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The effect of job loss on risky financial decision-making

Samuel D. Hirshman[a,1], Abigail B. Sussman[b], Carlos Vazquez-Hernandez[c], Daniel O'Leary[b], and Jennifer S. Trueblood[d]

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Job loss is a common and disruptive life event. It is known to have numerous long-term negative effects on financial, health, and social outcomes. While the negative effects of becoming unemployed on health and well-being are well understood, the influence of job loss on financial decisions has received little attention. Across a large-scale survey ($N = 37{,}854$), spending data from a bank ($N = 404{,}470$), and two online experiments (total $N = 1{,}403$), we find that job loss increases financial risk-taking. First, in survey data, job loss is associated with elevated levels of self-reported financial risk-taking and lottery ticket purchases. Next, using administrative data from a large bank, we find consistent causal evidence of the influence of job loss on gambling spending. Although total spending decreases after job loss, gambling spending is less affected than our control categories. Finally, we turn to two incentive-compatible manipulations of job loss operationalized in a lab setting. We find that this experimental manipulation increases the take-up of financial risks. The current finding that job loss increases financial risk-taking could accentuate long-term negative financial effects of job loss.

job loss | risk | financial decision-making | employment

Significance

Few life events are as detrimental to a person's well-being as job loss. It has a substantial effect on spending, mental and physical health, and behavior. However, less is known about its impact on decision making outcomes like risk-taking. We focus on job loss and risk-taking behavior, using a multimethods approach presenting correlational evidence from survey data, and causal evidence from administrative data on gambling spending from a large bank and an online lab experiment. Job loss shifts decision making toward more risky financial decisions. This tendency to take more financial risk could accentuate the negative outcomes associated with job loss.

Job loss is one of the most disruptive life events that a person can experience (1, 2). However, job loss is common, with societies regularly experiencing large-scale fluctuations in employment (3). The negative effects of job loss on physical and mental health (4–6) and on economic indicators are well studied (7, 8). For example, job loss has persistent negative effects on subsequent employment and earnings, regardless of age at the time of job loss (9). It also has been linked to increases in criminal behavior for both economically motivated and violent crimes (10). However, it is not clear whether job loss changes how individuals make decisions and, specifically, their approach to risk-taking.

The COVID-19 pandemic was marked by high levels of unemployment and changes in risk-taking, including increased financial risk-taking among some individuals. In the United States, the unemployment rate reached 14.7%, (i.e., 23.1 million people; 11), higher than at any time since the Great Depression (12). At the same time, sales of scratch-off lottery tickets increased by up to 83% in some parts of the United States (13). While a variety of factors could lead to increases in financial risk-taking, like buying lottery tickets, these patterns could partially reflect a relationship between peoples' economic distress and their willingness to take financial risks.

Basic economic models of risk-taking suggest that people should be more hesitant to lose money when they are facing worsened financial circumstances. Several papers examine the relationship between financial well-being (e.g., levels of wealth, income, and financial scarcity) and risk-taking. These papers tend to find that risk-taking increases with more income and wealth (14–17). On the other hand, income is consistently negatively associated with lottery ticket purchases (18–20). People may take on more risk as a way to achieve much-needed liquidity (21). The relationship between changes in financial outcomes and financial risk-taking has been underexplored.

Another stream of research focuses on how comparisons to reference points can drive financial risk-taking. People often increase risk-taking (i.e., become risk-seeking) when they are at a loss relative to a reference point (22). Job loss may induce perceived losses both compared to internal benchmarks like prior income, prior standard of living, or perceived needs, as well as compared to external benchmarks like perceptions of other people's wealth. Both types of benchmarks have been shown to increase risk-taking behavior. In the lab, risk-seeking in losses relative to internal benchmarks is a common and well-replicated phenomenon (23). Losses relative to others have also been shown to induce a variety of risk-taking behaviors (24–27). As a result, risk-seeking in the domain of losses may drive people who lose their jobs to make more financially risky decisions.

Using three different data sources and approaches across four studies, we demonstrate increased risk-taking behavior after job loss. In our first study, which analyzes Americans' attitudes toward risk during the COVID-19 pandemic, we found that job loss

Author affiliations: [a]Department of Economics, Norwegian School of Economics, 5045 Bergen, Norway; [b]Booth School of Business, University of Chicago, Chicago, IL 60637; [c]The University of Sydney Business School, University of Sydney, Darlington, NSW 2006, Australia; and [d]Department of Psychological and Brain Sciences, Indiana University, Bloomington, IN 47405

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[1]To whom correspondence may be addressed. Email: samuel.hirshman@nhh.no.

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corresponds to an increase in financial risk-taking behaviors. We draw this conclusion from data collected through a repeated cross-sectional survey, and it is supported by two indicators: first, a hypothetical gambling task assessing risk preferences, and second, self-reported lottery ticket purchases. Although these findings are correlational, they suggest a link between unemployment and increased financial risk-taking, laying the groundwork for our further causal investigations.

Our second study uses a difference-in-differences design to examine data from an Australian bank. After job loss, we find a relative increase in the likelihood and magnitude of gambling spending compared to other spending categories. While spending decreases across categories, it declines less for gambling. We interpret this relative increase in gambling spending as indicative of increased risk-taking behavior in response to job loss offsetting income effects.

In our third and fourth studies, we conduct laboratory experiments online to further isolate the causal effect of job loss on financial risk-taking. In the first lab experiment, wee find that after losing the ability to earn bonuses in our task, participants are more likely to take a gamble to double their earnings. In our second experiment, we preregister and replicate findings from experiment one and examine how offsetting the financial impacts of job loss affect risk-taking using two additional conditions. Compensating participants for their monetary losses reduces risk-taking behavior, as does allowing participants to continue earning money in the task but at a reduced piece rate.

Our main finding is that job loss causes people to be more willing to take financial risk. This finding runs contrary to the simple economic intuition that people should be more hesitant to lose money when they are facing worsened financial circumstances. The increased financial risk-taking we examine could also accentuate long-term negative effects of job loss if people are consistently losing money when they most need it (20).

Results

Survey Evidence. We examine the relationship between job loss and financial risk-taking using data from survey respondents in the United States collected during the first year of the COVID-19 pandemic. The data were collected using the Lucid Theorem online survey platform, which targets Census-based quotas to generate a representative sample of U.S. respondents (28). The evolving nature of the economic impacts of the pandemic coupled with our cross-sectional survey design spread throughout the year provided substantial variation in the likelihood of participants having recently lost their job ($N = 7{,}180$, 19.0% of our sample). To elicit financial risk-taking, participants completed a 9-item price list comparing $50 for certain to a set of gambles with decreasing chances to win $100 and reported the number of lottery tickets they had purchased in the last week on an 11 point scale (0 to more than 10). Participants who did not lose their jobs ($N = 30{,}674$) selected a mean of 2.72 risky choices in the gamble task and purchased a mean of 0.80 lottery tickets. By contrast, those who lost their jobs from COVID-19 selected a mean of 3.23 risky choices and purchased a mean of 1.58 lottery tickets. In our formal regression model including controls for gender, age, education, subjective social status, and whether people are unemployed and looking for work, participants who lost their jobs due to COVID-19 made more risky choices in our hypothetical gamble task ($\beta = 0.47$, 95% CI = [0.41, 0.53], t(32150) = 15.95, $P < 0.001$) and reported purchasing more lottery tickets ($\beta = 0.93$, 95% CI = [0.87, 1.00], t(32150) = 27.84, $P < 0.001$) than participants who did not lose their jobs (Fig. 1). Additional analyses in supplement examine potential mediators of the effect of job loss on financial risk-taking.

These results suggest a connection between job loss and changes in financial risk-taking behavior. We further explore this connection and provide evidence from two additional sources that support a causal relationship between job loss and increased financial risk-taking.

Evidence from Bank Data. To extend our correlational finding that job loss is associated with financial risk-taking, we turn to spending data from a large Australian bank. As a result of the COVID-19 pandemic, unemployment in Australia reached 7.4% in June and July of 2020, an increase of over 2 percentage points

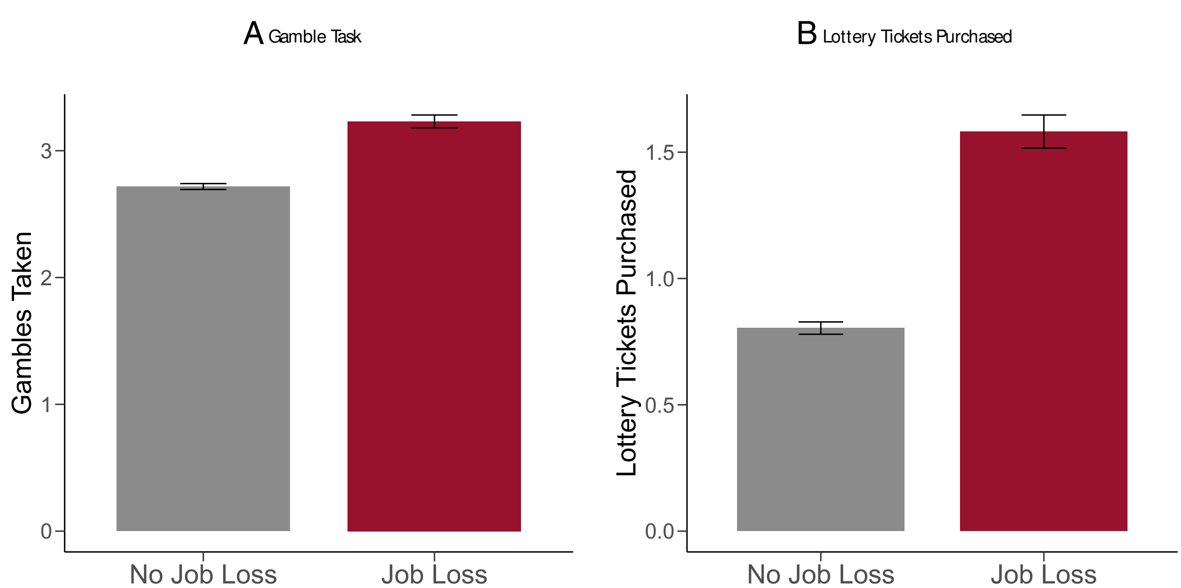

Fig. 1. The figure plots the results from our key measures in the cross-sectional survey. Gray bars show the no job loss group ($N = 30{,}674$) and red bars show the job loss group ($N = 7{,}180$). Panel *A* plots the number of gambles taken in our gamble task. Panel *B* plots the self-reported number of lottery tickets purchased. Error bars represent 95% CI.

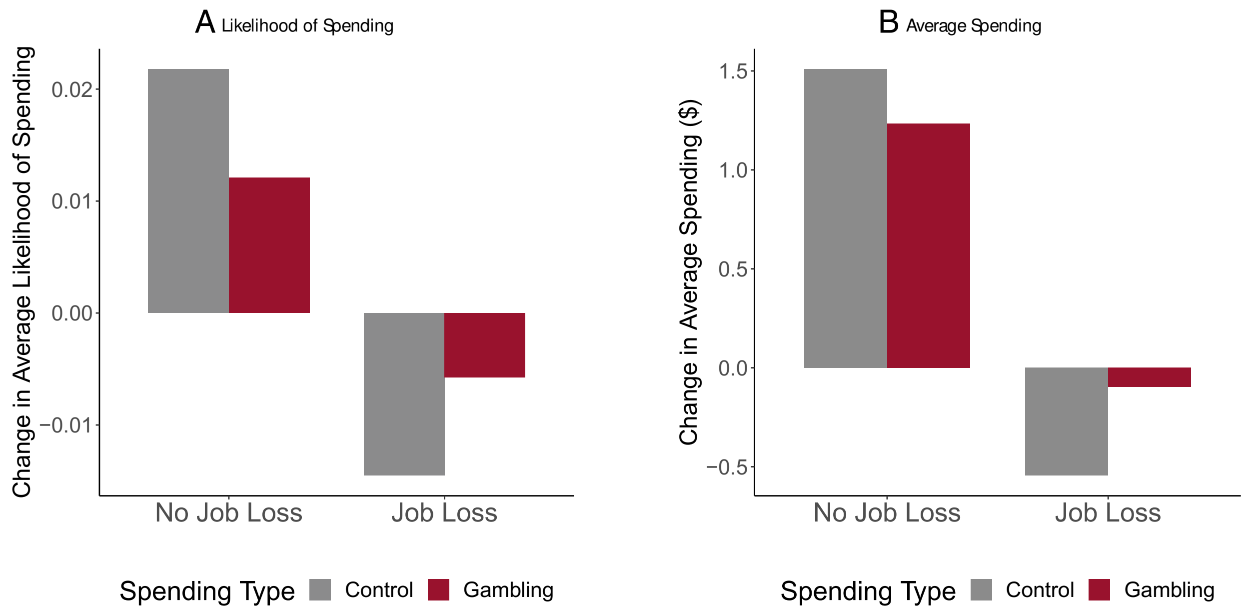

Fig. 2. Panel *A* shows the change in the likelihood of spending before and after the month in which the job loss group lost their job in both gambling and control categories. Panel *B* shows the change in the average amount of spending before and after the month in which the job loss group lost their job in both gambling and control categories. Gray bars represent the change for control categories, red bars represent the change for gambling spending. For the full model without controls, see *SI Appendix*, Table S11.

from before the pandemic (29). We use variation in the timing of bank customers losing their job to identify the causal impact of job loss on financial risk-taking using gambling spending as a proxy for financial risk-taking.

Our analysis examines both the likelihood of having any spending on gambling and the average amount spent. Specifically, we compare how spending evolves over time for people who lose their jobs compared to those who do not in the months before and after job loss. Our no job loss group is matched to cohorts of people who lost their jobs by job loss month. For example, for the job loss group who lost their job in February 2020, we use data for the no job loss group from August 2019 to August 2020 and define post job loss in calendar terms as February 2020 to August 2020. We examine a preregistered set of control categories involving discretionary spending. These control categories are intended to capture the income effect of job loss in standard economic theory (e.g., people with less income are likely to spend less overall, irrespective of risk preferences). Our key parameter of interest is the three-way interaction of gambling X job loss group X post job loss. If gambling spending evolves in the same way as other discretionary spending for the control and treatment groups, then this coefficient will be 0. If gambling spending is more sensitive to job loss than other forms of spending, we would expect a negative interaction in which spending on gambling decreases more than spending in other categories. Finally, if, as suggested by our survey evidence in study one, job loss induces more financial risk-taking, we would expect to see a positive interaction in which spending on gambling increases relative to spending in the other categories.

We present the change before and after job loss in the likelihood of spending (Fig. 2*A*) and the amount of spending (Fig. 2*B*) for both gambling and nongambling categories. Consistent with our hypothesis discussed above, the data show that gambling spending decreases less than nongambling spending for the job loss group. The triple interaction is statistically significant without controls for both the likelihood of having gambling spending ($\beta_{postXjoblossXgambling} = 0.018$, $se = 0.002$) and average spending ($\beta_{postXjoblossXgambling} = 0.723$, $se = 0.184$). Testing more formally, we present our stacked triple difference ordinary least squares specification in Table 1, accounting for individual, calendar month, and month of job loss effects (30). We find an expected overall decrease in both the likelihood and the amount of spending in the control categories after job loss. These coefficients reflect standard results in the job loss and spending literature (8). However, the decrease in spending is offset by a positive and significant triple interaction coefficient for both spending likelihood and amount. That is, spending on gambling and in casinos increases relative to our control categories. The relative increase for gambling offsets 55% of the decrease in spending likelihood and 38% of the spending amount from job loss in our other categories. We interpret the relative increase as consistent with an increase in financial risk-taking after job loss. Our results in the bank data suggest people are taking more financial risk in the period after job loss than they would have taken if they had not lost their jobs. Additional robustness analyses are available in *SI Appendix*.

Experimental Evidence. In the previous section, we showed a causal link between job loss and gambling spending. We turn to the more controlled environment of an experiment to replicate our findings in both the survey and bank data and to examine how offsetting the financial impact of job loss can affect financial risk-taking. We use an online marketplace where people are used to making money doing experiments. All participants begin the experiment with the opportunity to earn a bonus through their actions (i.e., their "job"), and we experimentally vary whether they lose the ability to earn bonuses. We use a paradigm where participants completed a reinforcement learning task to earn points. To mimic job loss, we manipulated whether or not participants lost the ability to earn additional points halfway through the task.* At the end of the reinforcement learning

*Participants knew that this was a possibility from the beginning of the task but did not know whether it would happen to them.

Table 1. Results from bank data triple difference specification

	Any spending	Avg. spending ($)
Post job loss	0.006	0.274
	(0.003, 0.01)	(−0.058, 0.605)
Is gambling spending	−0.108	−3.053
	(−0.111, −0.105)	(−3.499, −2.608)
Post × Job loss customer	−0.034	−1.925
	(−0.042, −0.027)	(−2.513, −1.337)
Post job loss × Is gambling spending	−0.01	−0.276
	(−0.02, 0.001)	(−1.243, 0.692)
Is gambling spending × Job loss customer	−0.006	−0.148
	(−0.011, −0.001)	(−0.464, 0.167)
Post × Gambling spending × Job loss customer	0.018	0.723
	(0.014, 0.023)	(0.362, 1.085)
Observations	5,694,402	5,694,402

Note: The key parameter of interest is the triple interaction, which compares how gambling spending changes relative to other spending for those who have lost their jobs. Each model uses customer, calendar month, and job loss cohort fixed effects. Parentheses contain 95% CI using SE two way clustered at the customer and job loss cohort level.

task, participants had the opportunity to take a gamble with a 50% chance to double their bonus payment and a 50% chance to lose it. Participants in the job loss condition (49.5%) were more likely to choose to gamble their bonus than were participants in the control condition (27%; Odds Ratio = 2.65, 95% CI = [1.48, 4.82], z = 3.24, P = 0.001; see Fig. 3*A*). One possible explanation for this result is that the budgets are different between no job loss and job loss conditions, so increase in risk-taking could be driven by the lower amount of money at stake for the job loss group. However, participants in our job loss condition also reported an increased willingness to gamble in a hypothetical lottery (for details, see *SI Appendix*). These results provide additional causal evidence that job loss leads to increased financial risk-taking.

We conducted a second experiment to replicate our findings and explore the role of risk-seeking in the domain of losses in driving increased risk-taking after job loss (22) by providing two conditions that ameliorate financial losses. We included a compensation condition where participants lost the ability to earn points during the task, but they received a lump sum payout at the end of the task as a proxy for unemployment insurance that compensates the participants for their lost income. In a second condition, participants continued to earn points during the task, but at half the rate in the second half of the task.

First, we replicate our prior findings that job loss increases risk-taking in the job loss condition (Control: 22%, Job Loss: 42% , OR = 2.62, 95% CI = [1.84,3.75], z = 5.29, $P < 0.001$; for hypothetical gamble, see *SI Appendix*). Second, the compensation condition reduced risk-taking relative to our job loss condition (Compensation: 28%, OR = 0.52, 95% CI = [0.37,0.73], z = 3.74, $P < 0.001$). This suggests that compensating individuals for the monetary impact of job loss can limit increased risk-taking. If participants have certain expectations about how much they will earn, then the compensation payment may shift them out of the loss domain. Third, the reduced rate condition also showed lower risk-taking than the job loss condition (Reduced Rate: 25% OR = 0.45, 95% CI = [0.32,0.63], z = 4.51, $P < 0.001$; see Fig. 3*B*). The ability to continue earning points in the reduced rate condition may keep people in the gain domain, even if they earn less than in the first half of the task. Additionally, the reduced rate condition helps alleviate concerns that the difference between our job loss and no job loss condition is coming from the size of bonuses gambled. People in the reduced rate condition gambled at approximately the same level as our control condition (Reduced rate vs. Control: OR = 1.17, 95% CI = [0.81,1.72], P = 0.40), but also have much lower points earnings than the control condition.

Discussion

Using three different sources of data and variation in job loss, we provide convergent evidence that losing a job leads to increased financial risk-taking. Our findings support a causal relationship between job loss and financial risk-taking in both spending data from bank customers and risky choices from online experimental participants. In the bank data, we observe a well-documented drop in spending after job loss across all categories examined; however, gambling spending is less affected by job loss than our control categories are. We interpret the relative increase in gambling spending as an increase in willingness to take financial risk that is offsetting the standard income effect. Using online experiments, we provide convergent evidence that job loss increased financial risk-taking. A follow-up experiment finds that offsetting the financial losses associated with job loss can substantially reduce risk-taking after job loss.

There has been a substantial focus in the literature, particularly in economics, on people's aggregate spending responses to unemployment and unemployment insurance, as well as job search behavior (e.g., refs. 8 and 31). In general, this work considers how overall spending responds to job loss and changes to unemployment benefits. Less work has focused on the impact of job loss on specific decision making outcomes like how job loss impacts financial risk-taking. Our work finds that losing a job alters risk preferences in a way that induces more financial risk-taking. This contributes to a growing literature on the stability of risk preferences and risky behavior (10, 32–35), suggesting a role for job loss to trigger risk-seeking behavior in the domain of losses. However, it is not clear from our studies how job loss shifts reference points and what kinds of comparisons induce risk-taking. People could be more affected by their losses relative to internal benchmarks, such as their prior income, or to external benchmarks like perceptions of others' wealth. Additionally, it is not clear how people adjust to job loss over time and how getting new jobs alters their expectations. Future work should examine the ways in which job loss impacts these different potential reference points and their downstream effects on risk-taking.

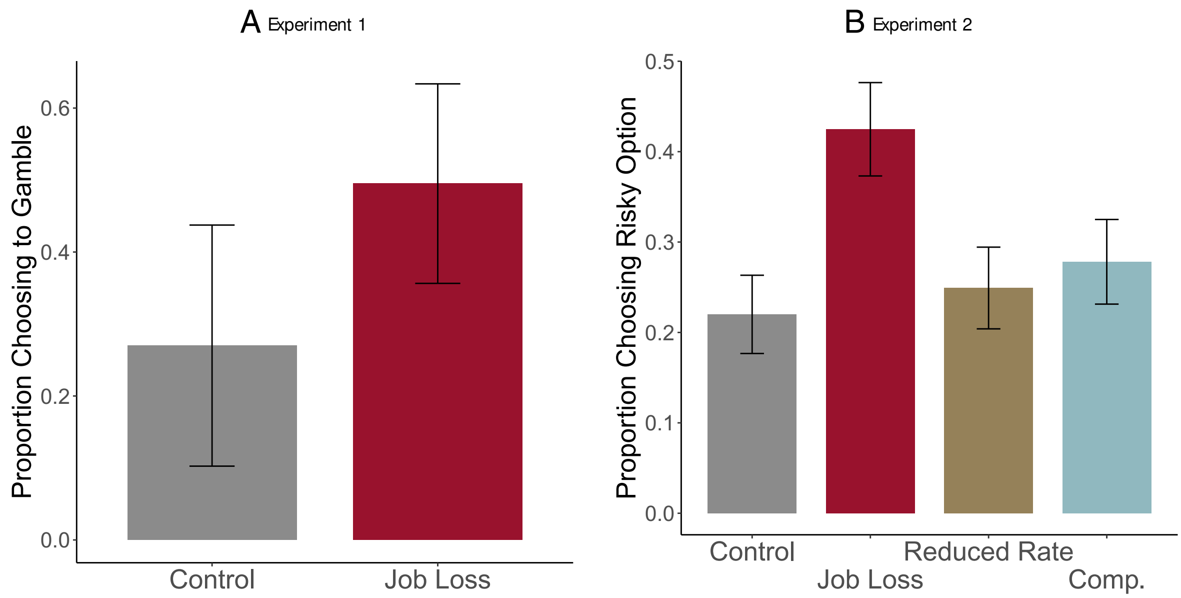

Fig. 3. The figure plots the proportion of participants choosing to gamble their earnings from Experiment 1 in panel *A* ($N = 201$) and Experiment 2 ($N = 1{,}202$) in panel *B*. Gray bars show the no job loss group and red bars show the job loss group for both experiments. For experiment two, the gold bar shows the reduced rate condition, and the blue bar shows the compensation condition. Error bars represent 95% CI.

Our results also speak to the literature on gambling as a liquidity-generating mechanism for those in financial constraint (21, 36) and risk-taking in response to lower relative financial status when compared to others (26, 27). More work should focus on how job loss can impact fundamental economic preferences and specific decision making outcomes.

The detrimental effects of losing one's job can extend beyond financial consequences, leading to long-lasting changes in life satisfaction (1) and physical health (4–6). Notably, brief shifts in risky decision-making could lead people to engage in riskier behaviors with consequences that extend well beyond the short term. For example, we find job loss increases gambling behavior, which may, via gambling losses, accentuate financial constraint. Extrapolating from these results, policy makers could take action to offset increased risk-taking by implementing policies that compensate for unemployment or that encourage firms to keep employees on the payroll even with fewer hours or lower wages.

Macroeconomic forces and recessions will continue to lead to major changes in employment and large-scale job losses (e.g., due to factors such as automation). Although providing a strong social safety net for people who have already lost their jobs is an important policy goal, our results suggest the importance of studying policies designed to keep people employed, perhaps at reduced hours or pay. Such policies could offset the increased risk-taking after job loss that we examined.

Materials and Methods

Survey Data. The data were collected using the Lucid platform (28) as part of a study examining the psychological and financial impacts of the COVID-19 pandemic (37). The data were a repeated cross-sectional sample of respondents in the United States that targeted Census quotas on a variety of demographic measures (see *SI Appendix* for additional details). New participants were recruited for each wave. In the initial stages of the pandemic (from 20 March 2020 to 21 April 2020), two waves of data were collected weekly. Beginning on 21 April 2020, one wave of data was collected weekly. Beginning in December of 2020 through March of 2021, one wave of data was collected monthly. The analyses in the main paper use data from waves 15 to 40. The data necessary to reproduce the results of the survey analyses and all analysis code are available on the Open Science Framework (OSF) at https://bit.ly/3cysZGn. The OSF also includes a preregistration for waves 15 and 16, and these preregistered analyses are available in *SI Appendix* (see p. 11). The analyses presented in the main text include more waves of data and a more stringent exclusion criteria for consistent job loss—described in the next paragraph—but are replicated in the preregistered analyses.

37,854 (21,382 women, 16,472 men, age: $M = 45.57$, $SD = 17.17$) individuals participated in the present research. The attrition rate was 25.6%. We restricted our sample to the 32,157 participants who consistently answered three questions related to job loss in our survey. These questions were: "Have you lost your job as a result of the current economic downturn related to COVID-19," "If you lost your job as a result of the current economic downturn related to COVID-19, how does the amount of money you are receiving for unemployment insurance compare to your income prior to becoming unemployed?," and "If you lost your job as a result of the current economic downturn related to COVID-19, how long ago did you lose your job?" For each question, there was an option to indicate that participants had not lost their job due to COVID-19. We only include participants who always report that they did or did not lose their job due to COVID-19. These participants ranged in age from 18 to 99, 18,706 were female (59%), with a mean reported income of between \$60,000 and \$70,000 a year.

Our key variables were reported COVID-19-related job loss as described in the first question above and two measures of financial risk-taking: a simplified version of a gamble ladder similar to ref. 38 and self-reported purchases of lottery tickets ranging from 0 to "more than 10." Our main analyses were linear regressions with the main variable of interest a binary variable for COVID-19-related job loss. We also included control variables for 2) general employment status, 3) education, 4) subjective social status, 5) gender, and 6) age.

Bank Data. We obtained data from a bank in Australia on customers' spending and salary deposits for January 2019 to May 2021 as well as some demographics. This sample included both people who were employed during 2019 and then who lost their job in 2020 ($N = 354{,}967$) as well as a control group of people who were employed during 2019 and who did not lose their job during 2020 ($N = 49{,}503$). 52.1% of the customers in our sample are male, median age band of 31 and 35, and an average customer tenure of 15.92 y, and earned a mean (median) of 4,317 (3,663) AUD per month in 2019. The mean in our sample is lower per month than in Australia as a whole with mean earnings of 5,218.8 AUD in May 2020 (39). The customers were spread out across Australia with some overrepresentation in larger states (see *SI Appendix* for a map of the population of our sample). People who lost their jobs tended to be younger ($\beta_{jobloss} = -3.37$, $se = 0.06$), have been with the bank for fewer years ($\beta_{jobloss} = -3.08$, $se = 0.051$), were more likely to be female ($\beta_{jobloss} = -0.017$, $se = 0.002$), and made less money per month in 2019 ($\beta_{jobloss} = -704.92$, $se = 0.14.57$).

The spending data from the bank are organized by spending categories used internally to classify spending. These categorizations rely on a classification of the merchant. For example, if a customer shops in Woolworths (a supermarket in Australia), the merchant category assigned is Supermarket/grocery store and the spending is categorized as "Groceries." Importantly for our study, one of the categories is "Betting/Casino Gambling," which we use to estimate the impact of job loss on financial risk-taking. We compare this category to a preregistered set of alternative spending categories (for preregistration information see http://bit.ly/3cysZGn) which were selected because they were discretionary categories, had fairly frequent spending as a proportion of consumer months, and were unlikely to be directly affected by COVID restrictions (e.g., vs. restaurant spending, which may have gone down due to lockdown restrictions and grocery spending, which may have gone up as a consequence of the restaurant restrictions). These were:

- Department Stores
- Men's, Women's Clothing Stores
- Digital Goods-Audiovisual Media Including Books, Movies, and Music
- Music Stores-Musical Instruments, Pianos, and Sheet Music

We observe all customer spending at the transaction level, but aggregate the data to the customer-category-month level to match our definition of job loss, which is at the month level. Our two key dependent measures are whether a customer has spending in a category and how much spending they have, with spending winsorized at the 95th percentile. We operationalize job loss as the month in which we first observe a customer receiving \$0 in salary deposited in their account.

We group the customers with job loss by month of job loss and create a paired control group for each job loss month, which we refer to as the job loss cohort, in a stacked triple difference-in-difference design (30). This allows us to define a pre-post window around the job loss month for both treatment customers, who lose their jobs in that month, and control customers who do not. We examine how gambling spending vs. spending in our other categories evolves after job loss using a 12-mo window around the month of job loss (i.e., 6 mo prior to 6 mo after) with the reference period being the month prior to our observation of \$0 in salary. Examining differences by spending category has been done in prior work on job loss and unemployment insurance (8). Under the parallel trends assumption that spending would evolve similarly in all spending categories absent job loss, our estimates causally identify the impact of job loss on spending in each category. The specification we estimate is

$$\begin{aligned} Y_{ict} \sim\ & \alpha + \beta_1 * Post_{it} \\ & + \beta_2 * IsGambling_{ict} \\ & + \beta_3 * Post_{it}xJobLossCustomer_i \\ & + \beta_4 * Post_{it}XIsGambling_{ict} \\ & + \beta_5 * IsGamblingXJobLossCustomer_{ic} \\ & + \beta_6 * PostXIsGamblingXJobLossCustomer_{ict} \\ & + \gamma_1 * ID_i + \gamma_2 * CalendarMonth_t \\ & + \gamma_3 * JobLossMonthGroup_i + \epsilon, \end{aligned}$$

where Y_{ict} represents our outcome variable for customer i in category c in month t with SE two way clustered at the customer id and job loss cohort level.

Experiment 1. 201 participants (108 women, 92 men, 1 nonbinary, age: $M = 41.50$, $SD = 12.76$) completed this study. Participants were recruited through Amazon Mechanical Turk using CloudResearch. 101 participants were in the treatment (i.e., job loss) condition and 100 participants were in the control condition. The attrition rate was 7.8%. This study was approved by the local Institutional Review Board (Vanderbilt #201466) and informed consent was obtained from participants prior to participating in the study.

Materials and procedure. We adapted a version of an 80 trial reinforcement learning task (40) to use as a proxy for work. There were four options (A, B, C, and D) with rewards drawn from normal distributions with means of 36, 40, 50, and 54, respectively (40). All distributions had a SD of 5 and were truncated at 3 SD above and below the mean. On each trial, participants saw two of the four options, represented by geometric figures. Only four of the six possible pairs of options were shown: AB, AC, BD, CD (40). Participants were told that each figure offered different numbers of points and that the figures varied in the range of possible points they provided. They were instructed to select whichever figure was associated with a greater number of points. However, they had to learn which of the options was most rewarding, and they were not told the point values or distributions ahead of time. Participants received full feedback on every trial, and the total number of points was displayed at the top of the screen. Participants received a bonus payment at a rate of 1 cent per 100 points earned in the task. This constituted their wage for the task, in addition to a base payment of \$1.00.

At the beginning of the task, participants were told that at some point while completing the task, they might lose their ability to earn additional money. They would not lose the money they had already earned, but they would lose the ability to earn more. Further, they would still need to pay attention to the task to earn the base payment for the experiment. We randomly assigned participants to one of two conditions. Participants in the control condition continued the task. Participants in the job loss condition lost the ability to earn money after trial 40.

After all 80 trials were completed, participants were told the total points that they earned during the task. They were then asked, "Overall, how much did you like or dislike this task?" Response options ranged from 1 = dislike a great deal to 7 = like a great deal. Next, participants were presented with an incentive-compatible risky decision. They could either keep the bonus payment that they had earned during the task, or they could choose to invest their winnings in an investment with a 50% chance of doubling their bonus and a 50% chance of losing their bonus. Decisions to gamble the bonus served as our central measure of risky decision-making. Participants also completed a hypothetical gamble question described in *SI Appendix*.

Experiment 2. In our second experiment, we replicated the methods of our first experiment and included two additional conditions. We preregistered this experiment using asPredicted (#98848). In the reduced rate condition, participants worked and earned points for the whole task, but from rounds 40 to 80 earned half as much as they had in rounds 1 to 40. In the compensation condition, participants were compensated for losing their job with a lump sum payment equal to the average amount participants typically earned in rounds 40 to 80. 1,202 participants (663 women, 533 men, 6 other gender; age: $M = 43.71$, $SD = 74.46$) completed this study.[†] The attrition rate was 5.8%. Participants were recruited through Amazon Mechanical Turk using CloudResearch. Participants were assigned to one of four conditions: 300 participants were in the control condition, 299 in the job loss condition, 301 in the reduced rate condition, and 302 in the compensation condition.

Data, Materials, and Software Availability. Survey and experimental data have been deposited in OSF Job Loss and Risk Taking (https://osf.io/jmy4f/) (41). The study based on data from an Australian Bank is proprietary, and we cannot make it public. The code we used to generate the analyses is available in the OSF repository. Our data use agreement with the bank does not allow us to reveal the identity of the bank. Amy Boonstra (amy.boonstra@chicagobooth.edu), who manages the contractual relationship between the University of Chicago Booth School of Business and the bank, can be contacted to facilitate requests to the bank for access to the archived data which will be contingent upon approval of the bank's research team.).

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[†]2 participants list ages that were above 100. Excluding those participants, the mean age is 40.71 with a SD of 12.53.

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