THE UNIVERSITY OF CHICAGO

VENTURE CAPITAL AND PRIVATE M&A CONTRACTING

A DISSERTATION SUBMITTED TO
THE FACULTY OF THE UNIVERSITY OF CHICAGO
BOOTH SCHOOL OF BUSINESS
IN CANDIDACY FOR THE DEGREE OF
DOCTOR OF PHILOSOPHY

BY
LAUREN JULES VOLLON

CHICAGO, ILLINOIS
JUNE 2022

To my wife, Julia, and kids, Eloise and Lukas.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ACKNOWLEDGMENTS

I greatly appreciate the guidance and support of my dissertation committee: Hans Christensen (chair), Steven Kaplan, Mark Maffett, and Delphine Samuels. I thank Philip Berger, Stefano Cascino, Anna Costello, João Granja, June Huang, Christian Leuz, Mike Minnis, Maximilian Muhn, Thomas Rauter, Carol Seregni, Gurpal Sran, Christopher Stewart, Sinja Sussek, and Ira Weiss , and participants at Bocconi University, INSEAD, KU Leuven, Rotterdam School of Business, University of Amsterdam, University of California Riverside, the University of Chicago, and University of Notre Dame for their helpful comments and insights. I thank Maggie Li and Ziyi (Angela) Chen for excellent research assistance. All errors are my own.

ABSTRACT

Using a proprietary dataset of private-startup M&A contracts, I study the role of venture capital firms (VCs) in the exit process of startups. I find M&A contracts are significantly less likely to include earnouts, a proxy for the degree of ex-ante information asymmetry between the contracting parties, when a VC is participating in the transaction. Exploiting within-VC variation, I further show that earnouts are more likely to be used in M&A transactions with high information asymmetry between the VC and the buyer. To explore a possible mechanism through which VCs alleviate ex-ante information-asymmetry problems, I find M&A contracts are less likely to include earnouts when the VC had a previous transaction with the buyer. Lastly, I document that the use of earnouts is lower when it is more difficult for the VC to monitor the startup after the acquisition and when the M&A transaction occurs later in the lifecycle of the VC fund, consistent with post-acquisition monitoring costs and the structure of VC funds playing a role in M&A contracting.

CHAPTER 1

INTRODUCTION

Venture capital is a source of financing for private startups with long-term growth potential. Existing evidence suggests venture capital firms (VCs) provide value through the allocation of capital to promising startups and subsequent advising and monitoring (e.g., Gompers and Lerner, 2004). This oversight increases the likelihood of a successful exit (e.g., Sapienza et al., 1996; Cumming and Johan, 2008; Kaplan et al., 2009; Bernstein et al., 2016). The startup's exit is a key phase in the startup life cycle and creates an ex-ante incentive for founders, investors, and employees to innovate by providing them a mechanism to realize a return on their initial investments (e.g., Cumming and MacIntosh, 2003b,a; McKaskill et al., 2004). However, empirical evidence on the role that VCs play in the M&A exit process, and whether and how they affect M&A contracting, has been lacking.

To study whether and how VCs affect M&A contracting, I focus on the M&A market for private startups. The M&A setting has a couple advantages. First, M&A transactions occur more frequently than IPOs.[1] VCs go through many M&A transactions resulting in a dataset that links VCs (and the underlying VC funds) to buyers over time which allows me to address several identification concerns and to study the role of prior relationships in the M&A market. Second, this setting allows me to study the underlying contract-design decisions in M&A transactions and shine a light on whether and how VCs affect the contracting outcomes in the M&A market.

Specifically, I explore how VCs affect the use of earnout provisions in M&A contracts in the M&A market for private startups. An earnout is an arrangement in the M&A contract where part of the merger consideration is made contingent on a future event or performance. Earnouts are an important contracting mechanism. In my sample, conditional on having an

1. In 2019, only 12.25% of VC-backed U.S. startups exited through an IPO, whereas the 87.75% exited through an M&A transaction (PwC/MoneyTree Report Q1 2020). In 2020, the global value of M&As for VC-backed startups was around $150 billion (Crunchbase).

earnout, on average, 30% of the total purchase price is contingent consideration. Prior literature has shown earnouts are used in M&A contracts to mitigate adverse selection caused by asymmetric-information problems between the seller and buyer, and moral hazard problems between key employees and buyer (e.g., Kohers and Ang, 2000; Datar et al., 2001; Cain et al., 2011; Quinn, 2013; Cadman et al., 2014; Jansen, 2020).

Information-asymmetry problems between buyers and sellers are especially prevalent in private startup M&A transactions (Ragozzino et al., 2007). Generally, the startup's insiders have superior information relative to the buyer on the value of the firm, which leads to an adverse-selection problem because the insiders are either unwilling or unable to credibly disclose private information.[2] VCs could potentially alleviate information-asymmetry problems between the startup's insiders and potential investors. Specifically, VCs play a repeated game in the M&A market, which disciplines their behavior (and that of the startups' insiders). Repeated interactions with buyers in the M&A market also allow VCs to build relationships potentially reducing information-asymmetry problems. Therefore, I hypothesize that VC participation in an M&A transaction is negatively associated with the use of earnouts and, importantly, that the use of earnouts varies with the ability of VCs to alleviate information problems.

Studying the association between VC participation and the use of earnouts in M&A contracts requires overcoming a data challenge. Commercially available data on contractual features of private M&As is sparse and generally incomplete.[3] To overcome this challenge, I collect proprietary data from an anonymous specialized private M&A financial services firm. The proprietary data include executed M&A contractual agreements and term sheets for a sample of 1,000 M&A transactions of startups. The sample includes both startups with

2. Insiders in the startup, such as founders and key employees, hold most of the private information on the startup. Thus, the information problem between the insiders and potential investor is key.

3. For instance, using a matched sample, I find that Pitchbook, a provider of VC, private equity (PE), and M&A data, underreports the use of earnouts by approximately 50% compared with what I document based on the actual contractual agreements.

and without VC backing. I compile detailed information on how merger considerations are allocated among the investors and hand-collect contractual data on the earnouts.

Consistent with VCs affecting the use of earnouts in the M&A market, I find that the likelihood of having an earnout in the M&A contract declines by approximately 30% if the startup is VC-backed than if it is not.[4] Although some factors are unobservable, I try to alleviate potential issues related to the comparability of VC-backed and non-VC-backed M&A transactions by comparing acquisitions of VC-backed and non-VC-backed firms with a similar purchase price (including the earnout) in the same industry and year (i.e., I include *Startup Industry* × *Purchase Price Quintile* × *Year* fixed effects).

An empirical challenge is justifying the assumption that the use of earnouts is driven by information asymmetry between the startup's initial investors and potential buyers. I argue that the earnouts in my sample are used primarily to address adverse-selection problems between the startup and buyer.[5] As validation whether VCs alleviate information-asymmetry problems in M&A markets, I separate M&A transactions that include a regulatory-based earnout, which are based on reaching certain regulatory events such as an FDA approval or passing a clinical trial. These clauses are designed to alleviate uncertainty about the regulator's decision and less about the information asymmetry between buyer and insiders. Therefore, if VCs alleviate information asymmetry, there should not exist an association between VC participation and regulatory-based earnouts, which is confirmed by my results.

4. In this paper I refer to VC-backed startups and VC-backed M&A transactions that are startups and M&A transactions that have VCs receiving over 10% the merger consideration.

5. Another theoretical reason proposed for the use of earnouts is to address moral-hazard problems between key employees (with an equity stake) and the buyer. In this case, the earnout is used to incentivize key employees. Importantly, under this scenario the outcome of the earnout must be related to the effort of the earnout participants. The argument that earnouts are used to solve moral-hazard problems has two issues. Participation in earnouts is generally based on the investors' pro-rata share in the firm and will, in general, include investors whose ex-post effort has no impact on the earnout. In my main sample, I exclude earnouts that are based on founders or key employees remaining for a specified period after the acquisition as these earnouts specifically address moral hazard problems. Most earnouts in my sample are based on the pro-rata ownership share and cover a diverse pool of investors. As a robustness test, I redo my analysis only using 'pro-rata' earnouts which address the information asymmetry problem.

Next, I further explore and confirm information asymmetry as one of the main determinants of earnouts using within-VC variation. To do this, I change the level of analysis from the M&A transaction-level to the VC-startup-buyer-level. This data structure allows me to introduce *VC* $\times$ *year* fixed effects, alleviating both endogenous matching issues between VCs and startups and between startups and buyers. First, I use the distance between the VC and buyer as a proxy for information asymmetry between both parties (Agarwal and Hauswald, 2010; Granja et al., 2022). Using this design, I find that the use of earnouts increases with information asymmetry. In other words, *for the same VC*, when the distance between the VC and buyer is above the median distance, the likelihood of earnouts in the M&A contract increases.

After establishing that VCs generally alleviate information problems in the M&A market, I investigate a potential mechanism how VCs do this, *through* the relationships that VCs build with buyers through their portfolio-firm network. First, I investigate whether relationships between VCs and buyers matter. I analyze, using the entire universe of Pitchbook data, whether a VC-backed startup is more likely to be acquired by a buyer that has a previous transaction with the startup's VC through the sale of one of the VC's other portfolio firms. I map out all relationships between VC-startup pairs and buyers between 1996 and 2020. I determine whether a (previous) relationship exists between VCs and buyers between 1996 and 2015 (pre-sample period). For the period between 2015 and 2020 (sample period), I determine counterfactual M&A transactions that could have happened but did not. To do so, I partition the entire sample into *Startup-Industry* $\times$ *Buyer-Industry* groups and assume any startup could have been acquired by any buyer in the pre-sample period and sample period within that group. I find M&A transactions between VCs and buyers with a previous transaction are about 2.5 times more likely than would be expected randomly, suggesting that previous relationships matter. Second, moving back to my proprietary sample, I test whether an M&A contract between a VC-backed startup and a buyer, where the VC has a prior relationship with the buyer, is less likely to include an earnout. Because I only have limited transactions that include a VC with a previous relationship in my sample of M&A transactions.[6] Again, the data structure allows me to introduce $VC \times year$ fixed effects, alleviating some of the empirical issues discussed earlier. Using this design, I find that a VC having a prior relationship with a buyer decreases the likelihood of having an earnout contract by approximately 10 percentage points.

The previous results are consistent with VCs providing value in the M&A process by alleviating information asymmetry. From the startup's perspective, *all else equal*, having an M&A contract without an earnout is better as long as both contracts with and without the earnout are feasible.[7] If the ex-ante expected return to investors is the same for an M&A contract with and without an earnout, a risk-averse investor would prefer the M&A contract without the earnout, because this amount is certain and allows the investor to reinvest the full merger consideration earlier. However, investors in a VC-backed startup can be made worse off if the expected return on the M&A contract with the earnout, on average, is higher than the expected return on the contract without the earnout and they are forced into the latter contract by the VC. This scenario could happen if the VC prefers the M&A contract without the earnout and is able to force the other investors into that contract even though they would be better off with the other contract. VCs and other investors could have different preferences over the two contracts, due to different opportunity costs and/or monitoring costs.[8]

To explore whether VC-specific preferences over the use of earnouts play a role in the

6. Forty-four out of the 582 VC-backed M&A transactions include a VC with a previous relationship with the buyer.

7. Ex-ante information frictions between the startup's insiders and buyer could be so large that a transaction between both parties can only happen with the inclusion of the earnout. In the discussion that follows, I assume that two contracts are always available to the startup's investors: one contract with an earnout and one without an earnout.

8. For instance, if we assume the opportunity costs and/or monitoring costs are higher for VCs than for other investors, the VC would be willing to forego more upfront merger consideration to avoid an earnout. This willingness could potentially lead to different contractual preferences of VCs and other investors.

M&A market, I focus on two potential frictions for VCs when using earnout provisions: post-acquisition monitoring costs and VC fund cyclicality. First, an important cost of using earnouts are post-acquisition monitoring costs as a result of post-acquisition moral-hazard problems (Holmström, 1979; Datar et al., 2001).[9] I show that the distance between the VC and startup is negatively associated with the use of earnouts, which is consistent with post-acquisition monitoring costs being a determinant of earnouts. Second, I investigate whether the structure of VC funds plays a role in the use of earnouts. A VC fund's life is not infinite but, on average, 10 to 12 years; a VC fund is "self-liquidating." (Gompers and Lerner, 2004) An earnout contract locks up part of the purchase price pushing out payment to the limited partners of the fund.[10] Under the assumption that VC funds invest in comparable firms throughout the fund's lifetime and no payout constraints, we would expect to find no differences in the use of earnouts over the lifetime of the fund. However, I show that later transactions in the life cycle of the fund have a lower likelihood to include an earnout compared to earlier transactions. This is consistent with both the VC funds changing their investment behavior over time and/or VC funds, all else equal, changing their preferences over the M&A contract within a VC fund's lifecycle.

This paper makes three contributions to the literature. First, it contributes to the literature that studies the role of VCs and how they affect the outcomes of their portfolio firms. Much of this literature has focused on the value of VC monitoring and VC screening (e.g., Hellmann and Puri, 2002; Chemmanur et al., 2011; Puri and Zarutskie, 2012; Bernstein et al., 2016). Most of the studies on VCs have focused on the IPO setting. Cumming (2008) is an exception in studying the determinants of the M&A decision compared to the IPO decision. My results are consistent with the hypothesis that VCs play a role in mitigating

9. After the acquisition, the buyer owns the startup and thus has the control rights directly affecting the outcome of earnouts. For the VC it is important to monitor the startup after the acquisition has happened because the contractual means to constrain the actions of the startup are limited.

10. Note that it is not easy to make transfers among funds or to borrow money in anticipation of the payout of the earnout because the outcome of the earnout is uncertain.

information frictions in the M&A process, highlighting that VCs add value through more than monitoring and screening. Additionally, I add to the literature studying the role of VC relationships. Hellmann et al. (2008) show that banks use venture capital investments to build lending relationships.[11] In my study, I explore the relationship between VCs and buyers and how these relationships solve information problems and consequently affect M&A contracting.

Second, closely related to my study is the literature on IPO underpricing. Beatty and Ritter (1986), in an extension of Rock (1986), shows IPO underpricing increases in the ex-ante uncertainty about the valuation of an issue. Generally, this framework contains both informed and uninformed investors, and firms have to underprice their IPO issue to entice informed investors to invest. Financial intermediaries, such as investment banks, enforce this underpricing equilibrium because they have repeated interactions in the IPO market and need to protect their reputation. Although the role of the VC in my setting appears similar to the role of the financial intermediary, some important differences exist. First, VCs own an equity stake in the startup and thus bear real economic risk in the M&A transaction, which they have to trade off with other incentives. Second, in the M&A setting, the VC alleviates information-asymmetry problems, whereas the financial intermediary does not; the investment bank merely enforces the underpricing equilibrium. Third, the M&A setting has only one buyer, which is different from the IPO setting, which has both informed and uninformed investors.

Third, this paper adds to the broader M&A contracting literature, and more specifically, the literature on the determinants of M&A contracts. I provide evidence that the ownership structure affects the M&A contract design, by focusing on an important clause in M&A contracting, the use of contingent payments. The use of earnouts has been empirically

11. Because most of the acquisitions in my sample are on a debt-free and cash-free basis, I am able to abstract away from the role of lenders. In a "debt-free," "cash-free" acquisition, the seller pays off all debt and extracts all excess cash prior to completion of the transaction.

associated with information asymmetry between the buyer and seller in M&A transactions (e.g., Kohers and Ang, 2000; Datar et al., 2001; Cain et al., 2011; Cadman et al., 2014; Jansen, 2020). A recurring result in many of these studies is that the use of earnouts is in general highest in M&A transactions involving private firms. However, data limitations have hampered further investigation into the M&A contract dynamics within the group of private firms. This study fills the void by studying a sample of private startups being acquired by both public and private buyers. Additionally, I show that heterogeneity exists in the use of earnouts and that they can address different types of uncertainty.

CHAPTER 2

CONCEPTUAL UNDERPINNINGS

My research setting is the M&A market for startups. A startup is an early-stage or emerging firm that is considered to have high growth potential through the development of innovative products or services, or through the creation of a niche market. When these startups get sold in the M&A market the information asymmetry between startups and potential buyers is potentially severe. First, historical information on the startups is likely limited because of their young age. Second, all startups are private and therefore not required to publicly disclose financial information.

Generally, in (private) M&A transactions, uncertainty exists concerning the value of the selling firm, due to information frictions between the seller and buyer. In the extreme, the information asymmetry between sellers and buyers can lead to market failures. In the next two sections, I lay out two different mechanisms that can address or alleviate adverse-selection issues in M&A transactions: (i) contract design, and (ii) VC participation in M&A transactions.

2.1 M&A Contract Design and Earnouts

One objective of the M&A contract is to address information-asymmetry problems between the buyer and seller. An important contractual mechanism for solving information-asymmetry problems is the use of earnout provisions, i.e., to split up the merger consideration into two portions: (i) an upfront unconditional consideration, and (ii) a payment that is conditional on the outcome of a future event or future performance. Earnouts are used as a screening mechanism to separate "good" from "bad" sellers and generally shift risk from the buyer onto the seller, who has an informational advantage in the transaction. Post-acquisition monitoring costs are an important cost associated with the use of earnouts.

Once the M&A transaction is consummated, the buyer gains control rights of the startup.[1] Therefore, it is important for the startup's initial investors to monitor the buyer in order to maximize earnout payouts.

2.2 VC Participation

Invested VCs potentially reduce uncertainty around the value of the startup lowering valuation disagreement between the startup's insiders and buyer in M&A transactions caused by information asymmetry problems.[2] VCs do this by certifying the startup's underlying value. Because VCs have repeated interactions in the M&A market, this disciplines the startup's insiders and lowers the probability that they opportunistically withhold information and increases the credibility of the information provided. Certification can also happen through the relationships VCs build with buyers in the M&A market reducing information frictions between the startup and buyer. Other investors in the startup, mainly consisting of founders and key employees, are likely unable to perform the VC's role because they take startups to market less frequently and are therefore less disciplined in their behavior.[3]

2.3 VC Participation and Earnouts

If earnout provisions and VC participation address similar information frictions, they can be used as substitutes. Therefore, I hypothesize a negative association between VC participation and the use of earnouts. However, other frictions related to the VC could affect their use of earnouts. First, post-acquisition monitoring costs could be disproportionally high for

1. For instance, the buyer has complete control of investments into the startup.

2. VC participation can also directly affect firm value but the focus of this study is on how VCs potentially decrease the uncertainty around the value of the startups.

3. Table B1 in the Appendix shows that, on average, 58% of the merger consideration is going to individuals, which includes founders, employees, and other non-institutional investors. VCs, on average, receive 31.5% of the merger consideration. Other investor types represent, on average, not more than 2%.

VCs.[4] This could lead to VCs aiming to avoid earnouts in M&A contracts, which would be consistent with a negative association between VC participation and the use of earnouts. Second, the structure of VC funds could make it more costly for VCs to use earnouts later in the lifecycle of the fund. Again, this would be consistent with the aforementioned negative association. To provide further evidence on which frictions drive the use of earnouts, I leverage the detailed structure of my proprietary data using within-VC variation.

4. VCs likely have high opportunity costs to monitor the startup after the acquisition.

CHAPTER 3

DATA

I collect data on 1,000 private M&A transactions between 2015 and 2020 from an anonymous specialized private M&A financial-services firm. The firm provides advisory services to a wide range of U.S. (and some foreign) startups. Generally, for each M&A transaction in the firm's portfolio, two types of data sources are provided: (i) the executed M&A agreement (including separate contingent-payment agreements) and (ii) the M&A term sheet.

3.1 Earnouts

For each M&A transactions, I determine whether the M&A contract includes an earnout provision and develop a list of all individual earnouts.[1] Table 1, Panel A, shows that of the 1,000 M&A transactions in my sample, 246 transactions include at least one earnout.[2] In Figure 1, I assess whether the propensity of earnouts varies over my sample period, by plotting the number of transactions with an earnout and the total number of transactions between 2015 and 2020. No systemic changes in the use of contingent payments are apparent for my sample period.

In untabulated analysis, I benchmark my data on the use of earnouts to data provided by Pitchbook and show that earnouts are generally underreported in commercially available datasets that rely on publicly available information. Specifically, I am able to match 922 M&A transactions in my proprietary sample to the Pitchbook data. Based on Pitchbook's earnout size variable, only 10.3% of the 922 M&A transactions included an earnout, whereas

1. An M&A transaction can have multiple different contingent-consideration clauses. In Table 1, Panel C, I show that, conditional on having a contingent consideration, an M&A transaction in my sample has, on average, almost four different earnout clauses in the M&A contract.

2. I report the propensity of the use of earnouts by the startup's industry. As expected, the use of earnouts is generally high in the healthcare industry.

in reality, 25.9% of those 922 M&A transactions had at least one earnout.[3]

3.2 VC Participation

Using the M&A term sheets, I calculate for each startup investor their relative share of the merger consideration, which is a proxy for their financial exposure in the M&A transaction (i.e., the amount of "skin" a startup investor has in the game). If data on the the merger consideration allocation are missing for a transaction, I use the investors' pro-rata share in the transaction's expense fund. Almost all transactions in my sample have an expense fund, which is a reserve to cover potential future expenses tied to the M&A transaction.[4] An investor's pro-rata share in the expense fund should be closely linked to their exposure in the overall M&A transaction.

Next, I manually categorize investors as individuals or institutional investors based on their names. I match the institutional investors to the Pitchbook dataset, which provides investor characteristics. Of the 1,257 institutional investors in my proprietary sample, I am able to match 1,051 investors to the Pitchbook data. I categorize an investor as a VC if the variable "Primary Investor Type" is equal to "Venture Capital." Table 2, Panel B, shows VC participation, on average, is 47.4%, conditional on having a VC participate. Additionally, an average M&A transaction in my sample has between three to four VCs receiving a portion of the merger consideration.

Finally, I aggregate the participation percentages of VCs for each M&A transaction. If the VC participation percentage is higher than or equal to 10%, I indicate an M&A transaction as a VC-backed transaction. I use a 10% threshold to ensure the VCs excercise influence on the design of the M&A contract. Table 2, Panel A, reports that 62.3% of the M&A

3. Additionally, untabulated, I benchmark my earnouts measure to the Dealstats data. Even though I am unable to match specific deals to this dataset, I calculate that the propensity of "earnouts" of all private M&A transactions between 2015 and 2020. I find that 14% of the private M&A contracts in the Dealstats dataset have an earnout, which is lower than what I find in my proprietary sample.

4. Examples are legal or consulting expenses that are incurred after closing.

transactions have at least one VC participating at or above 10% of the merger consideration.

3.3 Proprietary Sample

One concern is that my proprietary sample may not be representative of the total population of private startup M&A transactions. To assess whether my sample is representative, in Table B1, Panel A, I compare the distribution over the startup industry of my proprietary sample to that of all VC-backed M&A transactions in the Pitchbook dataset between 2010 and 2015. As in my sample, most VC-backed transactions in Pitchbook include a startup from the IT-software industry (44.4% of all M&A transactions). Overall, my proprietary sample of startups covers a range of startup industries similar to that of the Pitchbook data.

Next, I assess whether my transactions differ in size from the general population of startup M&A transactions. Specifically, in Table B1, Panel B, I show the summary statistics of the M&A purchase price (excluding earnouts) in my sample compared with the Pitchbook sample (based on Pitchbook's "Dealsize" variable). Data on deal size are sparse in the Pitcbhook dataset, likely due to the limited public availability of this data.[5] In the Pitchbook sample, deal size may be only available for the larger deals, which would explain why the M&A transactions are, in general, larger than the M&A transactions in my sample. I also show the summary statistics of the purchase price (based on the "MVIC" variable) of all private M&A transactions in the Dealstats database between 2015 and 2020. Dealstats, a database providing contractual features, is regularly used in research on private M&A transactions (Jansen, 2020). I show the distribution of the purchase price in the Dealstats dataset is similar to the distribution in my proprietary sample. However, the Dealstats data include a larger number of smaller deals and are more right skewed than my proprietary data.

5. Deal size is only available for 1,825 of the 4,516 M&A transactions.

3.4 Pitchbook Data

I complement my sample of M&A transactions with data from Pitchbook. I manually match the startups and buyers in my sample to Pitchbook data.[6] I use the Pitchbook data to categorize startups and buyers into industries based on the Pitchbook variables "primary industry group" and "primary industry sector."[7] An advantage of the Pitchbook data is that they allow me to map the relationships between VCs and buyers. Specifically, for all VCs in my sample (646 VCs in total), I download all investment links between VCs and startups between 1996 and 2020.[8]

3.5 Control Variables

Table 2 provides summary statistics on the control variables in my main analysis. Participation is calculated as the Herfindahl–Hirschman Index (HHI) using the merger consideration share of each startup investor. The maximum HHI is 10,000 points, which can be interpreted as only one investor receiving the full merger consideration. The lower the HHI, the more diverse the investor base of the startup. In my sample, the average age of a startup at the time of acquisition is approximately 10 years. The average M&A purchase price including earnouts (excluding earnouts) in my sample is around \$224.8 million (\$201.0 million).[9] Using the Pitchbook data, I calculate the startups age (*Firm Age*). Additionally, I categorize M&A transactions based on whether the buyer is a private equity (PE) firm or not (PE Deal

6. I am able to match all startups and 988 buyers to Pitchbook from the 1,000 M&A transactions in my sample.

7. I define 12 different industry classifications: Commercial Products, Commercial Services, Consumer Products, Consumer Services, Energy, Financial Services, Healthcare - Devices, Healthcare - Pharma and Biotech, Healthcare - Services, IT-non-software, IT-software, and Materials and Resources.

8. My proprietary sample includes a large number of different VCs and all large VC investors available in the Pitchbook data.

9. The M&A purchase price excluding earnouts is determined from the M&A contract or M&A termsheet. Additionally, for each earnout, I determine the maximum earnout amount that can be attained and add it to the purchase price to get the purchase price including earnouts.

Indicator). I find that 18.4% of transactions in my sample are PE deals (i.e., the buyer is a private equity firm); I categorize M&A transactions based on whether the buyer is public or private (Public Buyer Indicator). 53.4% (46.6%) of the buyers are public (private). Lastly, the majority of M&A transactions in my sample (83.5%) are cash-only transactions; that is, the merger consideration is paid out in cash only. I control for these variables because they may explain the use of contingent payments in addition to VC participation.

CHAPTER 4

VC PARTICIPATION AND INFORMATION ASYMMETRY

I examine the association between VC participation and the use of earnouts. If VCs alleviate information asymmetry, all else equal, the propensity of earnouts in VC-backed M&A contracts would be lower than in non-VC-backed contracts. I initially employ a simple empirical model, which captures the baseline underlying association between VC M&A participation and the use of earnouts:

$$\begin{aligned}\mathbb{I}(\text{Earnout})_{ijt} =& \beta_1 \mathbb{I}(\text{Venture Capital})_{ijt} + \beta_2 Controls_{(i)jt} \\ &+ \gamma_{u_i t} + \epsilon_{ijt}, \end{aligned} \tag{1}$$

where i is the startup, j is the buyer, t is year, u_i is startup industry, and $\gamma_{u_i t}$ are startup industry-year fixed effects.

β_1 captures the difference in the use of earnouts in VC-backed and non-VC-backed M&A contracts for startups that are in the same industry and are acquired in the same year.[1] This coefficient can be interpreted as the decrease in use of earnouts when a VC participates in an M&A under the assumption that VC-backed and non-VC-backed transactions are comparable. I cluster standard errors by industry $\times$ year groups.[2]

The dependent variable is $\mathbb{I}$*(Earnout)*, coded as 1 if the M&A contract includes an earnout, and 0 otherwise. $\mathbb{I}$*(Venture Capital)* is 1 if VC participation is at least 10%, measured by the percentage of the merger consideration going to VCs, and 0 otherwise. To alleviate general concerns that the use of earnouts could be driven by certain firm or deal characteristics over which the VC has no influence, I include several controls, includ-

1. Figure 2, provides a simple graphical representation of this difference, comparing the annual propensity in the use of contingent payments between VC-backed and non-VC-backed transaction. One caveat is that, in the graph, I am not accounting for the industry of the startup.

2. I do not cluster standard errors by startup industry because, given the inclusion of only 12 industries that are heterogeneous in size, this approach is likely to overstate or bias the standard errors.

ing *Ln(Investor Concentration)*, *Firm Age*, *Ln(Purchase Price including earnouts)*, whether the buyer is a PE firm (*PE Deal Indicator*), whether the merger consideration is cash only (*Cash Consideration Indicator*), and whether the buyer is public or private (*Public Buyer Indicator*).

To address concerns that my results are driven by moral hazard I exclude earnouts that are based on founders or key employees remaining for a specified period after the acquisition as these earnouts specifically address moral hazard problems. To further address concerns that the difference in earnout use between VC-backed and non-VC-backed contracts is purely driven by non-VC-backed startups having a higher propensity of founders and key employees, I control explicitly for the equity concentration of investors in the startup. Investor-base diversity should pick up the "efficiency" of addressing moral-hazard problems with an earnout contract. In other words, for a startup with a more diverse investor base, the use of an earnout contract is a less efficient way to address moral-hazard problems because earnout participation becomes more likely to include investors who cannot affect the earnout size through their effort. *Ln(Participation Concentration)* proxies for whether a startup has a diverse investor base. Investor-base diversity controls for the increased "incentive" benefits of the earnout contract to the buyer. In other words, if a startup has a similar investor base, the incentive benefits of the earnout contract should be more comparable. I expect the coefficient on *Ln(Participation Concentration)* to be generally positive because higher investor concentration should increase the use of earnouts for incentive purposes. [3]

Additionally, I add the following linear control variables. First, earnouts could be driven by a startup's age because information asymmetry is higher for young firms than old firms because less historical information is available for these firms. Second, I control for the

3. An alternative explanation for why to expect a positive coefficient on investor concentration is due to ex-post coordination frictions among investors in monitoring the buyer. An implicit cost of the use of earnouts is that the startup's investors need to monitor the buyer ex-post and verify the information provided by the buyer. If the investor base is very broad, coordination problems could arise among investors. Anticipating the future coordination frictions, startups with a broad investor base might be less inclined to accept an earnout clause.

purchase price of the M&A transaction to make sure the use of earnouts is not mechanically linked to the underlying enterprise value of the firm. Third, earnouts could depend on the type of buyer, and therefore, I control for whether the buyer is a private equity firm or a public firm.[4] Fourth, differences in payment methods could also explain the use of earnouts. Because of uncertainty around the future value of buyer shares, contingent payments in buyer shares is generally less common. I control for the payment method through the inclusion of the *Cash Consideration Indicator* variable.

I present results for the estimated average association between VC participation in the M&A and the use of contingent payments in Table 3. Column (1) shows that the association between $\mathbb{I}(ContingentPayment)$ and $\mathbb{I}(VentureCapital)$ without any fixed effects is approximately negative 8.7 percentage points. After adding startup-industry $\times$ year fixed effects, the baseline result in column (2) shows the use of earnouts is, on average, 7.5% lower when a VC participates in the M&A, which translates to a 30% decrease in the likelihood of having an earnout when a startup has a VC compared with when it does not. My empirical analysis is mainly descriptive and not causal, due to the endogeneity inherent in the M&A setting. However, to provide some structure, my empirical strategy for assessing whether VCs alleviate information-asymmetry problems relies on two identifying assumptions.

First, the use of earnouts is a contractual solution used mainly to address adverse-selection issues in M&A transactions. Second, the presence of VCs affects the use of earnouts only through an "information" channel and not through any other channel. Then, a negative association between VCs participating in M&As and the use of earnouts provides strong

4. I am agnostic as to the predicted sign on *PE Deal Indicator* and *Public Buyer Indicator*. PE deals could be less likely to involve contingent payments, enforcing contingent-payment contracts is costly for PE firms. However, PE firms, in their pursuit of riskier investments, could generally acquire startups that impose higher ex-ante information-asymmetry frictions, leading to a higher use of contingent payments. Similar arguments apply to whether the use of contingent payments is higher or lower for public buyers than for private buyers. Because public buyers must disclose financial information, enforcing the contingent-payment contracts may be easier, leading to a higher use of contingent payments in contracts with public buyers. However, public disclosure might also increase the likelihood of future litigation in cases with no contingent payment, because sellers will have more information with which to build a case against the buyer. This would lower the need for contingent payments.

descriptive evidence in support of my hypothesis that VCs alleviate ex-ante information problems in the M&A market. An alternative explanation for my results, invalidating the "information" channel explanation, is that VCs are generally better at negotiating with buyers and are able to negotiate M&A contracts with less earnouts, on average. To alleviate concerns that VC sophistication in M&A negotiations explains my main result, I add a *Startup Legal Advisor* fixed effect to the main model in column (4). If differences in the use of earnouts are driven by the fact that VCs are better at negotiating the M&A terms (and avoiding contingent-payment clauses) than founders, these differences could explain my results. Even though VCs are still providing value under the "negotiation-hypothesis," this does not line up with my hypothesis that VCs alleviate ex-ante information-asymmetry problems between startup insiders and buyers. Legal representation is an important determinant in M&A outcomes (Krishnan and Masulis, 2013). Startups represented by the same law firm are expected to be similarly sophisticated in negotiations. The association between $\mathbb{I}(ContingentPayment)$ and $\mathbb{I}(VentureCapital)$ in the model with *Startup Legal Advisor* fixed effects, presented in column (4), actually becomes stronger compared with the baseline, which provides some reassurance that my results are not explained by VC sophistication in M&A negotiations.

Second, endogenous matching between VC and startup is potentially problematic. VCs can incorporate into their selection procedures the likelihood of insiders posing future information-asymmetry problems with potential buyers. Second, VCs can help improve the information environment of their portfolio firms, through monitoring, auditing, or implementing control systems. To assess whether VCs alleviate ex-ante information-asymmetry problems not only through traditional channels, such as VC screening and monitoring, but also through the mere fact of their participation in the M&A transaction (and their repeated interactions in the M&A market), I would like to compare M&A transactions between identical startups and buyers where the only difference is that one startup has a VC, receiving a portion of the merger consideration, and the other startup does not have a VC.[5] To alleviate broad concerns regarding whether startups are comparable, I compare acquisitions of VC-backed and non-VC-backed firms with a similar purchase price in the same industry and year (by adding a startup industry × year × purchase price quintile-fixed effect). If the M&A market is efficient, two startups with a similar purchase price, a proxy for the gross market value of a company, is more likely to have similar risk-return trade-offs and therefore similar levels of underlying ex-ante information asymmetry. Consequently, any differences in the use of contingent payments are explained by how different types of investors alleviate information asymmetry. Column (5) shows the association between VC participation and earnouts still is statistically significant, even though the magnitude of the association slightly decreased relative to the baseline model.

Lastly, in an attempt to control better for endogenous matching between startups and buyers, I add Startup-Industry × Buyer-Industry × Year fixed effects in column (5) of Table 3, which means I am comparing VC-backed and non-VC-backed M&A transactions in the same year where both the startup and buyer are in the same industry. This alleviates concerns that the association between $\mathbb{I}(ContingentPayment)$ and *Venture Capital Indicator* is driven by startup-buyer industry compositions.[6]

4.1 Robustness Tests

To corroborate whether VCs alleviate ex-ante information-asymmetry problems in M&A markets, I separate M&A transactions that include a regulatory-based earnout, which are based on reaching certain regulatory events such as an FDA approval or passing a clinical trial. These clauses are designed to alleviate uncertainty around the regulator's decision and

5. Note that I am unable to fully control for systemic differences between VC-backed and non-VC-backed startups in later analyses I leverage within-VC variation, which alleviates the endogenous matching problem between startups and VCs.

6. Contingent payments are likely used more frequently in "across-industry" M&As than in "within-industry" M&As.

less about the information asymmetry between buyer and insiders. In table 4, Panel B, using the base model, I show that VC participation is not associated with regulatory-based earnouts as would be expected if these clauses are not relevant for addressing information-asymmetry problems.[7] Because regulatory earnouts are only used in a few industries (as shown in Panel A of table 4) I redo the analysis using only startup industries with regulatory earnouts in Panel C of table 4. Even though the association between the use of non-regulatory earnouts and VC participation weakens, the interpretation of the results are unchanged.

As discussed earlier, earnout contracts may address multiple information and agency frictions. However, for the interpretation of my results, the first-order motivation for using an earnout contract should be to alleviate adverse-selection problems. In the earnouts literature, agency frictions between key employees or founders and the buyer have been proposed to determine the use of earnouts (Kohers and Ang, 2000). To make sure I am capturing the use of earnouts to address information asymmetry problems, in table C1 of the Appendix, I keep only pro-rata earnouts (i.e., earnouts with low investor concentration), redefine $\mathbb{I}$(Earnout) based on pro-rata earnouts only and redo my analysis.[8] Results are unchanged.

In Table C1 of the Appendix, I show my results are robust for an alternative measure of VC participation. For this measure, I don't impose the 10% threshold but categorize any deal in which a VC receives a portion of the merger consideration as a VC-backed transaction. Additionally, I document a negative association between the size of an earnout (calculated as the percentage of the purchase price) and VC participation (see Table C2 in the Appendix). These results are consistent with VC-backed transactions not only having less earnouts but also having smaller-sized earnouts compared to non-VC-backed transactions. Next, I show a negative association between the use of earnouts and the number of participating VCs,

7. In the appendix, I employ a multinomial logistic regression to explore the association between VC participation and regulatory, and non-regulatory earnouts, respectively. This design allows me to model the different contract decisions into a categorical variable. The results in Table D1 provide similar insights as the results in 4. Figure D1 in the appendix provides a graphical representation of the model's results.

8. I only keep earnouts where the investor HHI is below 2,500.

which implies that having more VCs participating in the transaction translates to a smaller probability of having an earnout in the M&A contract (see Table C4 of the Appendix). Lastly, I investigate the relation between the earnout size and VC ownership percentage in Table C4 of the Appendix. When I model this relation linearly in Panel A the coefficient on VC Ownership is consistently negative but not statistically significant. I then employ a quadratic model to map this relation because it is likely that there is a VC ownership percentage threshold above which the marginal benefit of having more VC ownership on earnout size diminishes. The results show a negative coefficient on VC ownership and a positive coefficient on the quadratic term (albeit not all statistically significant) which is consistent with diminishing marginal returns to adding more VC ownership.

4.2 Within-VC Analysis

In this section I further assess whether information asymmetry plays a role in M&A contracting leveraging within-VC variation. Specifically, for the M&A transactions with *VC Participation* above 10% in my proprietary sample, I generate a dataset of 1,315 unique VC-startup-buyer triplets using the information I have on the underlying investors. Because VCs have multiple transactions with buyers over time, I can employ VC $\times$ year fixed effects which control for the endogenous matching between VCs and startups and alleviate concerns that the results are driven by endogenous matching between startups and buyers. My proxy for information asymmetry is based on the distance between the VC's and buyer's headquarters. For each VC, I categorize VC-buyers into high and low distance based on the median distance between the VC and buyers.[9]

9. I also construct a measure that is 1 when the VC's and buyer's headquarters are in different states and 0 otherwise. Results and inferences are similar.

I use the following baseline empirical model:

$$\begin{aligned} \mathbb{I}(\text{Earnout})_{ijt} =& \beta_1 (\text{Distance VC-Buyer}^{High})_{jvt} \\ & + \theta_{vt} + \sigma_{u_i t} + \epsilon_{ijvt}, \end{aligned} \tag{2}$$

where i is the startup, j is the buyer, v is the VC, t is the year, θ_{vt} are VC $\times$ year fixed effects, and $\sigma_{u_i t}$ are startup industry $\times$ year fixed effects. Standard errors are clustered at the VC level.

Table 5, Panel B, Columns (1) and (2) show that the use of earnouts is, on average, 10 to 11 percentage points higher when the same VC participates in a transaction with a buyer that is further away in distance from the VC. Additionally, as in my main analysis, I control for any unobservable and observable characteristics at the startup-industry $\times$ year-level. These results are consistent with information asymmetry between the VC and buyer playing an important role in the use of earnouts for VC-backed M&A transactions. These results also confirm that information asymmetry is a driver of the earnouts and therefore support my main hypothesis.

CHAPTER 5

MECHANISM: RELATIONSHIPS

After establishing the baseline association between VC participation in M&As and the use of earnouts, in this section, I explore a specific mechanism through which VCs can alleviate ex-ante information-asymmetry problems between the startup and buyer: *the existing relationships between VCs and buyers*. VCs invest in many different startups. Because M&As are a likely outcome for VCs, VCs deal with buyers on a regular basis. The M&A process is an intensive one in which the parties interact with each other frequently. VCs and buyers are likely to build relationships when VC-backed firms are acquired. In the next two sections, I first explore whether prior VC-buyer relationships play a role in the M&A market. I then investigate whether prior VC-buyer relationships are an additional mechanism by which VCs alleviate ex-ante information-asymmetry problems in M&A transactions.

5.1 Do Relationships Matter?

Using an empirical strategy consisting of multiple steps, I assess whether a previous relationship between a VC and buyer, in which a buyer has acquired one of the VC's portfolio firms, increases the likelihood that the VC and buyer will work together again in the future (i.e., the buyer will acquire another of the VC's portfolio firms in the future).

First, I download the entire universe of VC investments in portfolio firms between 1996 and 2020 available from Pitchbook.[1] Then, for each startup in the resulting dataset, I look up whether the startup was acquired anytime between 1996 and 2020.[2] I merge the M&A data onto the dataset with VC-startup investments and keep only VC-startup investments

1. For practical reasons, I focus on VCs that are also in my proprietary sample, which, as mentioned, is a very broad sample of VCs and contains all the top VCs.

2. If a startup has been acquired multiple times throughout the sample period, I only keep the information on the first acquisition.

that happened before the merger date. Because a VC can have multiple investments in a startup, I collapse the dataset such that only one VC-startup-buyer triplet remains. This process leads to a dataset at the VC-startup-buyer level.

Second, based on the dataset of VC-Startup-Buyer triplets, I split the dataset into a pre-sample period, between 1996 and 2015, and the sample period, between 2015 and 2020. The relationships established in the pre-sample period are categorized as previous relationships between VCs and buyers. To ensure a VC has enough previous relationships, I only keep VCs that were part of at least 100 (200) acquisitions in 2015.

Third, I create for each acquisition in the sample period a set of counterfactuals. Counterfactuals are constructed within startup industry × buyer industry groups. The assumption is that if an IT-software startup was purchased by a buyer in Consumer Products, for instance, the startup could have been purchased by any other buyer in Consumer Products that also bought an IT-software startup. As an example, imagine an acquisition between a startup A in the IT-software industry and a buyer B in the industry of Commercial Services. Now, the goal is to create counterfactuals for this specific transactions. I list all M&A transactions between any startup in the IT-software industry and any buyer in the Commercial Services industry in the pre-sample period and sample period, excluding the M&A transactions between startup A and buyer B. I assume startup A could have been acquired by any of the buyers on the list I created. Lastly, I create counterfactual VC-"startup A"-buyer triplets where the buyer is not buyer B but another buyer from the list of counterfactuals.

Now I have two datasets: one with the true VC-startup-buyer triplets in the pre-sample period, and one with the true and counterfactual VC-startup-buyer triplets in the sample period (sample-period dataset), constructed as discussed above. For all triplets in the sample-period dataset, I indicate whether the VC and buyer have a previous relationship in the pre-sample period.

I employ the following two-period empirical model:

$$\begin{aligned}\mathbb{I}(\text{Relationship VC-Buyer})_{ijv;t=1} =& \beta_1 \mathbb{I}\text{Relationship VC-Buyer}_{jv;t=0} \\ &+ \theta_v + \gamma_{u_i u_j} + \epsilon_{ijv;t=1},\end{aligned} \tag{3}$$

where i is the startup, j is the buyer, v is the VC, $t = 1$ is the sample period, $t = 0$ is the pre-period, θ_v are VC fixed effects, and $\gamma_{u_i \times u_j}$ are startup industry $\times$ buyer industry fixed effects. Standard errors are clustered at the VC level. Table 5 presents results. In columns (1) and (2) ((3) and (4)), I do the analysis for VCs with at least 100 (200) investments in 2015, resulting in a sample of 195 (86) VCs. In columns (1) and (3), I include specifications without fixed effects and provide the constant in the regression because doing so allows for a straightforward interpretation of the coefficients. The constant in columns (1) and (3) can be interpreted as the average probability that a VC-startup-buyer triplet has a previous relationship in the group of "counterfactual" triplets. For instance, in column (1), the coefficient on the constant implies that, on average, 0.29% of the counterfactual triplets have a previous relationship. The coefficient on $\mathbb{I}$Previous Relationship VC-Buyer captures the marginal increase in the probability that a VC-startup-buyer has a previous relationship in the group of "true" triplets. For instance, in column (2), this finding implies that, on average, 0.81% of the true triplets have a previous relationship, an increase of 0.29% compared with the group of counterfactual triplets. Therefore, these results show M&A transactions between a startup and buyer are statistically more likely when the startup's VC and buyer had a previous relationship.

In columns (2) and (4), I run the empirical model as specified in Equation (3). This regression is within a startup industry $\times$ buyer industry, which is how I defined the counterfactuals. Additionally, the VC fixed effects control for any observable and unobservable VC characteristics. The results in columns (2) and (4) show the average probability of having a previous relationship is approximately 2.5 times higher in the group of true VC-startup-buyer triplets than in the benchmark of counterfactual triplets.

In conclusion, the results in Table 5 show that repeated M&A transactions between VCs and buyers happen more than would be expected in random pairings and provide evidence in support of the supposition that previous relationships between VCs and buyers matter.

5.2 Do Relationships Alleviate Information Frictions?

Next, to assess whether previous relationships between VCs and buyers alleviate ex-ante information-asymmetry problems, I employ the same empirical model as in Section 4.2, Equation (2).

Table 6, Panel A, shows that I end up with 939 VC-startup-buyer triplets for 186 individual VCs. Of the 939 VC-startup-buyer triplets in my sample, 218 had a previous relationship between the VC and buyer in the pre-sample period. Table 6, Panel B, reports regression results. In column (2), which is the baseline model, I show M&A transactions are, on average, between 6.4% and 10.5% less likely to contain an earnout if the VC and buyer have a previous relationship. Because this specification includes VC $\times$ year fixed effects, this approach is akin to running the analysis within each VC, controlling for any observable or unobservable VC characteristics that affect the use of an earnout. Additionally, I include a startup-industry $\times$ year fixed effect, which controls for general industry-specific temporal variation in the use of earnouts.

CHAPTER 6

VC PREFERENCES

In this chapter, I explore whether VC preferences play a role in the M&A contracting. VCs and other investors could have different preferences over M&A contracts, due to different opportunity costs and/or monitoring costs. To explore whether VC-specific preferences over the use of earnouts play a role in the M&A market, I focus on two potential frictions for VCs when using earnout provisions: post-acquisition monitoring costs and VC fund cyclicality.

6.1 Post-acquisition Monitoring

Using the empirical design in Section 4.2, I further test whether the distance between the VC and the startup plays a role in the use of earnouts. The empirical relation between the VC-startup distance, as a proxy for information asymmetry between the VC and the startup, and the use of earnouts is ex-ante ambiguous. On the one hand, higher (ex-ante) information asymmetry between the VC and startup potentially could lead to a higher use of earnouts because the startup might be perceived more risky. Additionally, the VC might be less able to play its information role due to information frictions with the startup. On the other hand, higher (ex-post) information asymmetry can lead to a lower use of earnouts (as a contracting device) because it becomes more costly for the VC to monitor the startup after the acquisition.[1]

Table 5, Panel B, Columns (3) and (4) show that the use of earnouts is lower when the VC and startup are in different states.[2] These results are consistent with post-acquisition monitoring costs at least partially driving the use of earnouts. In columns (5) and (6) of

1. Note that earnouts are tied explicitly to the outcome of events and/or performance of the startup after the acquisition.

2. I also show that the use of earnouts decreases when the VC and startup are in different states or when the distance between the VC and buyer is above the median distance.

Panel B of Table 5 I introduce both the distance between the VC and startup as well as between the VC and buyer into the model and the results are similar.

6.2 VC Fund Structure

In this last section, I investigate whether the structure of VC funds is a determinant of the use of earnouts. A VC fund is "self-liquidating" and, on average, has a lifetime of 10 to 12 years. (Gompers and Lerner, 2004) The use of earnouts imposes liquidity constraints on the VC fund deferring payment.[3] I formally test whether the use of earnouts varies over time within VC funds. To do this, I move from the VC-level to the VC-fund level, where a VC can have multiple VC funds, and create a dataset at the "VC-fund"-VC-startup-buyer level.[4] For each VC fund, I categorize transactions into early and late deals based on the median transaction date of the VC fund.[5] Then I create an indicator variable that is 1 for later deals and 0 otherwise.

In the models in columns (1) and (3) of Table 8, I include VC-fund fixed effects effectively comparing early and late transactions within the VC fund. As in all my empirical tests, I incorporate my control variables and startup-industy $\times$ year fixed effects. For my sample of VC-backed transactions, late transactions in the lifecycle of the VC fund are less likely to have an earnout. In columns (2) and columns (3) of Table 8, I include VC $\times$ year fixed effects comparing an early and late transaction for the same VC in the same year. Note that the coefficient is negative but not statistically different from 0 at conventional confidence

3. Note that it is not easy to make transfers among funds or to borrow money in anticipation of the payout of the earnout because the outcome of the earnout is uncertain.

4. This dataset contains only one VC fund from a specific VC per M&A transaction. For example, imagine VC A has two different funds that are invested in startup A, fund A1 and fund A2. In this case only one of those two funds will remain in the dataset. I create two samples: (i) sample based on ownership percentage, and (ii) sample based on most constrained fund. In the first sample I retain the fund of VC A with the highest ownership percentage. In the second sample I retain the fund of VC A that has the earliest inception date.

5. See Panel A of Table 8 for descriptive statistics.

levels. One potential explanation for these results is that VCs time the exit of their portfolio firms, with less risky firms exiting last (as these less likely have an earnout). An alternative explanation is that VCs change their preferences over earnouts and aim to avoid them in later deals.[6] Overall, if VC funds invest in comparable firms throughout the fund's lifetime and have no payout constraints, I would not expect to find any differences in the use of earnouts over the lifetime of the fund.

6. Note that if the bargaining power between VC-backed startups and buyers is fixed over time then VCs are only able to avoid the earnout by taking a "lower" up-front price.

CHAPTER 7

CONCLUSION

An important exit strategy for startups is through an acquisition. When a startup is being acquired, information frictions between the buyer and the startup's initial investors are an important force impacting the transaction. In this paper, I examine whether VC participation in M&A transactions alleviates information-asymmetry problems between the buyer and the startup's insiders. Even though VCs can alleviate information frictions in many ways (e.g., through startup selection and monitoring), I explore whether the mere presence of VCs in M&A transactions can alleviate information problems ex-ante because VCs play a repeated game in the M&A market, disciplining startup's insiders' behavior. Additionally, I test whether existing relationships between VCs and buyers matter in the M&A contract design.

My empirical strategy relies on the use of earnouts in M&A contracts being a good proxy for ex-ante information-asymmetry problems. First, earnouts must be used primarily to address ex-ante information asymmetry. I rely on prior academic work that has shown earnouts are used when relatively high information frictions exist between buyers and sellers. Second, the presence of VCs should affect the use of earnouts through only one mechanism: their role in alleviating information problems.

Overall, my findings suggest VCs alleviate ex-ante information-asymmetry problems between startup insiders and buyers and that the mere presence of VCs in the M&A transaction is enough to alleviate information frictions. My results also suggest repeated interactions between VCs and buyers play a role in alleviating information problems in the M&A market.

My analysis is subject to two important caveats. First, because finding a proxy for ex-ante information asymmetry for private firms is difficult, I am unable to formally test for the relation between the use of earnouts and ex-ante information asymmetry between the contracting parties. To address this shortcoming, I rely on theoretical arguments to explain why contingent-consideration clauses address ex-ante information problems between the startup's investors and the buyer. Additionally, I explore within-VC variation to provide further evidence that information asymmetry problems are a determinant of earnouts and that relationships between VCs and buyers play an important role. Second, because I am using proprietary data from a specialized private M&A financial-services firm, the sample represents the firm's transaction base. Therefore, my sample may not be representative of the population of startup M&A transactions. I try to alleviate concerns about the sample composition by comparing my proprietary sample with the Pitchbook database, which tracks a comprehensive sample of VC-backed startups. Additionally, the VCs constituting my proprietary sample are a very diverse group that represents all major VCs active in the U.S.

REFERENCES

Sumit Agarwal and Robert Hauswald. Distance and Private Information in Lending. *The Review of Financial Studies*, 23(7):2757–2788, 04 2010. ISSN 0893-9454. doi: 10.1093/rfs/hhq001. URL `https://doi.org/10.1093/rfs/hhq001`.

Randolph P. Beatty and Jay R. Ritter. Investment Banking, Reputation, and the Underpricing of Initial Public Offerings. *Journal of Financial Economics*, 15(1-2):213–232, 1986.

Shai Bernstein, Xavier Giroud, and Richard R. Townsend. The Impact of Venture Capital Monitoring. *Journal of Finance*, 71:1591–1622, 2016.

Brian Cadman, Richard Carrizosa, and Lucile Faurel. Economic Determinants And Information Environment Effects Of Earnouts: New Insights From SFAS 141(R). *Journal of Accounting Research*, 52(1):37–74, 2014.

Matthew D. Cain, David J. Denis, and Diane K. Denis. Earnouts: A Study Of Financial Contracting In Acquisition Agreements. *Journal of Accounting and Economics*, 51(1-2): 151–170, 2011.

Thomas J. Chemmanur, Karthik Krishnan, and Debarshi K. Nandy. How Does Venture Capital Financing Improve Efficiency In Private Firms? A Look Beneath The Surface. *Review of Financial Studies*, 24(12):4037–4090, 2011.

Douglas Cumming. Contracts and Exits in Venture Capital Finance. *Review of Financial Studies*, 21(5):1947–1982, 2008.

Douglas Cumming and Sofia Johan. Information Asymmetries, Agency Costs and Venture Capital Exit Outcomes. *Venture Capital*, 10(3):197–231, 2008.

Douglas J Cumming and Jeffrey G MacIntosh. Venture-capital exits in canada and the united states. *The University of Toronto Law Journal*, 53(2):101–199, 2003a.

Douglas J Cumming and Jeffrey G MacIntosh. A cross-country comparison of full and partial venture capital exits. *Journal of banking & finance*, 27(3):511–548, 2003b.

Srikant Datar, Richard Frankel, and Mark Wolfson. Earnouts: The Effects Of Adverse Selection And Agency Costs On Acquisition Techniques. *Journal of Law, Economics, and Organization*, 17(1):201–238, 2001.

Paul Alan Gompers and Joshua Lerner. *The venture capital cycle*. MIT press, 2004.

João Granja, Christian Leuz, and Raghuram G Rajan. Going the extra mile: Distant lending and credit cycles. *The Journal of Finance*, 77(2):1259–1324, 2022.

Thomas Hellmann and Manju Puri. Venture Capital and the Professionalization of Start-up Firms: Empirical Evidence. *Journal of Finance*, 57(1):169–197, 2002.

Thomas Hellmann, Laura Lindsey, and Manju Puri. Building Relationships Early: Banks in Venture Capital. *Review of Financial Studies*, 21(2):513–541, 2008.

Bengt Holmström. Moral hazard and observability. *The Bell journal of economics*, pages 74–91, 1979.

Mark Jansen. Resolving Information Asymmetry Through Contractual Risk Sharing: The Case of Private Firm Acquisitions. *Journal of Accounting Research*, 58(5):1203–1248, 2020.

Steven N. Kaplan, Berk A. Sensoy, and Per Strömberg. Should Investors Bet On the Jockey Or the Horse? Evidence From the Evolution Of Firms From Early Business Plans To Public Companies. *Journal of Finance*, 64(1):75–115, 2009.

Ninon Kohers and James Ang. Earnouts in Mergers: Agreeing To Disagree And Agreeing To Stay. *Journal of Business*, 73(3):445–476, 2000.

C.N.V. Krishnan and Ronald W. Masulis. Law Firm Expertise and Merger and Acquisition Outcomes. *Journal of Law and Economics*, 56(1):189–226, 2013.

Tom McKaskill, K Mark Weaver, and Pat Dickson. Developing an exit readiness index: a research note. *Venture Capital*, 6(2-3):173–179, 2004.

Manju Puri and Rebecca Zarutskie. On the Life Cycle Dynamics of Venture-Capital- and Non-Venture-Capital-Financed Firms. *Journal of Finance*, 67(6):2247–2293, 2012.

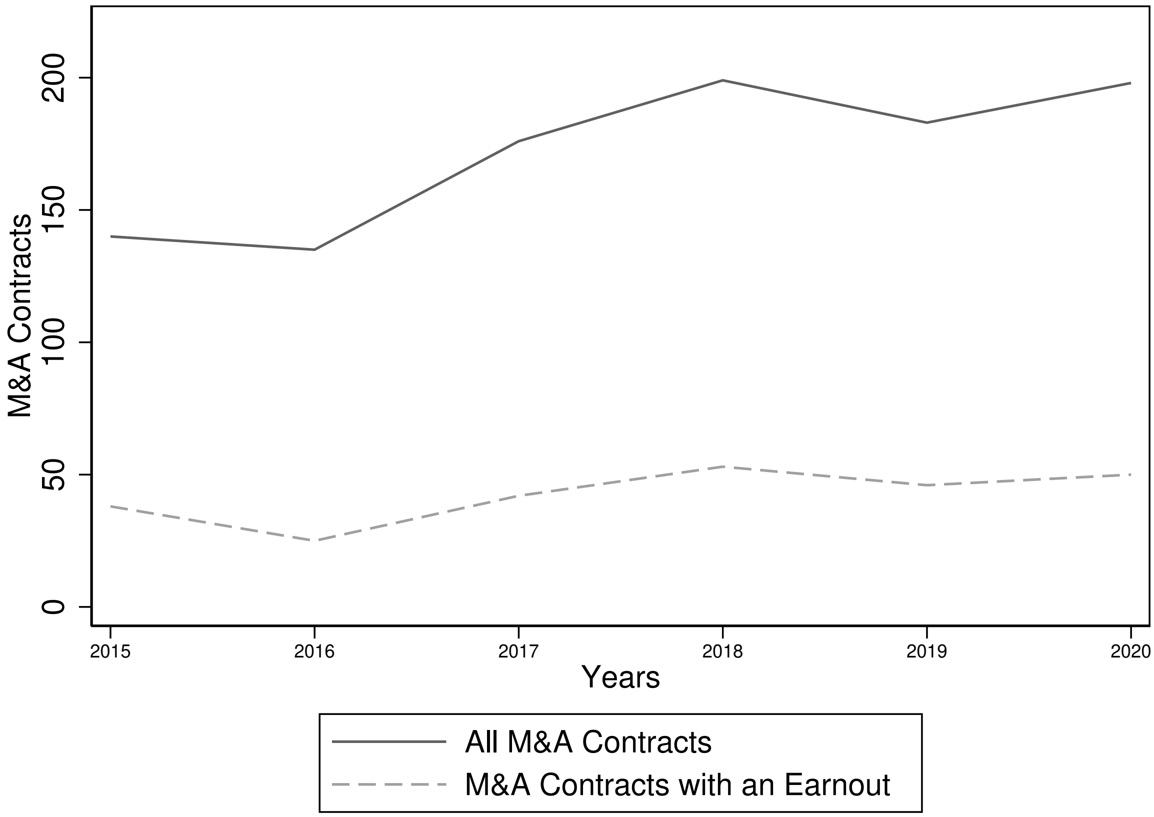
Brian J.M. Quinn. Putting Your Money Where Your Mouth Is: The Performance Of Earnouts In Corporate Acquisitions. *University of Cincinnati Law Review*, 81(1):127–172, 2013.

Roberto Ragozzino, Jeffrey J Reuer, et al. Mind the information gap: Putting new selection criteria and deal structures to work in m&a. *Journal of Applied Corporate Finance*, 19 (3):82, 2007.

Kevin Rock. Why New Issues are Underpriced. *Journal of Financial Economics*, 15(1-2): 187–212, 1986.

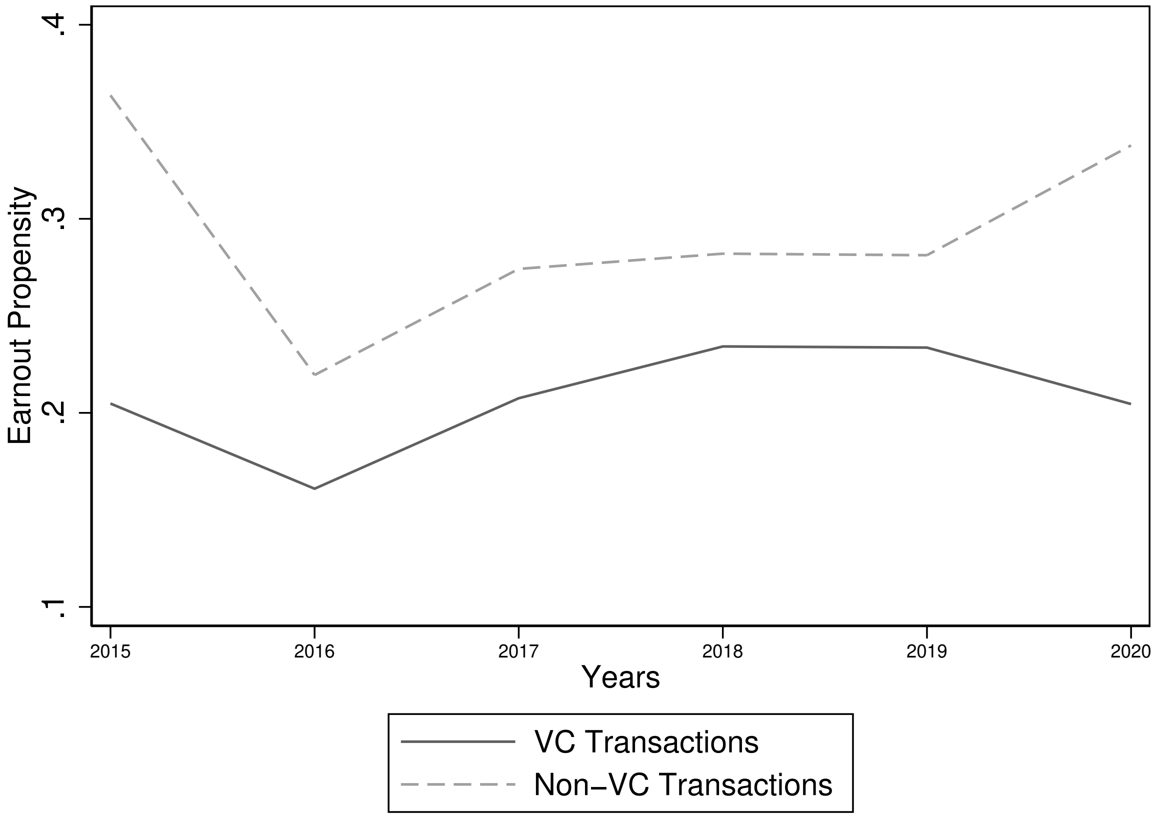
Harry J Sapienza, Sophie Manigart, and Wim Vermeir. Venture capitalist governance and value added in four countries. *Journal of Business Venturing*, 11(6):439–469, 1996.

Figure 1: M&A Contracts with an Earnout



This figure plots the number of total M&A contracts ("All M&A Contracts") and the number of M&A contracts that include at least one earnout ("M&A Contracts with Earnout") on an annual basis for my proprietary sample of M&A transactions. The sample period is from 2015 to 2020.

Figure 2: VC Participation and Earnout Propensity



This figure plots the propensity of M&A contracts with at least one earnout for the group of M&A transactions in which VCs receive at least 10% of the merger consideration ("VC Transactions") and the group of M&A transactions in which the VCs receive less or there is no VC ("Non-VC Transactions") on an annual basis for my proprietary sample of M&A transactions. The sample period is from 2015 to 2020.

Table 1: Earnout Summary Statistics

Panel A: Earnouts by Startup Industry

		Earnout	
Startup Industry	*Total*	*Yes*	Pct_{yes}
Commercial Products	36.0	5.0	13.9
Commercial Services	84.0	19.0	22.6
Consumer Products	47.0	9.0	19.1
Consumer Services	68.0	9.0	13.2
Energy	10.0	2.0	20.0
Financial Services	18.0	3.0	16.7
Healthcare - Devices	68.0	49.0	72.1
Healthcare - Pharma and Biotech	53.0	41.0	77.4
Healthcare - Services	59.0	17.0	28.8
IT-non-software	79.0	9.0	11.4
IT-software	475.0	81.0	17.1
Materials and Resources	3.0	2.0	66.7
Total	1,000.0	246.0	

Panel B: Descriptive Statistics

	N	Mean	SD	P25	Median	P75
Earnouts	252	3.790	4.640	1.000	2.000	5.000

This table reports summary statistics for my dependent variable, $\mathbb{I}$(Earnout). Panel A presents the number (percentage) of M&A contracts with at least one (performance-based and event-based) earnout in my sample. Panel B reports the use of (performance-based and event-based) earnouts for each startup industry. Panel C provides summary statistics for the number of (performance-based and event-based) earnouts in M&A contracts. Observations are at the M&A transaction level. The sample period is from 2015 to 2020. All variables are defined in Appendix A.

Table 2: Summary Statistics

Panel A: Entire Sample	N	Mean	SD	P25	Median	P75
𝕀(Venture Capital)	934	0.623	0.485	0.000	1.000	1.000
Investor Concentration	934	2,400	1,700	1,300	1,900	3,000
Firm Age	975	10.372	9.189	5.000	8.000	13.000
Purchase Price ($M)	981	200.998	750.043	23.000	67.000	180.000
Purchase Price incl. Earnouts ($M)	981	225.172	768.699	26.978	80.000	218.500
𝕀(PE Deal)	1031	0.184	0.388	0.000	0.000	0.000
𝕀(Cash Consideration)	1031	0.839	0.368	1.000	1.000	1.000
𝕀(Public Buyer)	1031	0.534	0.499	0.000	1.000	1.000

Panel B: VC-backed M&A Transactions	N	Mean	SD	P25	Median	P75
VC Ownership	582	0.474	0.231	0.295	0.435	0.628
Number of VC Firms	582	3.873	2.786	2.000	3.000	5.000
Investor Concentration	582	2,300	1,600	1,300	1,800	2,700
Firm Age	558	8.749	5.109	5.000	8.000	11.000
Purchase Price ($M)	559	231.559	963.176	23.000	73.000	190.000
Purchase Price incl. Earnouts ($M)	559	258.130	984.804	25.935	85.000	224.000
𝕀(PE Deal)	582	0.146	0.353	0.000	0.000	0.000
𝕀(Cash Consideration)	582	0.851	0.357	1.000	1.000	1.000
𝕀(Public Buyer)	582	0.572	0.495	0.000	1.000	1.000

Panel C: Non-VC-backed M&A Transactions	N	Mean	SD	P25	Median	P75
Investor Concentration	352	2,600	1,900	1,200	2,100	3,400
Firm Age	417	12.544	12.429	6.000	9.000	16.000
Purchase Price ($M)	422	160.516	277.579	23.000	62.750	175.000
Purchase Price incl. Earnouts ($M)	422	181.515	294.443	27.854	75.000	207.500
𝕀(PE Deal)	449	0.234	0.424	0.000	0.000	0.000
𝕀(Cash Consideration)	449	0.824	0.381	1.000	1.000	1.000
𝕀(Public Buyer)	449	0.486	0.500	0.000	0.000	1.000

This table reports summary statistics for the independent variable(s) and control variables. Panel A shows the descriptive statistics for the entire sample. Panel B (C) shows the descriptive statistics for the sample of VC-backed (non-VC-backed) M&A transactions. Observations are at the M&A transaction level. The sample period is from 2015 to 2020. All variables are defined in Appendix A.

Table 3: VC Participation and Earnouts

	No FE	Baseline	Additional FE		
Dep. variable: $\mathbb{I}$(Earnout)	(1)	(2)	(3)	(4)	(5)
Test variable:					
$\mathbb{I}$(Venture Capital)	-0.103***	-0.075**	-0.096*	-0.078*	-0.067**
	(-3.417)	(-2.521)	(-2.000)	(-1.886)	(-2.265)
Control variables:					
Ln(Investor Concentration)	0.038	0.027	0.044*	0.051**	0.026
	(1.665)	(1.475)	(1.876)	(2.408)	(1.176)
Firm Age	-0.004**	-0.003	-0.010***	-0.002	-0.004
	(-2.066)	(-1.528)	(-2.822)	(-0.477)	(-1.434)
Ln(Purch. Price incl. Earnouts)	0.045***	0.013	0.018	0.019	
	(2.753)	(1.098)	(1.213)	(1.307)	
$\mathbb{I}$(PE Deal)	-0.076	-0.003	-0.009	0.037	0.036
	(-1.309)	(-0.049)	(-0.156)	(0.489)	(0.676)
$\mathbb{I}$(Cash Consideration)	0.009	0.010	0.053	0.035	-0.014
	(0.192)	(0.215)	(0.886)	(0.691)	(-0.282)
$\mathbb{I}$(Public Buyer)	-0.050	-0.028	-0.058	-0.068	-0.010
	(-1.180)	(-0.818)	(-1.300)	(-1.646)	(-0.292)
Fixed effects:					
Startup-Industry × Year	N	Y	Y	N	N
Startup Legal Advisor	N	N	Y	N	N
Startup-Ind. × Buyer-Ind. × Year	N	N	N	Y	N
Startup-Ind. × PP Quintile × Year	N	N	N	N	Y
Adjusted R-Squared	0.029	0.191	0.211	0.218	0.232
Observations	851	851	549	648	760

This table reports results from my analysis of the association between VC Participation ($\mathbb{I}$(Venture Capital)) and the use of Earnouts in the M&A Contract ($\mathbb{I}$(Earnout)), using OLS regressions. My main specification in Column (2) includes Startup-Industry × Year fixed effects. The analysis is executed at the M&A transaction-level. The sample period is from 2015 to 2020. All variables are defined in Appendix A. Standard errors are clustered at the Industry × Year level. T-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

Table 4: Falsification Test

Panel A: Sample Overview

Startup Industry	*Total*	Non-Regulatory	Pct(%)	Regulatory	Pct(%)
Commercial Products	36.0	5.0	13.9	0.0	0.0
Commercial Services	84.0	19.0	22.6	0.0	0.0
Consumer Products	47.0	9.0	19.1	0.0	0.0
Consumer Services	68.0	9.0	13.2	0.0	0.0
Energy	10.0	2.0	20.0	0.0	0.0
Financial Services	18.0	2.0	11.1	1.0	5.6
Healthcare - Devices	68.0	23.0	33.8	26.0	38.2
Healthcare - Pharma and Biotech	53.0	8.0	15.1	33.0	62.3
Healthcare - Services	59.0	14.0	23.7	3.0	5.1
IT-non-software	79.0	9.0	11.4	0.0	0.0
IT-software	475.0	80.0	16.8	1.0	0.2
Materials and Resources	3.0	2.0	66.7	0.0	0.0

Panel B: Full Sample

	𝕀(Non-Regulatory)	𝕀(Regulatory)	Δ
𝕀(Venture Capital)	-0.098***	0.024	0.122***
	(-3.176)	(1.486)	
Adjusted R-Squared	0.019	0.483	
Observations	851	851	

Panel C: Only Startup Industries with Regulatory Earnout

	𝕀(Non-Regulatory)	𝕀(Regulatory)	Δ
𝕀(Venture Capital)	-0.063*	0.029	0.092**
	(-1.871)	(1.333)	
Adjusted R-Squared	0.013	0.488	
Observations	580	580	

Panel A of this table reports, by startup industry, the number (percentage) of M&A contracts in my sample with a non-regulatory earnout and a regulatory earnout, respectively. Panel B (C) reports results from my analysis of the association between VC participation (𝕀(Venture Capital)) and the use of non-regulatory earnouts (𝕀(Non-Regulatory Earnouts)) and the use of regulatory earnouts (𝕀(Regulatory Earnouts)), respectively, (for observations in startup industries where at least one M&A transaction has a regulatory earnout) using OLS regressions. The analysis is executed at the M&A transaction-level. The sample period is from 2015 to 2020. All variables are defined in Appendix A. Standard errors are clustered at the Industry $\times$ Year level. T-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively. Δ reports the difference between the coefficients on 𝕀(Venture Capital) in Columns (1) and (2), and ***, **, and * indicate statistical significance based on χ^2 test at the 1%, 5%, and 10% levels (two-tailed), respectively.

Table 5: Distance Analysis

Panel A: Sample Characteristics

		VC-Startup Distance:		
		Low	High	Total
VC-Buyer	Low	397	272	669
Distance:	High	324	246	570
	Total	721	518	1,239

Panel B: Regression

	Information Asymmetry		Post-acquisition Monitoring		Both	
Dep. variable: 𝕀(Earnout)	(1)	(2)	(3)	(4)	(5)	(6)
Test variables:						
High VC-Buyer Distance	0.110***	0.103***			0.111***	0.104***
	(5.300)	(5.225)			(5.423)	(5.321)
High VC-Startup Distance			-0.057**	-0.048**	-0.060**	-0.050**
			(-2.279)	(-2.043)	(-2.454)	(-2.178)
Control variables:	Y	Y	Y	Y	Y	Y
Fixed effects:						
VC × Year	Y	Y	Y	Y	Y	Y
Startup-Ind × Year	N	Y	N	Y	N	Y
Adjusted R-Squared	0.139	0.283	0.121	0.265	0.146	0.287
Observations	1239	1233	1239	1233	1239	1233

Panel A of this table reports the number of VC-startup-buyer triplets in my proprietary sample for which the VC and buyer, and the VC and the seller are located in different states. Panel B reports results from my VC-startup-buyer-level analysis of the association between whether the VC and buyer (seller) are located in a different state and the use of an earnout (𝕀(Earnout)). The sample period is from 2001 to 2015. All variables are defined in Appendix A. Standard errors are clustered at the VC-level. T-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

Table 6: Do Prior VC-Buyer Relationships Matter? Evidence from Pitchbook Data

Dep. variable:	VC with > 100 investments in 2015 Number of VCs = 195		VC with > 200 investments in 2015 Number of VCs = 86	
$\mathbb{I}$(Relationship VC-Buyer)	(1)	(2)	(3)	(4)
Test variables:				
$\mathbb{I}$(Previous Relationship VC-Buyer)	0.0052***	0.0053***	0.0045***	0.0047***
	(10.496)	(11.172)	(8.51368)	(9.152)
Constant	0.0029***		0.0035***	
	(24.320)		(20.868)	
Fixed effects:				
VC	N	Y	N	Y
Startup-Ind × Buyer-Ind	N	Y	N	Y
Adjusted R-Squared (%)	0.017	1.330	0.016	1.646
Observations	2,358,876	2,358,876	1,317,753	1,317,749

This table reports results from my analysis whether VC-backed startups are more likely to get acquired by a firm with whom the VC had a prior relationship, using OLS regressions. In columns (1) and (2), my sample includes all relationships between VCs, *with more than 100 existing investments in 2015*, and buyers through the VC's network of startups. In columns (3) and (4), my sample includes all relationships between VCs, with more than 200 existing investments in 2015, and buyers through the VC's network of startups. I split the sample into a pre-sample period and a sample period, where the pre-sample period ranges from 1996 until 2015 and the sample period ranges from 2015 until 2020. The pre-sample-period relationships between VCs and buyers define the prior relationships. In the sample period, I define for each Startup-Industry × Buyer-Industry group the counterfactual M&A transactions that could have happened but did not. I assume that, within this group, any buyer in the pre-sample period and the sample period could have purchased the startup. Next, I indicate for all transactions, both the pool of true M&A transactions and counterfactual M&A transactions, whether the VC had a previous relationship with the buyer. The coefficient on $\mathbb{I}$(Previous Relationship VC-Buyer) indicates the marginal increase in the likelihood that a VC in the pool of true M&A transactions has a previous relationship compared to the likelihood that a VC in the pool of counterfactual transactions has a previous relationship. All variables are defined in Appendix A. Standard errors are clustered at the VC level. T-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

Table 7: Earnouts and Previous VC-Buyer Relationships

Panel A: Sample Characteristics

	Number of Observations	Percentage (%)
VC-Startup-Buyer Triplets	939	100
Unique VCs	186	100
Prior VC-Buyer Relationship	218	23.2
No VC-Buyer Relationship	721	76.8

Panel B: Regression

	Within-VC Analysis	
Dep. variable: $\mathbb{I}$(Performance-based Earnout)	(1)	(2)
Test variables:		
$\mathbb{I}$(Previous Relationship VC-Buyer)	-0.105***	-0.064**
	(-3.446)	(-2.015)
Control variables:	Y	Y
Fixed effects:		
VC × Year	Y	Y
Startup-Ind × Year	N	Y
Adjusted R-Squared	0.173	0.318
Observations	939	939

Panel A of this table reports the number of VC-startup-buyer triplets in my proprietary sample and the number of VC-buyer pairs that had a prior relationship. Additionally, Panel A reports the number of unique VCs in my sample. Panel B reports results from my VC-startup-buyer-level analysis of the association between having a prior relationship with a buyer (VC Prior Relationship Indicator) and the use of an earnout ($\mathbb{I}$(Earnout)). The sample period is from 2001 to 2015. All variables are defined in Appendix A. Standard errors are clustered at the VC-level. T-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

Table 8: Earnouts and M&A Timing

Panel A: Sample Characteristics

	Sample based on Ownership Pct		Sample based on Most Constrained Fund	
	Number of Observations	Percentage (%)	Number of Observations	Percentage (%)
VC Fund-Startup-Buyer Triplets	499	100	502	100
Unique VC Funds	128	100	133	100
Unique VCs	44	100	44	100
Late M&A	221	44.3	227	45.2
Early M&A	278	55.7	275	54.8

Panel B: Regression

	Sample based on Ownership Pct		Sample based on Most Constrained Fund	
Dep. variable: $\mathbb{I}$(Earnout)	(1)	(2)	(3)	(4)
Test variables:				
$\mathbb{I}$(Later Deal)	-0.106**	-0.063	-0.100**	-0.059
	(-2.030)	(-1.461)	(-2.038)	(-1.288)
Control variables:	Y	Y	Y	Y
Fixed effects:				
VC Fund	Y	N	Y	N
VC × Year	N	Y	N	Y
Startup-Ind × Year	Y	Y	Y	Y
Adjusted R-Squared	0.309	0.290	0.389	0.343
Observations	499	494	502	497

Panel A of this table reports the number of VC Fund-startup-buyer triplets in my proprietary sample and categorizes triplets as late ("Late M&A") or early ("Early M&A") based on the median timing of the acquisition relative the inception of the VC fund. Additionally, Panel A reports the number of unique VC Funds and VCs in my sample. In the "Sample based on Ownership", for each individual VC, only the VC fund with the highest ownership percentage in a deal is retained in the sample. In the "Sample based on the Most Constrained Fund", for each individual VC, only the VC Fund with the earliest inception date in a deal is retained in the sample. Panel B reports results from my VC Fund-startup-buyer-level analysis of the association between whether the acquisition happens late in the life of the VC fund ("Later Deal Indicator"). The sample period is from 2001 to 2015. All variables are defined in Appendix A. Standard errors are clustered at the VC-level. T-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

Appendices

APPENDIX A

VARIABLE DEFINITION

Variable	Description	Data Source
$\mathbb{I}$(Cash Consideration)	Indicator variable that is 1 if the M&A merger consideration only consists of cash, and 0 otherwise.	Proprietary
Earnout	Also known as contingent consideration. A contractual arrangement whereby part of the merger consideration is made contingent on a future event or performance.	Definition
$\mathbb{I}$(Earnout)	Indicator variable that is 1 if the M&A contract includes at least one earnout.	Proprietary
Earnouts per M&A Contract	Each M&A contract can have multiple earnouts. This variable counts the number of earnouts in the M&A contract.	Proprietary
Earnout Size	Maximum earnout size as stipulated in the M&A contract divided by Purchase Price including Earnouts.	Proprietary
Firm Age	The age of the VC-backed or non-VC-backed startup at the moment it is being acquired.	Pitchbook
High VC-Buyer Distance	Indicator variable that is 1 if distance between the VC and buyer is above the median distance between the VC and all its buyers in the sample period, and 0 otherwise.	Pitchbook
High VC-Startup Distance	Indicator variable that is 1 if distance between the VC and startup is above the median distance between the VC and all its startups in the sample period, and 0 otherwise.	Pitchbook
Investor Concentration	Herfindahl–Hirschman Index of the investors' participation percentages (not including the VC's equity share).	Proprietary
$\mathbb{I}$(Later Deal)	Indicator variable that is 1 if timing of the M&A transaction is later than the median timing of M&A transaction within the VC fund, and 0 otherwise.	Pitchbook

(Continued)

Appendix A, continued

Variable	Description	Data Source
𝕀(Non-regulatory)	Any earnout that is not a regulatory earnout.	Proprietary
Number of VC Firms	The number of unique VCs that participate in the M&A transaction	Proprietary
𝕀(PE Deal)	Indicator variable that is 1 if the buyer in the M&A transaction is a private equity firm, and 0 otherwise.	Pitchbook
𝕀(Previous Relationship VC-Buyer)	Indicator variable that is 1 if any VC in the M&A transaction has a prior relationship with the buyer through one of its other portfolio firms.	Pitchbook
𝕀(Pro-rata Earnout)	Indicator variable that is 1 if the M&A contract includes at least one earnout with an investor HHI lower than 2.500. M&A transactions for which information on the underlying investors is missing are left out the sample.	Pitchbook
𝕀(Public Buyer)	Indicator variable that is 1 if a buyer in the M&A transaction is public, and 0 otherwise.	Pitchbook
Purchase Price excluding Earnouts	Enterprise value of the startup, not taking into account the earnouts, adjusted for the repayment of any debt (debt-free) and cash retained at closing (cash-free). I collected this variable from the actual M&A term sheets, which are excel sheets mimicking the M&A deal structure.	Proprietary
Purchase Price including Earnouts	Enterprise value of the startup, adjusted for the repayment of any debt (debt-free) and cash retained at closing (cash-free) plus the maximum earnout size as stipulated in the M&A contract. I collected this variable from the actual M&A term sheets, which are excel sheets mimicking the M&A deal structure.	Proprietary
Purchase Price (PP) Quintile	Within each industry, I split M&A transactions into five groups based on their purchase price including earnouts ranging from small to large.	Proprietary

(Continued)

Appendix A, continued

Variable	Description	Data Source
$\mathbb{I}$(Regulatory)	Indicator variable that is 1 if the M&A contract includes at least one non-regulatory earnout.	Proprietary
Sample based on Ownership Pct	Imagine VC A has two different funds that are invested in startup A, fund A1 and fund A2. In this case only one of those two funds will remain in the dataset. I retain the fund of VC A with the highest ownership percentage.	Proprietary
Sample based on Most Constrained Fund	Imagine VC A has two different funds that are invested in startup A, fund A1 and fund A2. In this case only one of those two funds will remain in the dataset. I retain the fund of VC A that has the earliest inception date.	Proprietary
Startup Industry	I use Pitchbook's industry classifications (i.e., Pitchbook variables: primary industry sector and primary industry group). I categorize startups into 12 industry groups: Commercial Services, Commercial Products, Consumer Services, Consumer Products, Apparel and Accessories, Consumer Non-Durables, Healthcare - Services, Healthcare - Pharma and Biotech, Healthcare - Devices, Healthcare - Services, IT-non-software, and IT-software based on their industry classification.	Pitchbook
$\mathbb{I}$(VC-Buyer Different State)	Indicator variable that is 1 if VC and buyer are located in different states, and 0 otherwise.	Pitchbook
$\mathbb{I}$(VC-Startup Different State)	Indicator variable that is 1 if VC and startup are located in different states, and 0 otherwise.	Pitchbook

(Continued)

Appendix A, continued

Variable	Description	Data Source
VC Ownership	The investor-level M&A participation percentage is determined by the consideration received by an investor at closing divided by the total consideration. If this variable is missing, I use the percentage of the investor in the M&A deal's expense fund, which is set up to cover any possible costs ex-post, including for instance legal and consulting fees. I then aggregate the ownership percentage of all underlying VCs (as defined by Venture Capital Firm).	Proprietary
Venture Capital Firm (VC)	Any venture capital firm (as defined by Pitchbook) that is not an angel investor, corporate venture capital department, incubator/accelerator, or public/government investors.	Definition
$\mathbb{I}$(Venture Capital)	Indicator variable that is 1 if the venture capital participation percentage of an acquired startup is larger than or equal to 10%, and 0 otherwise.	Proprietary
$\mathbb{I}(\text{Venture Capital})_{Alt}$	Indicator variable that is 1 if any underlying VC receives any merger consideration, and 0 otherwise.	Proprietary

This table provides the descriptions and sources of variables used in this paper.

APPENDIX B

PROPRIETARY SAMPLE OF M&A CONTRACT

Table B1: Benchmarking Proprietary Sample

Panel A: Sample Distribution by Startup Industry

	Proprietary Sample		Pitchbook Sample	
Startup Industry	Obs	Pct(%)	Obs	Pct(%)
Commercial Products	36	3.6	67	1.5
Commercial Services	84	8.4	502	11.1
Consumer Products	47	4.7	288	6.4
Consumer Services	68	6.8	441	9.8
Energy	10	1.0	72	1.6
Financial Services	18	1.8	110	2.4
Healthcare - Devices	68	6.8	189	4.2
Healthcare - Pharma and Biotech	53	5.3	318	7.0
Healthcare - Services	59	5.9	162	3.6
IT-non-software	79	7.9	343	7.6
IT-software	475	47.5	2,004	44.4
Materials and Resources	3	0.3	20	0.4
Total	1,000		4,516	

Panel B: Summary Statistics of M&A Purchase Price

Purchase Price (in millions)	N	Mean	SD	P25	Median	P75
Proprietary Sample	981	200.998	750.043	23.000	67.000	180.000
Pitchbook Sample	1,825	620.220	1,730.368	27.577	103.100	400.000
DealStats Sample	1,761	240.546	596.813	2.200	24.402	180.689

This table presents sample characteristics of my proprietary sample compared to data from Pitchbook data and DealStats data. Panel A reports the sample distribution by startup industry for my *Proprietary Sample* and the *Pitchbook Sample* between 2015 and 2020. I present both the total number of observations (Obs) in each industry and the corresponding percentage relative to the entire sample (Pct(%)). Panel B reports summary statistics for the variable M&A Purchase Price for my proprietary sample, the Pitchbook sample and the Dealstats sample, respectively. My *Proprietary Sample* covers all the contracts between 2015 and 2020 for which I found a *Purchase Price*. The *Pitchbook Sample* covers all M&A contracts of startups in the venture capital and private equity dataset between 2015 and 2020 for which the variable *Dealsize* is available. The *Dealstats Sample* covers the entire universe of M&A transactions between 2015 and 2020 for which the variable MVIC Price is available. All other variables are defined in Appendix A.

APPENDIX C

MAIN ANALYSIS: ROBUSTNESS TESTS

Table C1: Alternate Definition of $\mathbb{I}$(Earnout)

	No FE	Baseline	Additional FE		
Dep. variable: $\mathbb{I}$(Pro-rata Earnout)	(1)	(2)	(3)	(4)	(5)
$\mathbb{I}$(Venture Capital)	-0.114***	-0.088***	-0.098**	-0.101**	-0.064**
	(-3.913)	(-3.059)	(-2.091)	(-2.574)	(-2.111)
Control variables:	Y	Y	Y	Y	Y
Fixed effects:					
Startup-Industry × Year	N	Y	Y	N	N
Startup Legal Advisor	N	N	Y	N	N
Startup-Ind. × Buyer-Ind. × Year	N	N	N	Y	N
Startup-Ind. × PP Quintile × Year	N	N	N	N	Y
Adjusted R-Squared	0.030	0.192	0.201	0.220	0.237
Observations	812	812	525	615	721

This table reports results from my analysis of the association between VC Participation ($\mathbb{I}$*(Venture Capital)*) and the use of pro-rata earnouts in the M&A Contract ($\mathbb{I}$*(Pro-rata Earnout)*), using OLS regressions. Pro-rata earnouts are earnouts in which a broad group of equityholders participate. The analysis is executed at the M&A transaction-level. M&A transactions with missing information on the underlying shareholder participants are left out of the sample. The sample period is from 2015 to 2020. All variables are defined in Appendix A. Standard errors are clustered at the Industry × Year level. T-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

Table C2: VC Participation and Earnout Size

	No FE	Baseline	Additional FE		
Dep. variable: Earnout Size	(1)	(2)	(3)	(4)	(5)
$\mathbb{I}$(Venture Capital)	-0.033**	-0.016	-0.023	-0.025*	-0.018
	(-2.342)	(-1.437)	(-1.462)	(-1.676)	(-1.597)
Control variables:	Y	Y	Y	Y	Y
Fixed effects:					
Startup-Industry × Year	N	Y	Y	N	N
Startup Legal Advisor	N	N	Y	N	N
Startup-Ind. × Buyer-Ind. × Year	N	N	N	Y	N
Startup-Ind. × PP Quintile × Year	N	N	N	N	Y
Adjusted R-Squared	0.068	0.361	0.369	0.400	0.437
Observations	851	851	549	648	760

This table reports results from my analysis of the association between VC Participation ($\mathbb{I}$*(Venture Capital)*) and the earnout size, calculated as the maximum earnout size divided by the purchase price including earnouts, using OLS regressions. The analysis is executed at the M&A transaction-level. The sample period is from 2015 to 2020. All variables are defined in Appendix A. Standard errors are clustered at the Industry × Year level. T-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

Table C3: Alternate Definition of $\mathbb{I}$(Venture Capital)

	No FE	Baseline	Additional FE		
Dep. variable: $\mathbb{I}$(Earnout)	(1)	(2)	(3)	(4)	(5)
$\mathbb{I}$(Venture Capital)$_{Alt}$	-0.066**	-0.057*	-0.095**	-0.045	-0.055**
	(-2.257)	(-1.954)	(-2.218)	(-1.031)	(-2.035)
Control variables:	Y	Y	Y	Y	Y
Fixed effects:					
Startup-Industry × Year	N	Y	Y	N	N
Startup Legal Advisor	N	N	Y	N	N
Startup-Ind. × Buyer-Ind. × Year	N	N	N	Y	N
Startup-Ind. × PP Quintile × Year	N	N	N	N	Y
Adjusted R-Squared	0.020	0.187	0.208	0.213	0.230
Observations	851	851	549	648	760

This table reports results from my analysis of the association between VC participation ($\mathbb{I}$(Venture Capital)$_{Alternative}$) and the use of earnouts in the M&A contract ($\mathbb{I}$*(Earnout)*), using OLS regressions. The analysis is executed at the M&A transaction-level. The sample period is from 2015 to 2020. All variables are defined in Appendix A. Standard errors are clustered at the Industry × Year level. T-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

Table C4: Number of VC Firms and Earnouts

	No FE	Baseline	Additional FE		
Dep. variable: 𝕀(Earnout)	(1)	(2)	(3)	(4)	(5)
Number of VC Firms	-0.020***	-0.007*	-0.014**	-0.007	-0.002
	(-3.677)	(-1.754)	(-2.299)	(-1.377)	(-0.515)
Control variables:	Y	Y	Y	Y	Y
Fixed effects:					
Startup-Industry × Year	N	Y	Y	N	N
Startup Legal Advisor	N	N	Y	N	N
Startup-Ind. × Buyer-Ind. × Year	N	N	N	Y	N
Startup-Ind. × PP Quintile × Year	N	N	N	N	Y
Adjusted R-Squared	0.031	0.186	0.208	0.213	0.227
Observations	851	851	549	648	760

This table reports results from my analysis of the association between the number of (participating) VC firms and the use of Earnouts in the M&A Contract (𝕀*(Earnout)*), using OLS regressions. The analysis is executed at the M&A transaction-level. The sample period is from 2015 to 2020. All variables are defined in Appendix A. Standard errors are clustered at the Industry × Year level. T-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

Table C5: VC Ownership and Earnout Size

Panel A: Linear Model					
Dep. variable: Earnout Size	(1)	(2)	(3)	(4)	(5)
VC Ownership	-0.018	-0.014	-0.011	-0.022	-0.019
	(-0.719)	(-0.698)	(-0.381)	(-0.897)	(-0.833)
Adjusted R-Squared	0.061	0.359	0.366	0.398	0.436
Observations	851	851	549	648	760

Panel B: Quadratic Model					
Dep. variable: Earnout Size	(1)	(2)	(3)	(4)	(5)
VC Ownership	-0.215***	-0.053	-0.119	-0.090	-0.093**
	(-3.041)	(-1.088)	(-1.633)	(-1.417)	(-2.022)
$(\text{VC Ownership})^2$	0.264***	0.051	0.147	0.089	0.098
	(2.768)	(0.821)	(1.417)	(1.100)	(1.459)
Adjusted R-Squared	0.070	0.359	0.367	0.397	0.436
Observations	851	851	549	648	760

Panel C: Other Model Specifications					
	No FE	Baseline	Additional FE		
Control variables:	Y	Y	Y	Y	Y
Fixed effects:					
Startup-Industry × Year	N	Y	Y	N	N
Startup Legal Advisor	N	N	Y	N	N
Startup-Ind. × Buyer-Ind. × Year	N	N	N	Y	N
Startup-Ind. × PP Quintile × Year	N	N	N	N	Y

This table reports results from my analysis of the association between VC Ownership (percentage) and the use of Earnouts in the M&A Contract ($\mathbb{I}$*(Earnout)*), using OLS regressions. Panel A (B) employs a linear (quadratic) model. Panel C describes the overlapping model specifications. The analysis is executed at the M&A transaction-level. The sample period is from 2015 to 2020. All variables are defined in Appendix A. Standard errors are clustered at the Industry × Year level. T-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

APPENDIX D

FALSIFICATION TEST: MULTINOMIAL LOGISTIC REGRESSION

Table D1: Falsification test: Multinomial Logistic Regression

Panel A: Descriptive Statistics

	$\mathbb{I}$(Venture Capital)		
Earnout Categories	0	1	Total
Cat 1: {Regulatory = 0 & Non-regulatory = 0}	222	420	642
Cat 2: {Regulatory = 0 & Non-regulatory = 1}	77	80	157
Cat 3: {Regulatory = 1 & Non-regulatory = 0}	18	34	52
Total	317	534	851

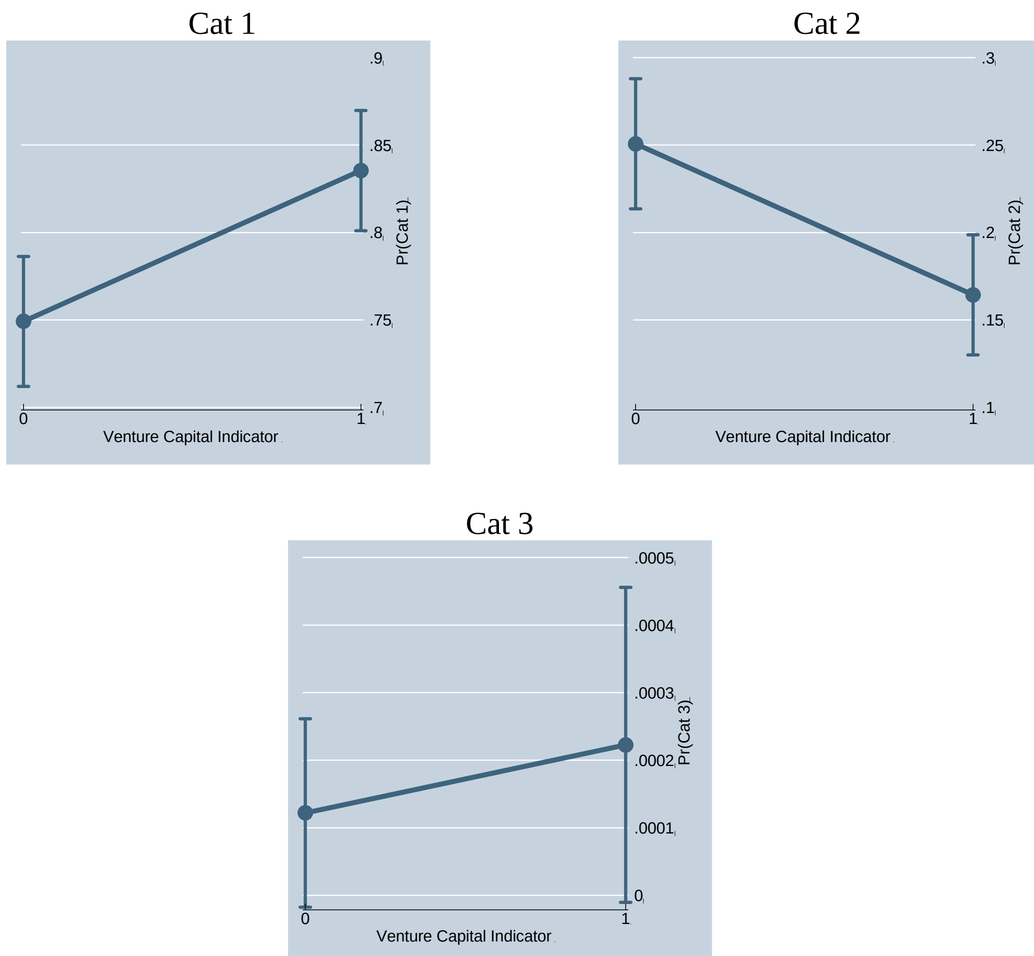
(Continued)

Table D1 (continued)

Panel B: Multinomial Logistic Regression Results					
Earnout Categories	Coeff.	Std. Err.	Odds	z-score	$P > \|z\|$
Cat 1: (Base Outcome)					
Cat 2:					
$\mathbb{I}$(Venture Capital)$_2$	-0.531***	0.184	0.588	-2.89	0.004
Cat 3:					
$\mathbb{I}$(Venture Capital)$_3$	0.475	0.424	1.642	1.12	0.262
χ^2*-test:*					
Δ($\mathbb{I}$(Venture Capital$_{2,3}$)	1.006**				
	($P > \chi^2 = 0.025$)				
Control variables:	Y				
Startup Industry fixed effects:	Y				
Year fixed effects:	Y				
Pseudo R-Squared	0.203				
Observations	851				

Panel A of this table reports descriptive statistics on the categories that the outcome variable can take in this analysis. Panel B reports results from a multinomial logistic regression of the categorical variable, as described in Panel A, and $\mathbb{I}$(Venture Capital), including control variables as in Table 3. Additionally, I add startup-industry and year fixed effects. Due to model limitations, I simplify the industries into three categories: (i) healthcare (Healthcare - Services, Healthcare - Pharma and Biotech, Healthcare - Devices, Healthcare Services), (ii) IT (IT-non-software, and IT-software), and (iii) other (the remaining industries). I report the estimated coefficients on $\mathbb{I}$(Venture Capital) and corresponding inferential statistics. Additionally, *Odds* ($e(\beta)$ are odds ratios for VC-backed M&A transactions to be in a specific category compared to the reference group (*Cat 1*). The analysis is executed at the M&A transaction-level. The sample period is from 2015 to 2020. All variables are defined in Appendix A. Standard errors are clustered at the Industry $\times$ Year level. Δ($\mathbb{I}$(Venture Capital$_{i,j}$) is the difference between $\mathbb{I}$(Venture Capital$_i$) and $\mathbb{I}$(Venture Capital$_j$) and ***, **, and * indicate statistical significance based on χ^2 test at the 1%, 5%, and 10% levels (two-tailed), respectively. "p-value" gives the associated p-value.

Figure D1: Multinomial Logistic Regression Visualization



These figures refer to the model in Table D1, and plot the predicted probability of having an M&A contract as specified in each category for VC-backed and non-VC-backed transaction, holding all other variables in the model at their means.

APPENDIX E

DISTANCE ANALYSIS: ROBUSTNESS TEST

Table E1: Distance Analysis

Panel A: Sample Characteristics

		VC-Startup in different states:		
		No	Yes	Total
VC-Buyer in	No	257	72	329
different states:	Yes	477	509	986
	Total	734	581	1,315

Panel B: Regression

	Information Asymmetry		Post-acquisition Monitoring		Both	
Dep. variable: $\mathbb{I}$(Earnout)	(1)	(2)	(3)	(4)	(5)	(6)
Test variables:						
$\mathbb{I}$(VC-Buyer Different State)	0.094***	0.093***			0.102***	0.098***
	(4.166)	(3.647)			(4.404)	(3.832)
$\mathbb{I}$(VC-Startup Different State)			-0.072**	-0.056**	-0.081***	-0.062**
			(-2.474)	(-1.986)	(-2.813)	(-2.237)
Control variables:	Y	Y	Y	Y	Y	Y
Fixed effects:						
VC × Year	Y	Y	Y	Y	Y	Y
Startup-Ind × Year	N	Y	N	Y	N	Y
Adjusted R-Squared	0.148	0.284	0.144	0.278	0.155	0.288
Observations	1315	1309	1315	1309	1315	1309

Panel A of this table reports the number of VC-startup-buyer triplets in my proprietary sample categorizes triplets as having a high or low distance between the VC and buyer (startup) based on the median distance of a VC with their startups (buyers). Panel B reports results from my VC-startup-buyer-level analysis of the association of the distance between VC and buyer (startup) and the use of an earnout ($\mathbb{I}$(Earnout)). The sample period is from 2001 to 2015. All variables are defined in Appendix A. Standard errors are clustered at the VC-level. T-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.