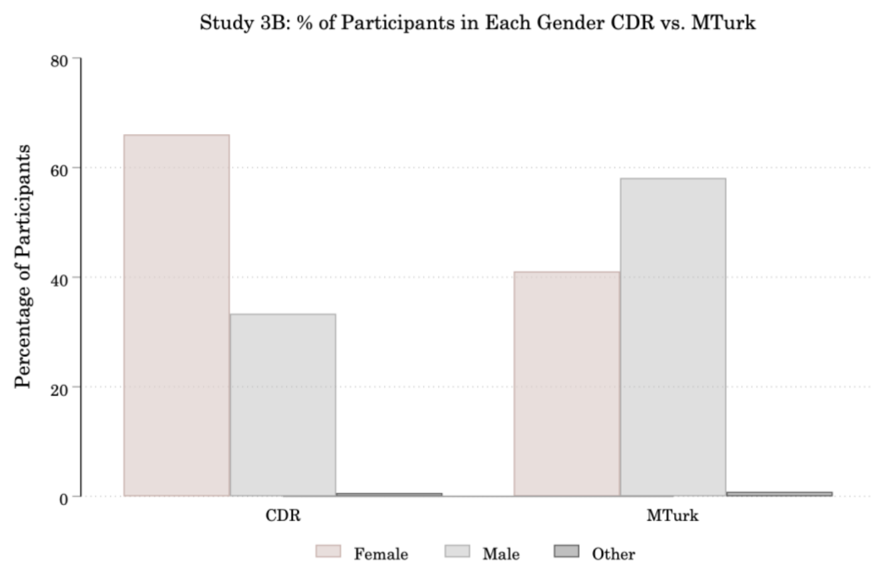


Figure A.4.6. Study 3B: Gender – CDR versus MTurk. Around 65% of CDR participants identified as female. Close to 40% of MTurk participants identified as female.

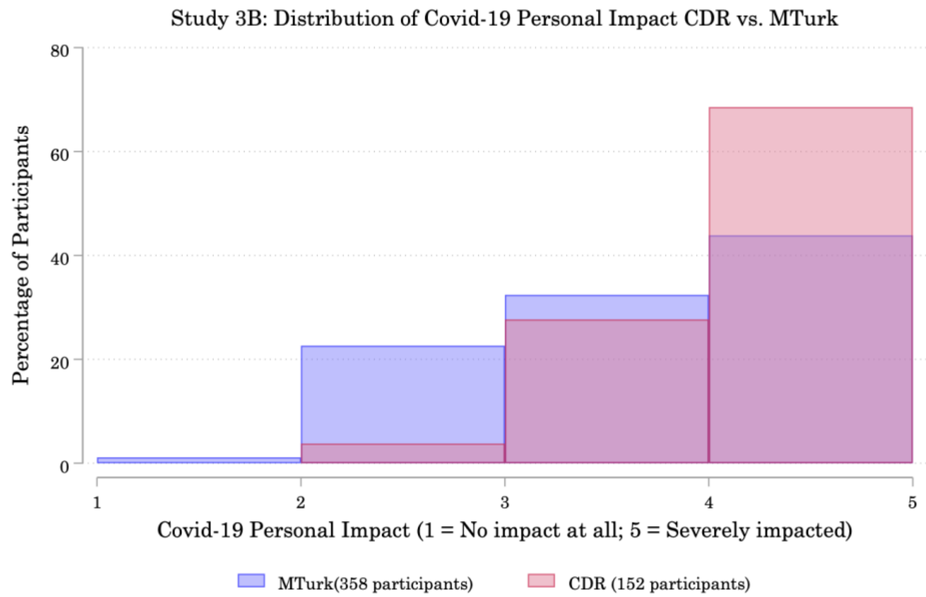


Figure A.4.7. Study 3B: Covid-19 Impact – CDR versus MTurk. The percentage of CDR participants who reported that they were severely personally impacted by Covid-19 was larger than the percentage of MTurk participants who reported severe personal impact.

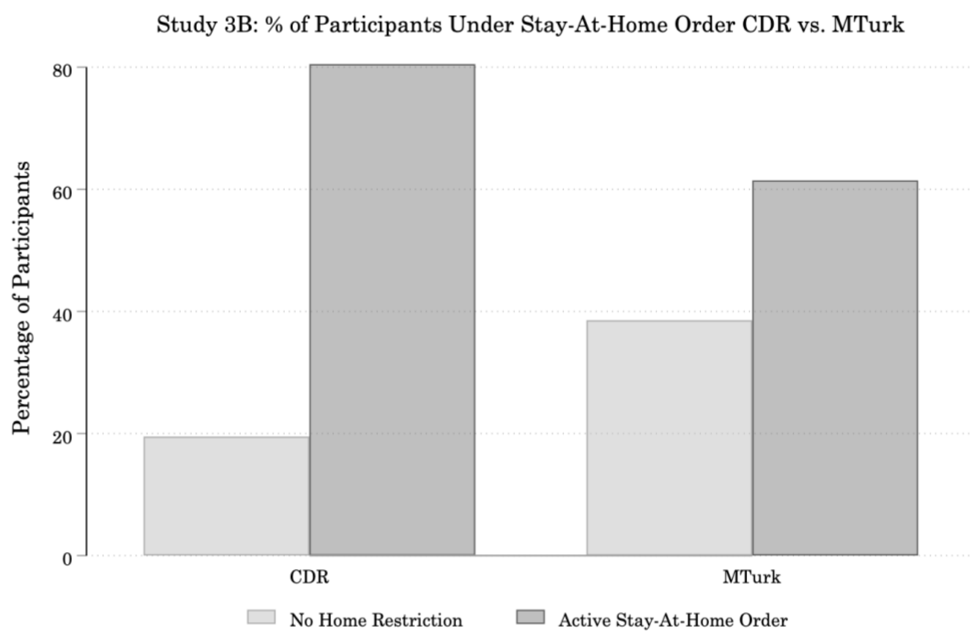


Figure A.4.8. Study 3B: Stay-At-Home Order – CDR versus MTurk. The percentage of CDR participants who reported that they were currently living under a stay-at-home order was larger than the percentage of MTurk participants who reported living under a stay-at-home order.

Table A.4.4. Study 3B: Individual Differences – CDR and MTurk. Summary of individual differences, by Condition. N = 517 (Abundance = 168† ; Control = 177; Scarcity = 172). Excludes dropouts. Continuous variables reported as means (stdev in parentheses). Categorical variables reported as percentage of sample.

	Abundance	Control	Scarcity	*All Conditions*
Continuous Variables				
Age	34.40 (10.95)	34.47 (12.12)	35.17 (12.04)	34.68 (11.71)
Work Experience	13.21 (10.35)	13.18 (11.91)	13.98 (11.54)	13.46 (11.28)
Number of Contacts	3.29 (0.81)	3.34 (0.80)	3.23 (0.94)	3.29 (0.85)
Average Closeness	81.49 (13.66)	82.02 (12.83)	81.81 (15.18)	81.78 (13.89)
Cov19: Familiarity	4.14 (0.68)	4.17 (0.68)	4.19 (0.64)	4.17 (0.67)
Cov19: Impact	3.54 (0.97)	3.49 (1.03)	3.44 (0.91)	3.49 (0.98)
Categorical Variables				
Female	45.24%	52.54%	48.26%	48.74%
Highest Degree				
No Degree	1.19%	0.56%	0.00%	0.58%
HS Degree	25.00%	22.60%	23.26%	23.60%
2-Year / Skilled Trade	13.10%	14.12%	13.95%	13.73%
4-Year College	45.83%	46.89%	41.86%	44.87%
Masters +	14.88%	15.82%	20.93%	17.21%
Region				
West	22.62%	18.08%	20.93%	20.50%
Midwest	27.98%	29.38%	30.81%	29.40%
South	32.14%	26.55%	25.58%	28.05%
Northeast	13.69%	20.34%	19.77%	17.99%
US Territory	1.79%	0.00%	0.00%	0.58%
Not Disclosed	1.79%	5.65%	2.91%	3.48%
Industry Division				
Division A	0.00%	1.69%	0.00%	0.58%
Division B,C,D	5.95%	9.04%	6.40%	7.16%
Division E	15.48%	13.56%	12.79%	13.93%
Division F,G	13.10%	6.78%	15.12%	11.61%
Division H	7.14%	10.73%	11.05%	9.67%
Division I	50.60%	48.59%	44.19%	47.78%
Division J	2.38%	2.26%	3.49%	2.71%
No Experience	5.36%	7.34%	6.98%	6.58%

† Demographics are missing for two CDR participant in the Abundance Condition

Table A.4.4. Study 3B: Individual Differences – CDR and MTurk. (*Continued*.) Summary of individual differences, by Condition. N = 517 (Abundance = 168† ; Control = 177; Scarcity = 172). Excludes dropouts. Continuous variables reported as means (stdev in parentheses). Categorical variables reported as percentage of sample.

	Abundance	Control	Scarcity	*All Conditions*
Professional Role				
Self-Employed, Partner	11.31%	8.47%	6.98%	8.90%
Trained Professional	23.81%	22.60%	16.86%	21.08%
Skilled Laborer	7.14%	16.95%	10.47%	11.61%
Consultant	4.17%	3.95%	5.23%	4.45%
Sales Staff	8.33%	0.56%	5.23%	4.64%
R&D	5.95%	5.65%	7.56%	6.38%
Admin, Support Staff	15.48%	20.34%	20.93%	18.96%
Management	17.86%	12.99%	19.77%	16.83%
No Experience	5.95%	8.47%	6.98%	7.16%
Not Disclosed	0.00%	0.00%	0.00%	0.00%
Stay-At-Home Order	71.43%	66.10%	64.53%	67.31%
Laid Off	10.71%	10.73%	12.79%	11.41%

† Demographics are missing for two CDR participant in the Abundance Condition

Table A.4.5. Study 3B: Individual Differences – CDR. Summary of individual differences, by Condition. N = 159 (Abundance = 50† ; Control = 59; Scarcity = 50). Excludes dropouts (A = 2; C= 1; S = 4). Continuous variables reported as means (stdev in parentheses). Categorical variables reported as percentage of sample.

	Abundance	Control	Scarcity	*All Conditions*
Continuous Variables				
Age	28.18 (12.06)	26.12 (8.14)	28.14 (8.57)	27.40 (9.66)
Work Experience	7.30 (10.41)	5.22 (8.10)	7.58 (8.74)	6.62 (9.08)
Number of Contacts	3.42 (1.16)	3.24 (0.75)	3.26 (1.26)	3.30 (1.06)
Average Closeness	81.41 (16.18)	81.57 (13.73)	79.59 (17.67)	80.90 (15.75)
Cov19: Familiarity	4.14 (0.67)	4.47 (0.61)	4.16 (0.77)	4.19 (0.68)
Cov19: Impact	3.84 (0.74)	4.03 (0.83)	3.70 (0.79)	3.87 (0.80)
Categorical Variables				
Female	70.00%	67.80%	60.00%	66.04%
Highest Degree				
No Degree	2.00%	0.00%	0.00%	0.63%
HS Degree	36.00%	22.03%	26.00%	27.67%
2-Year / Skilled Trade	4.00%	6.78%	8.00%	6.29%
4-Year College	44.00%	52.54%	34.00%	44.03%
Masters +	14.00%	18.64%	32.00%	21.38%
Region				
West	24.00%	16.95%	20.00%	20.13%
Midwest	34.00%	42.37%	46.00%	40.88%
South	12.00%	10.17%	6.00%	9.43%
Northeast	18.00%	13.56%	18.00%	16.35%
US Territory	6.00%	0.00%	0.00%	1.89%
Not Disclosed	6.00%	16.95%	10.00%	11.32%
Industry Division				
Division A	0.00%	0.00%	0.00%	0.00%
Division B,C,D	0.00%	5.08%	4.00%	3.14%
Division E	12.00%	13.56%	10.00%	11.95%
Division F,G	6.00%	1.69%	6.00%	4.40%
Division H	2.00%	5.08%	6.00%	4.40%
Division I	64.00%	52.54%	48.00%	54.72%
Division J	4.00%	1.69%	4.00%	3.14%
No Experience	12.00%	20.34%	22.00%	18.24%

† Demographics are missing for two CDR participant in the Abundance Condition

Table A.4.5. Study 3B: Individual Differences – CDR. (*Continued*.) Summary of individual differences, by Condition. N = 159 (Abundance = 50† ; Control = 59; Scarcity = 50). Excludes dropouts (A = 2; C= 1; S = 4). Continuous variables reported as means (stdev in parentheses). Categorical variables reported as percentage of sample.

	Abundance	Control	Scarcity	*All Conditions*
Professional Role				
Self-Employed, Partner	8.00%	5.08%	2.00%	5.03%
Trained Professional	18.00%	8.47%	16.00%	13.84%
Skilled Laborer	6.00%	10.17%	4.00%	6.92%
Consultant	4.00%	11.86%	8.00%	8.18%
Sales Staff	8.00%	1.69%	6.00%	5.03%
R&D	14.00%	11.86%	14.00%	13.21%
Admin, Support Staff	12.00%	20.34%	10.00%	14.47%
Management	16.00%	6.78%	18.00%	13.21%
No Experience	14.00%	23.73%	22.00%	20.13%
Not Disclosed	0.00%	0.00%	0.00%	0.00%
Stay-At-Home Order	84.00%	84.75%	72.00%	80.50%
Laid Off	14.00%	11.86%	12.00%	12.58%

† Demographics are missing for two CDR participant in the Abundance Condition

Table A.4.6. Study 3B: Individual Differences – MTurk. Summary of individual differences, by Condition. N = 358 (Abundance = 118; Control = 118; Scarcity = 122). Excludes 8 dropouts (Abundance = 2; Control = 2; Scarcity = 4). Continuous variables reported as means (standard deviations in parentheses). Categorical variables reported as percentage of participant sample.

	Abundance	Control	Scarcity	*All Conditions*
Continuous Variables				
Age	37.04 (9.31)	38.65 (11.63)	38.06 (12.09)	37.92 (11.08)
Work Experience	15.72 (9.28)	17.16 (11.53)	16.63 (11.55)	16.50 (10.83)
Number of Contacts	3.24 (0.61)	3.39 (0.82)	3.22 (0.79)	3.28 (0.75)
Average Closeness	81.52 (12.52)	82.25 (12.41)	82.73 (14.02)	82.17 (12.99)
Cov19: Familiarity	4.14 (0.68)	4.12 (0.71)	4.20 (0.59)	4.16 (0.66)
Cov19: Impact	3.42 (1.03)	3.21 (1.02)	3.34 (0.95)	3.32 (1.00)
Categorical Variables				
Female	34.75%	44.92%	43.44%	41.06%
Highest Degree				
No Degree	0.85%	0.85%	0.00%	0.56%
HS Degree	20.34%	22.88%	22.13%	21.79%
2-Year / Skilled Trade	16.95%	17.80%	16.39%	17.04%
4-Year College	46.61%	44.07%	45.08%	45.25%
Masters +	15.25%	14.41%	16.39%	15.36%
Region				
West	22.03%	18.64%	21.31%	20.67%
Midwest	25.42%	22.88%	24.59%	24.30%
South	40.68%	34.75%	33.61%	36.31%
Northeast	11.86%	23.73%	20.49%	18.72%
US Territory	0.00%	0.00%	0.00%	0.00%
Not Disclosed	0.00%	0.00%	0.00%	0.00%
Industry Division				
Division A	0.00%	2.54%	0.00%	0.84%
Division B,C,D	8.47%	11.02%	7.38%	8.94%
Division E	16.95%	13.56%	13.93%	14.80%
Division F,G	16.10%	9.32%	18.85%	14.80%
Division H	9.32%	13.56%	13.11%	12.01%
Division I	44.92%	46.61%	42.62%	44.69%
Division J	1.69%	2.54%	3.28%	2.51%
No Experience	2.54%	0.85%	0.82%	1.40%

Table A.4.6. Study 3B: Individual Differences – MTurk. (*Continued*.) Summary of individual differences, by Condition. N = 358 (Abundance = 118; Control = 118; Scarcity = 122). Excludes 8 dropouts (Abundance = 2; Control = 2; Scarcity = 4). Continuous variables reported as means (standard deviations in parentheses). Categorical variables reported as percentage of participant sample.

	Abundance	Control	Scarcity	*All Conditions*
Professional Role				
Self-Employed, Partner	12.71%	10.17%	9.02%	10.61%
Trained Professional	26.27%	29.66%	17.21%	24.30%
Skilled Laborer	7.63%	20.34%	13.11%	13.69%
Consultant	4.24%	0.00%	4.10%	2.79%
Sales Staff	8.47%	0.00%	4.92%	4.47%
R&D	2.54%	2.54%	4.92%	3.35%
Admin, Support Staff	16.95%	10.17%	25.41%	20.95%
Management	18.64%	16.10%	20.49%	18.44%
No Experience	2.54%	0.85%	0.82%	1.40%
Not Disclosed	0.00%	0.00%	0.00%	0.00%
Stay-At-Home Order	66.10%	56.78%	61.48%	61.45%
Laid Off	9.32%	10.17%	13.11%	10.89%