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NBER Working Paper No. 27690
August 2020, Revised in September 2020
JEL No. G0,G00,G1,G10,G12,G19

ABSTRACT

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September 6, 2020

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We thank Marco Sammon, Morten Sorensen, and participants at the 2020 AFA Meeting for their valuable comments. We thank Honghao Wang and Tiange Ye for excellent research assistance. We thank Lintong Li for sharing his codes for analyzing the patent data. Shumiao Ouyang thanks the Julis-Rabinowitz Center for Public Policy & Finance (JRCPPF) for funding. All errors are our own.

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1 Introduction

Most studies in the literature that examine the profitability of investing in ventures have focused on the return to limited partners in venture capital (VC) funds.[1] There are fewer articles that examine the return to individual ventures. In part this is due to missing venture-level valuation information for many of the funding rounds in publicly available databases. To address this issue, Korteweg and Nagel (2016) use data from Sand Hill Econometrics, which employs proprietary valuation models to fill in the missing valuations data (Hall and Woodward, 2010).[2] While the study greatly enhanced our understanding of the return to investing in ventures, there remains one limitation – the proprietary valuation models are not easily accessible to general investors and researchers.

In this paper, we propose a measure of the return to investing in individual ventures that addresses the data limitations in a different manner. Our measure is the net present value (NPV) of each individual venture's life-cycle cash flows, which represents the return to a hypothetical representative investor who participates in all the funding rounds of the venture. When discounting the cash flows to calculate the NPV, we use the Public Market Equivalent Method proposed by Kaplan and Schoar (2005) and Generalized Public Market Equivalent Method proposed by Korteweg and Nagel (2016). We apply this measure to a large sample of US-based ventures in the SDC VentureXpert database, involving data on 16,396 ventures and 57,884 funding rounds between 1980 and 2018, and analyze the returns to investing in ventures over their life cycles.

The advantage of our approach is that it circumvents many of the funding-round-level data limitations, including sparse valuation data, selection bias, and infrequent cash flows. Also, it avoids the need for analyzing the allocations of cash flow rights in each funding round between founders and outside investors delineated by the complex VC contracts. The shortcoming is that we only examine the return to all investors as a group instead of investors in any particular funding round.

Funding round-level valuation data is sparse in the widely used VC databases in the literature. [3] Our approach takes advantage of the fact that some funding-round variables are better recorded than others – in our sample, although the post-money valuation data is missing for 76.3% of the rounds, amount raised data is missing for less than 3% of the rounds (See Figure 1). Our NPV measure relies mainly on the amount raised data.

[1]See Rin, Hellmann, and Puri (2013) for a survey of venture capital research.

[2]See the white paper of Sand Hill Econometrics at link.

[3]See Lerner (1995), Kaplan, Strmberg, and Sensoy (2002), and Maats, Metrick, Yasuda, Hinkes, and Vershovski (2011).

The only valuation data used in the measure is the post-money valuation in the first round. [4] Although the sample of ventures with first-round post-money valuation data may be different from the rest, it represents a large and economically important sample of ventures. [5] We split the ventures into two samples – those with and without first-round post-money valuation data. While we focus on the sample with first-round valuation data, separately for those without, we also provide their NPVs based on imputed valuations using a statistical model.

Sparsity of round-level valuation data is accompanied by a selection bias issue. The selection bias – the fact that ventures performing better are more likely to report their valuations, needs to be corrected in any consistent estimation of venture's risk and return. On that front, Cochrane (2005) conjectures a selection function for venture valuation disclosure, under the assumption that the probability of obtaining new financing smoothly increases with the value of the venture, and uses the estimated selection function to correct for the bias. Korteweg and Sorensen (2010) build a dynamic selection model, and estimate the parameters as well as the unobserved valuations using Bayesian methods. Our approach also addresses the selection bias issue, but without using a selection model. Our NPV measure only requires the post-money valuation data of the first round. It is not subject to selection bias in the later rounds when we focus on the sample of ventures with the first-round post-money valuation data.

Since cash flows are random and occur infrequently at random unknown times in the future, when evaluating the returns, we cannot directly apply the standard linear multi-factor based methods for risk adjustments such as the CAPM. We use both the Public Market Equivalent (PME) method (Kaplan and Schoar, 2005) and the Generalized Public Market Equivalent (GPME) method (Korteweg and Nagel, 2016) to compute the risk-adjusted discount rate and overcome this issue. The PME method matches the VC investments at each time period to an investment in the publicly traded market index proxy portfolio, and use the realized market return to risk adjust the VC investment return. [6] The GPME method nests PME, and ensures the modeled SDF can accurately reflect risk-free rates and returns of public equity markets.

Gornall and Strebulaev (2017) find that cash flow rights are allocated differently to

[4] An example in Appendix A.2 shows how a small amount of missing valuation data could severely affect the calculation of round-to-round return and round-to-exit return, but not our NPV measure.

[5] 24.3% of the first rounds have post-money valuation data, and they account for about 29.3% of the total amount raised in the first rounds.

[6] Sorensen and Jagannathan (2015) point out that using the PME is equivalent to discounting using the stochastic discount factor (SDF) corresponding to the dynamic Rubinstein CAPM for a particular choice of the wealth portfolio of the evaluator.

shares issued in different stages of the venture's life cycle. Ignoring this may lead to significant biases in round-to-round and round-to-exit returns. Besides, Ewens, Gorbenko, and Korteweg (2018a) find that the split of value between founders and VCs are usually complex, heterogeneous, and generally not observable. Both findings imply that measuring the return to a particular group of investors requires information on the financing contract's terms, which is typically unavailable in common VC databases. Our NPV measure represents the return to all the equity holders taken together as a group, including the founders, thus avoids using information on the contracting details. Of course, the obvious shortcoming is that it cannot measure the return to any specific group of investors. However, the measure still offers a useful metric on venture returns, and as we will see, reveals interesting patterns in the data.

We apply the NPV measure to a large sample of US-based ventures in the SDC VentureXpert database. The NPV measure, as well as most other venture return measures, requires data on the venture's exit events (whether through an IPO or an acquisition or through bankruptcy) and the corresponding exit values. In order to improve the data coverage on the exit events, we cross-checked the exit events of ventures using multiple data sources like PitchBook, Bloomberg, NASDAQ, Crunchbase and other Internet sources. We find that a large number of ventures with no recorded exit events in VentureXpert experienced bankruptcies or were acquired according to the other data sources. Taking into account these exit events improves the accuracy of our measure.

We document several interesting patterns in the data. When we consider the portfolio of all ventures that had their first funding round in a given calendar quarter, we find large variation in the time to break-even. In particular, for the portfolio of ventures that had their first funding round in a given quarter between 1992 and 2006, it takes between 5 to 60 quarters for the present value of cash flows to become positive, depending on the quarter of the first round.[7] Moreover, we find a structural break in the time series of aggregate normalized NPVs – i.e., the NPV of all ventures that had their first rounds in a given quarter normalized by that quarter's aggregate first-round amount raised, in the second quarter of 1999. After the break, the aggregate normalized NPV drops from significantly positive on average to weakly positive on average.

The structural break follows the passage of the National Securities Markets Improvement Act (NSMIA), which would have increased the supply of capital to ventures, ac-

[7]Also, a hypothetical investor holding all ventures, regardless of the first funding round time, takes approximately 5 years for the present value of cash flows to become positive. This is consistent with the stylized facts in Ramsinghani (2014).

cording to a careful examination of the act's impact by Ewens and Farre-Mensa (2019). They find that after NSMIA, the founders are using their increased bargaining power vis-à-vis investors to stay private longer. To understand the effects of NSMIA on venture valuations, and the VC's role in a venture's success, we develop a model characterizing the matching process of ventures and VCs and the how their relative bargaining power affects the ownership given to the VCs. The model suggests that expected returns of investing in ventures will decrease after the increased supply of capital. And consistent with the model's predictions, we find that after the structural break in 1999, ventures have lower NPVs – i.e., a lower expected return since we compute NPV per dollar invested keeping the discount rate the same, and that the fraction of ownership founders give up in the first round to *experienced* VCs relative to other VCs becomes smaller.

We find that experienced VCs in general add value to the ventures in which they participate. [8] Specifically, first round participation by more experienced VCs – i.e., those who have invested in more ventures in the past, signals better performance of the venture as measured by its NPV as well as the likelihood of successful exit. Such a relationship, significantly weakens after the structural break in 1999 when performance is measured by venture NPV, but remains similar when measured by the likelihood of successful exit. Using quantile regressions, we find that the relationship between VC experience and the venture's performance is especially strong for ventures with high realized NPVs. Finally, we find that experienced VCs tend to invest in innovative ventures – ventures that have more patent grants over their life cycle – in the first funding round both before and after the structural break.

Related Literature

The literature on measuring risk adjusted returns to investing in ventures is large. Kaplan and Schoar (2005) and Korteweg and Nagel (2016) develop methods for risk-adjusting venture capital cash flows and returns based on the stochastic discount factor framework. Cochrane (2005) and Korteweg and Sorensen (2010) study the selection bias and information incompleteness in venture's disclosure. Driessen, Lin, and Phalippou (2011) propose a modified internal rate of return method. Gupta, Stern, and Nieuwerburgh (2019) propose a "strip-by-strip" method for risk adjustment. Ang, Chen, Goetzmann, and Phalippou (2018) develop a Bayesian Markov Chain Monte Carlo method for

[8]VCs provide valuable services to investors in their funds. They identify the set of ventures that have potential, monitor their performance over time, and participate in the high level management of the ventures. Bernstein, Giroud, and Townsend (2016) find that VC's involvement with their ventures leads to an increase in both innovation and the likelihood of a successful exit.

private equity (PE) returns using cash flows accruing to limited partners and factor returns from public capital markets. We build on Kaplan and Schoar (2005) and Korteweg and Nagel (2016) to account for data limitations when using venture-level data. Our NPV measure of venture-level returns to all the equity holders offers a computationally simpler alternative to addressing the data limitations.

Ljungqvist and Richardson (2003) find a return premium to investing in PE relative to the public equity market, which potentially compensates for the illiquidity of PE investments.[9] Harris, Jenkinson, and Kaplan (2015) find that the performance of VC funds varies over time, and VC funds that started when the venture sector received high capital inflows had lower performance. Harris, Jenkinson, and Kaplan (2014a) show that VC funds outperformed public equities in the 1990s, but under-performed in the 2000s. Nanda and Rhodes-Kropf (2013) find that VC-backed startups receiving initial investment in hot markets are more likely to go bankrupt. Our NPV measure indicates there is a risk-adjusted return premium to investing in ventures before the structural break in 1999, which comes down afterwards, generally consistent with these findings in the literature.

There is some consensus in the literature that VC experience is related to the performance of ventures (Sorensen, 2007).[10] When considering the time variation in such a relationship, Harris, Jenkinson, Kaplan, and Stucke (2014b) find evidence on the persistence of VC fund performance both pre- and post-2000. Our finding that VC experience matters before the structural break in 1999 but matters less afterwards, contributes to this literature.

Some caveats about our NPV measure should be mentioned. First, since we do not take into account employee stocks and stock option grants, our measure of the return to investors and founders may have an upward bias. Second, focusing on the subsample of the ventures with non-missing first-round post-money valuations may also introduce a selection bias – these ventures may have systematically better performance and growth opportunity. However, early-stage valuations of ventures are very unreliable (Kerr, Nanda, and Rhodes-Kropf, 2014; Ewens, Nanda, and Rhodes-Kropf, 2018b).[11] The first-round valuation may not convey much information about the growth opportunity and overall

[9] In contrast, Moskowitz and Vissing-Jrgensen (2002) find that the return to investing in PE is not higher relative to the public equity.

[10] Further, the age (Gompers, 1996; Ramsinghani, 2014) , network connections (Hochberg, Ljungqvist, and Lu, 2007; Du and Hellmann, 2019), and reputation (Nahata, 2008; Hsu, 2004) of VCs, as well as the active involvement of VCs (Bottazzi, Da Rin, and Hellmann, 2008; Bernstein et al., 2016; Akcigit, Dinlersoz, Greenwood, and Penciakova, 2019) also matter for venture performance.

[11] This is why the "spray and pray" investment approach is common among VCs in the early stages.

valuation of a venture. Hence we argue that this selection bias may be small, and importantly, our measure is not subject to selection bias in any later rounds. Furthermore, there is no forward-looking bias in our approach – the strategy of investing in the ventures with non-missing first-round valuation is realizable for investors with access to ventures, without the need of any future information. Finally, we assume that all convertible preferred shares used in the funding rounds automatically convert upon exit. While this is generally true, there may be exceptions, and to that extent out measure has a downward bias. Further, we consider ventures that had their first funding rounds in 2006 or earlier, in order to capture the cash flows over the entire life cycle of ventures – most ventures take as long as 12 years to exit. It is possible that cash flow characteristics have changed for latter ventures.

The rest of the paper is organized as follows. Section 2 explains the data we use for analysis. Section 3 explains our NPV measure of the return to investing in ventures and discusses the findings. Section 4 presents the model, the hypotheses and their tests. Section 5 concludes.

2 Data

2.1 Data Sources and Data Cleaning

Our sample comes from the universe of ventures in VentureXpert, which is the standard database for many venture capital studies. We augment VentureXpert with data on funding rounds and exit events from multiple sources. Our data ends in 2018, and we limit attention to ventures that had their first funding rounds before 2006.[12]

We first collect data on venture funding rounds from VentureXpert that includes the time, amount raised, and post money valuation of each funding round. Then, we collect data on the exit events of these ventures. Based on information in VentureXpert, we classify a venture's exit event as IPO, MA, or bankruptcy. Ventures whose VentureXpert status is "Went Public" are classified as exiting through an IPO. Those whose VentureXpert status is "LBO", "Merger", "Acquisition" or "Pending Acquisition" are classified as exiting through an MA. Those whose VentureXpert status is "Defunct", "Bankruptcy – Chapter 7" or "Bankruptcy – Chapter 11" are classified as exiting through a bankruptcy. Finally, we classify the final outcome of a venture having none of these exit events as Alive. For the ventures that exited through an IPO or MA, we further collect the data

[12]This allows for a minimum life cycle length of 12 years.

on their exits from SDC Merger and Acquisition and SDC Global New Issues databases.

Some of the ventures in VentureXpert either have no recorded exit events or have exit events but not the associated exit values. We therefore cross-checked the exit events of those ventures using other data sources, in order to enhance the data coverage on venture exits. Specifically, for 10,533 US-based ventures that received the first funding round between 1992 and 2006, and did not experience bankruptcy according to VentureXpert, we cross-checked their exit events with data from PitchBook, Bloomberg, NASDAQ, Crunchbase and other internet sources. As shown in Table 1, of the 2,026 ventures that are shown as being alive in VentureXpert, 604 exited through bankruptcy, 14 through IPO, and 455 through MA according to other sources.[13] Only 953 remained active.

After identifying the exit events of the ventures, we combine data from various sources to get the exit values of the ventures. As shown in Table 2, data from the other sources improved the coverage of exit values. For MAs, in our cross-checked sample of ventures, 4,569 ventures exited through MA according to VentureXpert, out of which 2,194 have pre-MA valuation data recorded in the SDC databases, and the other data sources are able to provide valuation data for another 396 ventures. Besides, there are 242 ventures whose pre-MA valuations recorded in the SDC databases conflict with those in other data sources[14]. For these cases, we adopted the data that appears more reliable. Finally, thanks to the other data sources, we identify 501 additional venture exits through MAs, out of which 91 have valuation data.

For IPOs, we are particularly mindful of the data quality of the pre-IPO valuations. We note that there are cases where SDC data can be incorrect. For example, the pre-IPO market value of Targanta Therapeutics Corp is reported as 0.3 million dollars, however from the prospectus we know that the pre-IPO market value is about 152 million dollars.[15]

To ensure the data is correct, we calculate three measures of the pre-IPO market value and cross-validate them. The first measure is the product of pre-IPO shares outstanding and the IPO offering price. The second measure is the difference between post-IPO market value and the IPO proceeds. The third measure is the pre-IPO market value as reported in SDC database. If large discrepancy is observed across these three measures, we manually check the prospectus and use the prospectus value. Overall, we find the first measure to be most reliable. In calculating these three measures, we closely examine

[13]For the 14 exits through IPOs, we list the ventures' names, IPO exchanges, IPO dates and CRSP PERMCO in Table IA.1 in the Internet Appendix.

[14]We regard the exit values in SDC as conflicting with other sources if they differ by more than 5%

[15]According to the prospectus, there were 15.2 million pre-IPO shares and its offering price was $10 per share.

other detailed data issues. First, shares outstanding data in SDC might be missing for some NASDAQ IPOs, for which we use the shares outstanding on the first trading day in CRSP for calculation. Second, in some foreign IPOs the offering prices are in foreign currencies instead of US dollars, for which we either avoid using offering price, or use the ratio of proceeds and offering shares to back out the price in dollars.

Utilizing other data sources to cross-check and supplement the standard SDC data gives us a more comprehensive and accurate coverage of the ventures' exit events. This strengthens our measure of venture investment returns, which heavily relies on the valuations of ventures at exit events.

2.2 Sample Selection

As mentioned earlier, we restrict our sample to the US-based ventures that received the first funding round before 2006. There are two reasons for this sample restriction. First, our data ends in 2018, so we are not yet able to observe the full life cycle of ventures that started recently. Looking at the observed total number of funding rounds of ventures receiving their first rounds in different years, as shown in Figure 1 and Figure 2, we see that the data censorship problem becomes severe for ventures that had their first rounds after 2006. Second, for the majority of ventures that went to successful exits – IPOs and MAs, the time between the first round to the exit falls within 10 years.[16] Restricting to the sample that had the first round before 2006, if a venture has not had a successful exit as observed by 2018, it most likely never will. Such a venture may even already be defunct, just with its status not updated in the database. We assume the exit value of such ventures to be zero. Without the sample restriction, gauging the exit value of such a venture will be difficult.

We further separate the ventures into two groups. Group A includes ventures that have post-money valuation data for the first funding round. Group B includes the rest. For Group B ventures, we exclude the initial funding rounds whose records are not informative using a filtering procedure. Specifically, from the beginning of the funding process, we sequentially drop the funding rounds with neither amount raised nor post-money valuation data, until a funding round that has either variable recorded. Then, we reclassify that funding round as the venture's first funding round, and the subsequent rounds as the second, third, and so on. Table 3 shows the effect of the filtering procedure.

[16] The time from the first funding round to exit is within 10 years for 92.0% of the ventures that went to IPO and 87.6% of those that went to MA.

We see that initially Group A has 3,885 ventures and Group B has 13,357 ventures, and that 846 (3.33%) of the Group B ventures were effectively dropped by the filtering procedure.[17] Due to the concerns that Group A and Group B ventures have distinct natures, we conduct analysis on them separately.

2.3 Imputation of Missing Values

We utilize statistical models described in Appendix A.1 to impute the missing values in the variables essential to our analysis – including first-round ownership given up, [18] amount raised in the funding rounds, pre-IPO valuations and pre-MA valuations, based on observable information. Table 4 summarizes the data that were missing and imputed. We see that imputed values are mainly for pre-MA valuations and first-round ownership given up. For Group A ventures, we imputed only 0.4% of the first-round ownership data, but for Group B ventures, we imputed 99.1% of the data. For both groups of ventures, we imputed around 50% of the pre-MA valuation data. The imputed first-round ownership given-up is similar to the actual data, but the imputed pre-MA valuations are on average lower than the actual valuations.[19]

To measure the fitness of an imputation model, we rely on the out-of-sample R^2, in addition to the standard in-sample R^2. We use the ten-fold cross-validation method to calculate the out-of-sample R^2. First, we randomly partition the sample that enters the regression model, into ten equal-sized sub-samples. Second, we iterate over each one of the ten subsamples, while in each iteration, we calculate the fitted values for the subsample from the model estimated by the rest nine subsamples, and record the R^2 of the fitted values. After ten iterations, we compute the average of these out-of-sample R^2's for the subsamples. Finally, we repeat the random sample partition and out-of-sample calculation procedure ten times, and report the average as the out-of-sample R^2 of the overall model, as cross-validation Pseudo-R^2.

For the first-round ownership given up data, the imputation uses logit models. Specifically, we estimate a logit model relating the ownership given up in each round to a rich set of variables, where we cumulatively add the log amount raised in the round and its

[17]This introduces a (potentially small) look ahead bias for Group B, since we excluded some ventures based on future information.

[18]First-round ownership given up measures the ownership given up by the venture founders to the first rounds investors, and is calculated as the ratio of first-round amount raised to the first-round post-money valuation.

[19]This may suggest that those venture MAs with no valuation records tend to have lower valuations, if our imputation model is correct.

square, log cumulative amount raised starting from the first round, and controlling for fixed effects on industry, funding stage, the number of rounds that have occurred, time and the number of investors. Table IA.2 in the Internet Appendix shows that the most saturated model results in the highest cross-validation Pseudo-R^2 of 0.484, which is what we adopt for the imputation.

For the amount raised data, the imputation uses linear regression models. For each round separately, we first estimate the relationship between the amount raised and the number of investors who participated, the amount raised in the previous round, as well as industry fixed effects, funding stage fixed effects and time fixed effects. [20] There are few funding rounds after the ninth round and they are all in late stages, so we treat them all together as a group. For them, instead of relating the amount raised in a round to the previous round's, we relate it to the ninth round's. The fitted values from the model are the imputed values. Table IA.3 in the Internet Appendix shows the estimation results of the imputation models.

For the pre-IPO and pre-MA valuations, the imputation uses linear regression models. Specifically, we estimate the relationship between the pre-MA or pre-IPO valuation, and a rich set of observables including extrapolated valuations[21], days from last available post-money valuation to the exit event, the interaction of these two, final-round raised amount, days from final round to the exit event, NASDAQ return from final round to the exit event, together with fixed effects for industry, funding stage, number of rounds received, and exit time. Table IA.4 and Table IA.5 in the Internet Appendix report the estimation results of the imputation models.

2.4 Descriptive Findings

The upper panel of Figure 3 plots the per-round amount raised by the ventures over time. Before 2000, there is an upward trend in the average amount raised per-round by ventures. This number peaked at \$14.4 million in 2000. After 2000, it first dropped significantly and then stabilized between \$7.7 million and \$9.8 million until 2006, and trended upward to as high as \$19.2 million after 2006. The uptrend after 2006 is to be expected since the

[20] For the first round, there is no previous round, so the model relates the amount raised to a set of fixed effects.

[21] Extrapolated valuation is based on last available post-money valuation and NASDAQ stock return. It equals the last available post-money valuation multiplied by the cumulative NASDAQ stock return from that last valuation date to venture's exit event. We use NASDAQ returns as the benchmark because NASDAQ firms are generally smaller and resemble the risk profile of the ventures better (Cochrane, 2005).

rounds after 2006 are more likely to be later rounds and hence larger, because we only include ventures that had the first rounds before 2006. Also, the plotted percentiles of the per-round amount raised shows a wide dispersion among ventures. The bottom panel of the figure instead plots the amount raised in the ventures' first funding rounds over time. Before 2000, there is an upward trend in the average first-round amount raised by ventures. The number peaked at $8.9 million in 2000. After 2000, this number first dropped and remained stable.

Figure 4 plots the fraction of ownership given up in the first round over time. The ownership given up data used here includes the imputed values. We see that on average the venture founders give up 30% of the ownership to investors in the first funding round.

Ventures in our data eventually reach one of the four final outcomes: IPO, merger and acquisition, bankruptcy, or alive. [22] Figure 5 decomposes the final outcomes by the ventures' first-round years. We see that the fraction of ventures that eventually went to IPO decreases until 2000, and remains stable at around 6% afterwards. The fraction of ventures that eventually went to MA increases before 2000 and remains relatively stable at around 45% afterwards. The fraction of ventures that eventually declared bankruptcy remains stable at around 8% over time.

After receiving a funding round, one of the five following events may ensue: receive another funding round, IPO, MA, bankruptcy, or no further events are observed. Figure 6 decomposes the "next events" by the funding round number. We see that after receiving the first or second round, most ventures continue to receive additional funding rounds and the probability of directly going to IPO, MA or bankruptcy is low. After about five rounds, the probability of a venture subsequently going to IPO, MA or bankruptcy peaks.

3 Net Present Value of Ventures' Life Cycle Cash Flows

3.1 Methodology for Computing Present Values

In this section we describe our net present value (NPV) approach to measuring the return to investing in ventures. The NPV measure is based on the cash flows that the venture received from all the equity investors in the various funding rounds taken together as a group, and the cash flow or value received by them upon the venture's exit. Essentially

[22]We classified the ventures with no observed outcomes as alive.

it represents the return to a hypothetical investor who participates in all the funding rounds of a venture and provides all the financing cash flows. Appendix A.2 offers an example of the NPV measure calculation for a hypothetical venture.

The amount raised in each funding round is the cash flow that the venture receives from the outside investors. We hereafter use the term VCs to denote all the outside investors. Before the VCs' investments, the founders of the venture usually have already invested various resources, including their effort and financial resources. Consequently, the founders are also equity holders and receive a fraction of the venture's value at its exit. We use the pre-money valuation of a venture in the first round as a proxy for the total investment made by the founders.[23] To summarize, the pre-money valuation in the first round and the amount raised in all the rounds are the cash flows received by the venture.

The cash flow received by equity holders upon the venture's exit is measured by its equity value. If a venture exits through an MA, then the equity value at exit is computed using the fraction of equity transacted and the transaction value. If the venture exits through an IPO, then the equity value at exit is the pre-IPO equity value. For the other exit events, we regard the exit equity value as zero.[24]

To calculate the present value of the cash flows of ventures, we need to appropriately adjust for the risk of the cash flows. For that purpose, we use the Generalized Public Market Equivalent (GPME) method developed by Korteweg and Nagel (2016) and the Public Market Equivalent (PME) method (Kaplan and Schoar, 2005).

The GPME and PME involve computing the realized present value at time 0 of a cash flow, C_t, that occurs at a random time t in the future as $M_t C_t$, where M_t is the stochastic discount factor for bringing time t cash flows to time 0. In the case of the PME, M_t equals the inverse of the time t value of a dollar invested at time 0 in the market portfolio of all stocks, i.e., $\frac{1}{(1+R_{m1})...(1+R_{mt})}$, where R_{ms} is the market portfolio's rate of return during time period s. It answers the question, how much would you have to invest in the market portfolio at time 0 to get C_t at time t. The net present value of all the cash flows becomes,

$$NPV = E_0[-\sum_{t=0}^{T-1} M_t C_t + M_T C_T] \tag{1}$$

[23]For Group B ventures where first-round post money valuation is not available, we utilize the imputed ownership given up in the first round (by the founders) to calculate the pre-money valuation.

[24]Note that this may lead to a conservative measure of the returns to equity holders, although successful exits are very unlikely if the time from the first round exceeds 10 years.

where $E_0[.]$ denotes the expected value at time 0. Note that all cash flows except the exit value C_T are outflows. C_0 is first-round post-money valuation, which is the sum of the first-round pre-money valuation and first-round amount raised, and C_1 ,... C_{T-1} are the cash contributions by equity holders in subsequent funding rounds. The case of no discounting corresponds to $M_t = 1$, and the NPV is just the terminal value minus the cash flows at all funding rounds including what the founder brought into the first founding round.

In the GPME, the stochastic discount factor (SDF) is specified as: [25]

$$M_t = exp(at - br_{m,t}) \tag{2}$$

where M_t is the stochastic discount factor, t is the time of a funding round or exit time, with the first round of the venture taking place at time $t = 0$, a and b parameters that are positive constants, and $r_{m,t}$ is the log cumulative return on the publicly traded equity market portfolio since the first round. [26]

We use the parameter values, a = 0.033, and b = 1.444, which are the values estimated by Korteweg and Nagel (2016) using round to round returns on ventures.[27]

In the following sections, we sometimes take an additional step to normalize the net present value (NPV) by the first-round post-money valuation, i.e., the amount raised by outside equity investors in the first round plus the value brought in by the founder – corresponding to C_0 in the NPV formula given in equation 1. The normalized NPV is given by:

$$Normalized\ NPV = E_0[-\sum_{t=0}^{T-1} \frac{M_t C_t}{C_0} + \frac{M_T C_T}{C_0}] \tag{3}$$

We refer to it as the normalized NPV measure. It measures the net present value per dollar invested in the first round of funding (NPV). Under the null hypothesis that venture does not earn higher risk premium, $Normalized\ NPV = 0$. Note that we do not observe $Normalized\ NPV$ since we do not observe $E_0[.]$. We therefore characterize the

[25]This comes from Equation (1) in Korteweg and Nagel (2016).

[26]To simplify the calculation, we treat the cash flows after 15 years from the first round as occurring in the 15th year. Few ventures still receive funding or successfully exit after 15 years from the first round.

[27]See Table 6 of Korteweg and Nagel (2016). We also re-estimated the SDF parameters based on round-to-round returns using our sample of data. All the results are qualitatively similar under the re-estimated parameters.

properties of the time series of realized value of:

$$Realized\ Normalized\ NPV = -\sum_{t=0}^{T-1} \frac{M_t C_t}{C_0} + \frac{M_T C_T}{C_0}. \tag{4}$$

Average $Realized\ Normalized\ NPV$ will be a reasonable proxy for $Normalized\ NPV$. For notational convenience, we will omit 'Realized' and referred to $Realized\ Normalized\ NPV$ as $Normalized\ NPV$ whenever it does not lead to any confusion.

3.2 Characteristics of Life Cycle Cash Flows of Ventures

3.2.1 Portfolio of All Ventures

To examine the cash flows over the life cycle of the ventures, we construct the cumulative discounted cash flows of each individual venture within a period of time from the first round, and then aggregate across all the ventures. To illustrate how the present value of cash flows change over the venture's life cycle, Figure 7 plots the aggregate cumulative cash inflows, cash outflows and net cash inflows (for investors) against the time from the first funding round. There are two observations. First, the cash outflows from investors (hence inflows to the venture) is on average larger during the initial funding stages. Around 70% of the total funding is invested within 8 quarters from the first round. Second, in the aggregate, investors have to wait 10 to 25 quarters or more from the first funding round date for the NPV of cash flows from the ventures to become positive (i.e. ex post or realized break-even), depending on the discounting method used. That is, the VC investments are "locked" in the ventures for a significantly long time. [28]

The figure first examines this break-even time in the sample of Group A ventures, those with first-round post-money valuation data. It also examines the break-even time when pooling Group A ventures and Group B ventures together – henceforth, the Group AB sample. We find that the break-even time of Group A ventures is about 10-15 quarters, shorter than the break-even time of 20-25 quarters for Group AB ventures, consistent with that ventures releasing the valuation information are likely better. The figure also presents the present value of cumulative cash flows under three discounting specifications, NoDisc, PME and GPMEround. The shapes of average cumulative cash flows curve and

[28]Other metrics also suggest the illiquidity of venture investments. On average, ventures that exit through an IPO take 5.01 years and require 5.67 additional dollars per first round dollar. The corresponding numbers are 6.65 and 4.03 for ventures that exit through a merger or an acquisition; 11.27 and 2.15 for ventures that exit through bankruptcy or do not exit at all even after 12 years.

hence the break-even times are robust across the three specifications.

3.2.2 Portfolio of Ventures by First Round's Time

Based on the realized NPV measure, i.e., the present value of the life-cycle cash flows, we examine how the return to investing in ventures changes over time. In particular, we construct a portfolio of ventures that had the first rounds at the same time, and study how the time to realized break-even for that portfolio changes as the first round's time changes.

First, for each venture, we discount its cash flows, and construct the cumulative discounted cash flows for each individual venture over its life cycle.[29] Then for each quarter from 1992Q1 to 2006Q4, we aggregate the cumulative discounted cash flows of the ventures that had the first funding round in that quarter, and then calculate the break-even time of a hypothetical investor who invests in all the ventures that received the first funding round in that quarter.

Figure 8 shows the time series of the break-even time. We see that the break-even time varies from 5 quarters to 60 quarters, depending substantially on the time of the first round. When the investor invests in the ventures that receive the first funding rounds after 1999Q2 rather than before, the break-even time is substantially longer .

In Figure 9, for each quarter from 1992Q1 to 2006Q4, we plot the present value (PV) of the cash inflows and cash outflows of the portfolio of ventures that had the first rounds in that quarter, as well as the net present value (NPV) normalized by the aggregate first-round post-money valuation in that quarter. This normalized NPV measures the net present value per dollar invested in the first round of funding (NPV). We see that it is significantly positive on average and higher before 1999. A further statistical examination indicates there is a structural break in the NPVs – they are significantly lower after 1999, which is the main theme of the next section.

In sum, utilizing our NPV measure of the return to investing in individual ventures, we document that investing in ventures is risky (the NPV of ventures is volatile even in the aggregate) and illiquid (the NPV's break-even time is relatively long), and most of the return comes from a few successful ventures (more than 64% of ventures have negative normalized NPV [30]), consistent with related findings in the literature.

[29] When discounting the cash flows, the cash flows that occurred after 15 years from the first funding round are considered to occur exactly at the 15th year from the first funding round.

[30] In comparison, Bessembinder (2017) finds that 70.6% of stocks that first appeared in the CRSP database during 1997-2006 period have a buy-and-hold return that is less than holding value-weighted

The average realized net present value per dollar invested in the first round of funding (NPV) is 1.65 in our sample for Group A firms and 1.56 for Group A and B firms taken together. These values are statistically different from zero.[31] For every dollar of investment in the first round, on average 3.75 dollars was invested in the rounds that followed till exit.

4 Effect of Increased Supply of Funds to Ventures

A casual examination of the time series plot of the realized normalized NPVs suggest that there is a structural break around 1999 (see Figure 9). The average normalized NPV is larger and significantly positive with a mean of 2.46 in the subsample before 1999. The sample mean is lower in the subsample following 1999, with a mean of 0.72. [32] Later, we confirm the structural break in 1999 using statistical methods. The structural break follows the passage of the National Securities Markets Improvement Act (NSMIA). Ewens and Farre-Mensa (2019) argue that NSMIA increased the supply of capital to the ventures, leading private firms to stay private for a longer period of time. In this section, we study whether the increased capital supply led by NSMIA can rationalize the structural break we observe by examining its other implications for venture investments.

Two distinct provisions of NSMIA have helped increase the supply of private capital, including venture capital. First, NSMIA exempts qualified private security issuers from having to comply with the blue sky laws of each state. Traditionally, a venture seeking external financing needed to comply with the laws governing the issuance of securities in each state where its securities were sold, commonly known as blue sky laws. Compliance with blue sky laws required significant time and efforts. NSMIA exempts private issuers from compliance with blue sky laws in each and every state, as long as all investors are "accredited investors", hence facilitated venture's security issuance. Second, NSMIA makes it possible for VC and PE funds to raise capital from a large number of investors but without registering under the Investment Company Act (ICA) of 1940, enabling VC and PE funds to raise fund at lower cost.[33] The passage of NSMIA would have helped

market return until their delisting or the end of the sample at December 31, 2016 (See Table 2B, Panel A in Bessembinder (2017)).

[31] Realized NPVs should have an MA structure since they involve forward-looking sums. Bayesian Information Criterion suggests ARMA(1,0) is a reasonable approximation of the realized NPV process. Standard errors are based on ARMA(1,0).

[32] Section 4.2 gives details on how we compute the sampling errors.

[33] The ICA required VC and PE funds to register with the SEC and imposed extensive regulations on registered entities, including investment and leverage restrictions, restrictions on related party trans-

existing ventures in their subsequent funding rounds as well as new ventures that had their first funding rounds after NSMIA. Hence, the effect on the normalized NPV would be a bit gradual and not sharp. However, it could still be sharp, if NPVs of the later rounds are closer to zero and the main effect is concentrated in the first round. Interestingly we are still able to detect the regime shift in the time series of realized normalized NPVs, which suggests that the earlier rounds contribute more to the realized normalized NPV.

4.1 A Matching Model of Ventures and VCs

To examine the effects of an increased supply of capital due to NSMIA, we develop a model characterizing the matching of ventures with VCs, and the bargaining between them. We interpret NSMIA as increasing the relative supply of low-ability VCs, i.e., the fraction of low-ability VCs in the economy. Our model predicts that such a change will decrease the average normalized NPV of the ventures, and let founder keep a higher share in ventures that have more high-ability VCs, consistent with our empirical findings. The force driving our results is that as the fraction of low-ability VCs in the economy increases, the expected value added by VCs will decline, which decreases the value of the venture per dollar invested and increases bargaining power of founders in those ventures that more high-ability VCs participate, which tend to be of higher quality as well. We need several simplifying assumptions in the model to focus on this main force. To preserve space, all the proofs are relegated to the appendix.

Ventures and VCs

Consider a two-period economy consisting of ventures and VCs. There are N ventures, with each owned by a founder. And there is a continuum of VCs, with a total mass of 1. In the first period, a group of VCs invest in a given venture. In the second period, VCs and the founder of the venture receive payoffs based on their shares of the ventures.

The ventures are of different qualities. The quality of a venture i is measured by Q_i, where Q_i is drawn from a uniform distribution $U(0, 1)$. For notational convenience, we drop the subscript i. The fundamental value of a venture with quality Q is $v = QV$, where V is the highest fundamental value a venture can have before the VCs' investments. In the first period, the venture's type is unknown to anyone. Assuming that all the participants in the economy do not infer the type of the ventures, the fair pre-money valuation of a venture is an average of the fundamental value of all types, which is

actions, and ongoing reporting requirements. NSMIA to a large extent allows exemptions of these regulatory requirements, for certain classes of investors.

$\bar{v} = \int_0^1 QVf(Q)dQ = \frac{V}{2}$.

The VCs also are of different abilities. Each VC can be of either high ability (H-type) or low ability (L-type). And the fraction of high-ability VCs in the economy is p, where $0 < p < 1$. The value added by a high-ability VC is H and the value added by a low-ability VC is L, where $H > L$. Suppose ρ is the fraction of high-ability VCs among the VCs investing in a venture, then the average value added is $\alpha = \rho H + (1 - \rho)L$. We assume the value added is a multiplicative shifter of the venture's value. That is, the final value of the venture, denoted as s, is the product of the venture's fundamental value and the average value added by the VCs, that is

$$s = \alpha v \tag{5}$$

Matching

Every venture gets funding from VCs in the first period. The matching between a venture and the VCs is governed by a simple matching function where the matching efficiency is exogenously assumed to be λ. The matching efficiency λ measures the effectiveness/assortativeness of the process for matching high-quality ventures to high-ability VCs, and is assumed to range from 0 to 1. Specifically, we assume the fraction of high-ability VCs among the VCs investing in a venture $\rho = p(1 - \lambda) + \lambda Q$, which captures the matching process.

The interpretation of the matching function is that, the fraction of high-ability VCs among VCs funding a venture is a linear function of the matching efficiency parameter λ. When $\lambda = 0$, it means the matching of VCs to ventures is fully random. So $\rho = p$, that is, the fraction of high-ability VCs among VCs funding any venture would just be the fraction of high-ability VCs in the economy. When $\lambda = 1$, it means the matching of VCs to ventures is $\rho = Q$, depending only on the quality of the venture. In this case, ventures with the highest qualities will only be invested by high-ability VCs, and ventures with the lowest qualities will only be invested by low-ability VCs.

Equilibrium

We define the equilibrium to be derived from a Nash Bargaining game over the ownership acquired by the VCs after their investments. For simplicity, we assume that the VCs collectively invest a fixed fraction θ of the venture's fair pre-money valuation in the first period. That is, the amount raised by a venture is $\theta\bar{v}$, where $\bar{v}$ is the pre-money valuation of each venture and θ is an exogenous constant.

The VCs face an outside option if not investing in the venture, which is an asset with a constant return of m, which is also exogenous. Suppose x is the fraction of ownership acquired by the VCs in the first period, then the Nash Bargaining equilibrium can be formalized by the solution to the following problem

$$\max_x \mathbb{E}[(s(1-x)-v)(sx-m\theta v)] \tag{6}$$

where, $\mathbb{E}[m\theta v]$ is the expected outside option value of the VCs, and $\mathbb{E}[v]$ is the expected outside option value of the founder. Note that in the first period, although nobody knows the type of the venture, but everyone may observe the type of each VC that invests in the venture. Although the composition of VCs investing in a venture may reveal information about the venture's type (as the matching function depends on the venture's type), we assume that neither the VCs nor the founder infer the venture type from the composition of VCs. We further assume that the founder offers the same terms to both high-ability and low-ability VCs. Both assumptions will be relaxed in the later analysis.

We can show that the following propositions hold in the equilibrium. Proposition 1 characterizes the ownership acquired by the VCs in the equilibrium. Proposition 2 characterizes the NPVs to VCs, the founder, and all equity holders after the final value of the venture is realized in the second period. Note that here when we characterize the NPVs, we regard the venture's fair pre-money valuation $\bar{v}$ as the cash flow invested by the founder. This treatment is consistent with the NPV measure we proposed.

Proposition 1 *The ownership given up by the founder to the VCs, x, that solves the Nash Bargaining problem in Equation 6 is given by:*

$$x = \frac{\alpha+\theta m-1}{2\alpha} = \frac{H(-\lambda p+p+\lambda Q)+(\lambda-1)Lp-\lambda LQ+L+\theta m-1}{2(H(-\lambda p+p+\lambda Q)+(\lambda-1)Lp-\lambda LQ+L)} \tag{7}$$

■

Note that θ will in general be much smaller than 1, and m only slightly above 1. So $1-\theta m>0$. In this case, $\frac{\partial x}{\partial \rho} \geqslant 0$ and $\frac{\partial^2 x}{\partial \rho \partial p} \leqslant 0$, which means that ventures that are invested by more high-ability VCs give up more ownership to VCs, but the difference shrinks as p, the fraction of high-ability VCs in the economy, decreases.

Proposition 2 *The normalized NPV of investments of all investors taken together, γ; of VCs taken together, γ_{VC}; and of founders taken together γ_{FD} are given by:*
(1) All equity holders

$$\gamma = -\frac{\theta-2HQ(-\lambda p+p+\lambda Q)+2LQ(-\lambda p+p+\lambda Q-1)+1}{\theta+1} \tag{8}$$

(2) VCs

$$\gamma_{VC} = \frac{2Qx(H(-\lambda p + p + \lambda Q) + (\lambda - 1)Lp - \lambda LQ + L)}{\theta} - 1 \tag{9}$$

(3) Founders

$$\gamma_{FD} = 2Q(1-x)(H(-\lambda p + p + \lambda Q) + (\lambda - 1)Lp - \lambda LQ + L) - 1 \tag{10}$$

■

Regarding the normalized NPV of all equity holders taken together, i.e., γ, we have the following observations. First, $\frac{\partial \gamma}{\partial p} \geqslant 0$, which means that NPV to all equity holders decreases as p decreases. Second, $\frac{\partial \gamma}{\partial \rho} \geqslant 0$ and $\frac{\partial^2 \gamma}{\partial \rho \partial p} \geqslant 0$, which means that ventures that are invested by more high-ability VCs deliver higher NPV to all equity holders, but the difference shrinks as p decreases.

We interpret the passage of NSMIA as increasing the relative supply of low-ability VCs, which would decrease the fraction, p, of high-ability VCs in the economy, in the model. With this interpretation, Propositions 1 and 2 lead to the following testable hypotheses.

Hypothesis 1. The passage of the NSMIA causes a structural break in the operating environment of ventures. Average NPV decreases after the structural break.

Hypothesis 2. Ventures that had participation by more high-ability (H-type) VCs have higher NPV than the others, but the difference shrinks after the structural break.

Hypothesis 3. Ventures that had participation by more high-ability (H-type) VCs tend to be high-quality (h-type) ventures, both before and after the structural break.

Hypothesis 4. Ventures that had participation by more high-ability (H-type) VCs give up more ownership to VCs than the others, but the difference shrinks after the structural break.

Extension

In the following analysis, we relax the assumption that all the participants infer nothing about the venture type from the composition of VCs, and that the founders offer the same terms to both high-ability and low-ability VCs.

First, note that the composition of VCs investing in a venture is public information. The matching function induces a one-to-one mapping between the venture's type and the composition of the VCs. Therefore, the investors will be able to infer the venture type by observing the composition of the VCs participating in a venture. We therefore relax the assumption that investors do not infer the venture type based on public information.

Second, we now allow different terms to be offered to high-ability and low-ability VCs. We now assume that for each unit of investment, the amount of shares acquired by a high-ability VC is $\frac{H}{L}$ times of that acquired by a low-ability VC.

Propositions 3 and 4 below are analogues of Propositions 1 and 2. They characterize the ownership given to the VCs and the normalized NPVs of investments made by different participants.

Proposition 3 *Under the assumptions mentioned above, the ownership given up by founders to high-ability and low-ability VCs taken together, x, that solves the Nash Bargaining problem in Equation 6 is given by:*

$$x = \frac{\alpha + \theta m - 1}{2\alpha} = \frac{H(-\lambda p + p + \lambda Q) + (\lambda - 1)Lp - \lambda LQ + L + \theta m - 1}{2(H(-\lambda p + p + \lambda Q) + (\lambda - 1)Lp - \lambda LQ + L)} \tag{11}$$

■

Note that a venture's type is fully revealed in equilibrium. Therefore the expected fundamental value of a venture is the same as its fundamental value. Therefore, $\mathbb{E}[v] = v = QV$. In spite of this, the ownership given up by founders to VCs continues to be the same as that given in Proposition 1.

Proposition 4 *The normalized NPV of investments of all investors taken together, γ; of all VCs taken together, γ_{VC}; of all high-ability VCs taken together, γ_{VC}^H; of all low-ability VCs taken together, γ_{VC}^L; and of founders γ_{FD} taken together are given by:*

(1) All equity holders

$$\gamma = \frac{-\theta + H(-\lambda p + p + \lambda Q) + (\lambda - 1)Lp - \lambda LQ + L - 1}{\theta + 1} \tag{12}$$

(2) VCs

$$\gamma_{VC} = \frac{x(H(-\lambda p + p + \lambda Q) + (\lambda - 1)Lp - \lambda LQ + L)}{\theta} - 1 \tag{13}$$

(3) High-ability VCs

$$\gamma_{VC}^H = \frac{Hx}{\theta} - 1 \tag{14}$$

(4) Low-ability VCs

$$\gamma_{VC}^{L} = \frac{Lx}{\theta} - 1 \tag{15}$$

(5) Founders

$$\gamma_{FD} = (1-x)(H(-\lambda p + p + \lambda Q) + (\lambda - 1)Lp - \lambda LQ + L) - 1 \tag{16}$$

■

We have the following observations regarding the normalized NPV, γ, of all equity holders taken together. First, $\frac{\partial \gamma}{\partial p} \geqslant 0$, which means that the normalized NPV of all equity holders taken together decreases as p decreases. Second, $\frac{\partial \gamma}{\partial \rho} \geqslant 0$ and $\frac{\partial^2 \gamma}{\partial \rho \partial p} = 0$, which means that ventures that have more high-ability VCs have higher normalized NPV. However, the difference does not depend on p, the fraction of high-ability VCs in the economy.

We note that the *Hypothesis 1, 3* and *4* continue to hold in this extended model. The first part of *Hypothesis 2* will hold. Ventures that had participation by more high-ability (H-type) VCs will have higher normalized NPVs. However, the second part of *Hypothesis 2* will not hold. The difference in the normalized NPVs of ventures with more and less high-ability VCs will not change after the structural break. As we will see later, the data is consistent with both parts of *Hypothesis 2*. This implies that the quality of the ventures are not fully revealed (i.e., not inferred) in equilibrium.

4.2 Structural Break in NPV Time Series

We now test *Hypothesis 1* of the model, that there exists a structural break soon after the NSMIA regulatory change and that the average normalized NPV of ventures declines after the structural break.

In Figure 9, for each quarter from 1992Q1 to 2006Q4, we plotted the net present value (NPV) normalized by the aggregate first-round post-money valuation in that quarter. This normalized NPV measures the net present value per dollar invested in the first round of funding (NPV). We see that it is significantly positive on average before 1999, and only slightly positive afterwards. Now we conduct formal statistic tests of the existence of a structural break in the aggregate normalized NPV time series.

We start by assuming the aggregate normalized NPV follows a time series model. Here we consider two basic time series models. The first one assumes that the aggregate normalized NPV is a constant over time and the second one assumes that the aggregate normalized NPV follows an AR(1) model. Then we apply a Supremum Wald test (Quandt, 1960; Andrews, 1993) for a structural break in the parameters of the model, at an unknown break time. The method involves a series of Wald tests over all the possible break times in our sample horizon, where each individual Wald test compares the parameters estimates from the sample before and after a break time. Not all the times can be tested as break times because there are insufficient observations to estimate the parameters if it is too near the beginning or the end of the sample. Thus, following Andrews (1993), we trimmed 15% of the observations that are too close to the beginning and the end of the sample before the Wald tests.

Table 5 shows the test statistics from the structural break tests with different specifications. Column (1)-(3) are results from tests assuming the aggregate normalized NPV is constant over time. Column (4)-(6) are results from tests assuming the normalized NPV follows an AR(1) model. Even though the realized normalized NPV process is a moving-average of random order, Bayesian Information Criterion (BIC) suggests that ARMA(1,0), i.e., AR(1), is a good approximation. Regardless of the discounting methods we use for the NPV calculation, and regardless of the sample of ventures we conducted the tests on (either Group A sample or the full sample), the results all indicate that there is a structural break around the end of the second quarter of 1999, using the supremum Wald test.

4.3 Experienced VCs and Venture Performance

We now test *Hypothesis 2* of the model, showing that ventures invested by high-ability VCs have higher NPV than the others, but the difference shrinks after the structural break. In this test, we use the experience of a VC as a proxy for ability. So more experienced VCs correspond to high-ability VCs in our model.[34]

This test is also related to the question that if possible, how to identify ventures that are more likely to succeed. It is related to the large body of literature that shows that, among many factors, VC characteristics like experience, age, network, and reputation are associated with the performance of venture investments. [35] Albeit the large body of literature, our test adopts a slightly different perspective. Specifically, we study whether experienced VCs have the ability to differentiate the high-NPV ventures from the others

[34]Although a VC's ability has many dimensions, they are probably all highly correlated with VC experience. And we regard the VC experience as a sufficient statistic of ability.

[35]See Sorensen (2007); Gompers (1996); Hochberg et al. (2007); Nahata (2008).

in as early as the *first round*. In a way this is a test of our assumed matching model – that higher ability VCs are more likely to be matched with higher quality ventures.

We start by constructing a measure of the experience of the VC team that invested in the first funding round of each venture. At any point of time, the experience of an individual VC is measured by the VC's rank among all the existing VCs based on the number of total funding rounds the VC had invested in the immediately preceding 10 years. We refer to a VC who ranks in the top 30 as a Top 30 VC. Then for each venture, if its first round's VC team includes a Top 30 VC, the venture is regarded as having an experienced VC team. If that is the case, we assign the venture an indicator variable Top 30 VC = 1, otherwise we assign the venture the indicator variable Top 30 VC = 0. So the indicator variable Top 30 VC is our measure of VC experience.

We first examine whether the cumulative discounted cash flows from investing in a venture whose first round involves a Top 30 VC (Top 30 VC = 1), is different compared to investing in one that doesn't (Top 30 VC = 0). Figure 10 plots the present value of the aggregate normalized cumulative cash flows of these two types of ventures over their life cycles. We see that the ventures with Top 30 VC in the first rounds eventually have higher cumulative cash flows, no matter when they received the first rounds. This suggests that indeed ventures invested by more experienced VCs generally have higher normalized NPV. Also, for both groups of ventures, the cumulative cash flows curves are much flattened if the first rounds are received after the structural break in 1999.

Second, we regress the venture's normalized NPV on the experience of the VC team that invested in the venture's first funding round, together with control variables including the first round's raised amount, year fixed effects, industry fixed effects and year-industry fixed effects. The cash flows are discounted using the GPMEround specification when calculating the NPVs. Besides the Top 30 VC measure, we also consider alternative measures of VC experience. For example, at any point in time, we compute the fraction of funding rounds an individual VC had invested in the past 10 years that are associated with observed ventures' successful exits, by that time. A higher fraction of rounds that lead to successful exits means the VC is more experienced, so this fraction serves as a measure experience. Similarly we compute the fractions of funding rounds that are associated with continued financing, or bankruptcy. They also serve as measures of individual VC's experience. Then for each venture, the experience of its first-round VC team is measured by the weighted average of the experience measure of all the individual VCs that invested in the venture's first round. As for the weights, we use each individual VC's total number of rounds invested in the past 10 years. Here we use the weighted average in order to not over-emphasize the performance of small VCs which is noisily measured as they only invested in a few rounds and a few ventures.

Table 6 reports the regression results. We see that having a Top 30 VC in the first round is significantly positively related to the venture's normalized NPV before the structural break in 1999. This reflects that high-quality ventures are matched with more experienced VCs. However, after the structural break, the relationship between VC experience and venture's performance becomes insignificant (as indicated by results in Column (3) and Column (6)). This seems to suggest the experience gained by the VCs from their past investments before the structural break seems to less relevant afterwards. These findings are consistent with the predictions of our model. The results are robust regardless of whether the regression uses the sample of all ventures (Group AB), or the subsample of ventures whose first funding round post-money valuation data is non-missing (Group A). The standard errors are double clustered by quarter of the first round and quarter of the last event, which could be the last round or the exit. We use the double clustered standard errors to address the error term correlations of the venture-level regression model introduced by the overlaps of life cycles of different ventures. The correlation in error terms could be especially strong for the ventures which raise the first round funding or exit at the same time.

We also conduct quantile regressions to study the heterogeneity of the relationship between VC experience and venture performance, across ventures with different levels of normalized NPVs. The quantile regressions study the relationship between any quantile of the outcome variable with explanatory variables. Before the structural break, although having a Top 30 VC in the first round is on average positively related to venture's normalized NPV, this "average effect" is mainly driven by and concentrated at the high end of the distribution of normalized NPV. The coefficient on the Top 30 VC dummy is close to zero for ventures with normalized NPVs below the 30% percentile, meaning that experienced VC is not so good at keeping away from the "bad" ventures. Instead, the coefficient has a sharp increase for ventures with normalized NPVs above the 70% percentile, meaning that experienced VC is very good at cherry-picking the best ventures. More detailed results from the quantile regressions can be found in the Internet Appendix.

As a robustness check, instead of using our NPV measure to proxy for the performance of the ventures we also use successful exits including IPO and MA as the proxy. Specifically, we regress the measure of the venture's performance – an indicator variable for successful exits, on the experience measures of the VC team invested in the venture's first funding round, together with control variables. Table 7 reports the results. The standard errors are double clustered by quarter of the first round and quarter of the last event. Having a Top 30 VC in the first round is significantly positively related to the venture's successful exits before the structural break in 1999. However, after the structural break, the relationship becomes insignificant. These are consistent with the previous results.

Value Added by VCs

We showed that first-round VCs' experience is positively related to the probability of a venture's successful exit including IPO and MA. However, VCs can influence the venture's exit decisions, either by making the exit process easier[36] or by persuading the founders directly. If there is conflict of interest between VCs and other venture shareholders, or if the VCs simply make sub-optimal exit decisions, an exit – even being a successful one, can still for example occur too early and too late, and may not necessarily maximize the value (NPV) of the venture. Therefore, we also examine the relationship between VC experience and venture performance at the intensive margin, namely whether experienced VC is positively associated with ventures with higher normalized NPV conditional on ventures that successfully exited. Specifically, in the sample of ventures with successful exits (IPO and MA), we regress the venture's NPV normalized by the first round's amount raised on a set of experience measures of the VC team invested in the venture's first funding round, together with control variables including the first round's amount raised, year fixed effects, industry fixed effects and year-industry fixed effects. The cash flows are discounted using the GPME method when calculating the NPVs, with parameters calibrated to round-to-round returns.

Table 8 reports the regression results. The standard errors are double clustered by quarter of the first round and quarter of the last event. We see that having a Top 30 VC in the first round is significantly positively related to the venture's NPV normalized by the first-round amount raised before the structural break in 1999. This reflects that experienced VCs is associated with higher NPVs even conditional on the ventures having successful exits. However, after the structural break, the relationship is not significant (as indicated by results in Column (3) and Column (6)). The results are robust regardless of whether the regression is based on the Group AB sample, or the Group A sample.

Pre-Break and Post-Break Sub-Samples

[36]For example, corporate venture capitals (CVC) have connections with many firms, and may persuade them to acquire or merge with the venture they invested in. Some VCs can also facilitate the IPO process.

In the previous section where we used the entire sample, we essentially imposed the restriction that the industry fixed effects are the same before and after the structural break, which may not be true since we know the industry composition of the ventures changed greatly. To address this concern, we estimate the regression models using data for the pre-break and post-break sub-periods.

Table 9 reports the regression results. Still, we see that before the structural break in 1999, having a Top 30 VC in the first round is significantly positively related to the venture's performance measures including normalized NPV, successful exit, as well as on the intensive margin (normalized NPV conditional on successful exit). But these relationships are not significant after the structural break. The results in Table 9 are based on regressions in the Group A sample. The results are similar when we use the full sample, but omitted to preserve space.

Robust Standard Errors

In all regressions above, the outcome variable – the venture's normalized NPV or successful exits, depends not only on the time of the venture's first round, but also the market conditions over the entire life cycle of the venture. The overlaps of life cycles of different ventures introduce correlations in the error term of the regression model among ventures. The dependent variables are also likely subject to serial correlation over time. These correlations make it hard to calculate appropriate standard errors of the coefficient estimates of the regressions. The double clustered standard errors partially addressed these issues. Besides the double clustered standard errors, we also provide robust standard errors using an Fama-MacBeth standard errors approach modified from Fama and MacBeth (1973).

We first run multiple cross-sectional regressions relating the venture's performance to the VC's experience, where each cross section consists of ventures receiving the first funding round in a given quarter. After collecting the cross-sectional regression coefficients, we adopt their average as the point estimate. Then we use three methods to calculate the standard errors of the point estimates. The first method is based on the sample standard deviation of the coefficients from the cross-sectional regressions. The second method uses Newey-West adjusted standard errors with 3 lags. The third method uses Bootstrap standard errors. Specifically, we first fit the best ARMA model to the time series of cross-sectional regression coefficients according to AICc (Akaike Information Criterion corrected for small sample). Then we bootstrap the error terms from the best ARMA model, construct the series of regression coefficients in each bootstrap iteration according to the ARMA model and calculate their average. Then the sample standard deviation of these averages is the bootstrap standard errors. To preserve space, all the additional robust standard errors results are relegated to the Internet Appendix. All the findings we have (including those in the following sections) are qualitatively similar under these robust standard errors.

4.4 Experienced VCs and Venture Quality

Now we test the *Hypothesis 3* of the model, that ventures invested by more high-ability (H-type) VCs tend to be high-quality (h-type) ventures, both before and after the structural break. In this test, we proxy the quality of a venture by the number of innovations it creates. Although a venture's quality can be viewed in many dimensions, in reality one important criteria that the VCs use to select the ventures to invest is whether the venture is innovative enough. By being innovative, the venture can develop a competitive edge and make profit in the future, hence being more valuable.

On that front, we study the relationship between VC experience and the venture's innovation activity. For this purpose we use the number of patent grants and patent citations during the life time of a venture as the measure of its innovation ability. We regress the venture's lifetime number of patents and patent citations on the experience measures of the VC team invested in the venture's first funding round, together with control variables including the first round's amount raised, year fixed effects, industry fixed effects and year-industry fixed effects. Table 10 reports the regression results. We see that VC's past experience is highly correlated with venture's innovation ability, either measured by lifetime number of patents or by patent citations, and this relationship holds both before and after the structural break. This means that although experienced VCs are not more likely to invest in high NPV ventures in the first round, they still tend to invest in ventures that tend to be more innovative later on. So the results are consistent with the model's prediction. And the results are robust regardless of whether the regression uses Group A ventures or the full sample (Group AB ventures).

4.5 Bargaining Power of Founders and Experienced VCs

Here we test the model's *Hypothesis 4*, that ventures invested by more high-ability (H-type) VCs give up more ownership to VCs than the others, but the difference shrinks after the structural break.

We focus on the ownership given up by the venture founder in the first round. Specifically, we regress the venture founder's first-round ownership given up on the experience measures of the VC team invested in the venture's funding round, together with control variables including the first round's amount raised, year fixed effects, industry fixed effects and year-industry fixed effects. Table 11 reports the regression results. We see that VC's past experience is highly correlated with the venture's first-round ownership given up before the structural break in 1999, suggesting that more experienced VC is able to acquire more shares from the venture in the first round. However, this relationship is not significant after the structural break. This is consistent with the predictions of our model: the bargaining power of experienced VCs relative to the venture founders declines after the structural break. The results are also consistent with the findings of Ewens and Farre-Mensa (2019).

5 Conclusion

In this paper we make a contribution to the empirical literature on venture capital by characterizing the risk adjusted return to investing in ventures. To address the sparsity of valuation data at various funding round levels, we measure the return to all equity holders as a group, including the founders, from the venture's first funding round till exit. The measure we develop has the advantage that it requires valuation data for the first round only, apart from amount raised in various funding rounds, which are available for most funding rounds. Thus, the NPV measure minimizes the need for imputing missing data, or relying on proprietary valuation models. The shortcoming is that we cannot examine how the returns vary across different groups of investors and different rounds of a venture.

The NPV measure is based on discounting the cash flows that the venture received from all the equity holders in the various funding rounds, and the cash flow (value) to all equity holders upon the venture's exit. It represents the return to a hypothetical investor who participates in all the funding rounds of a venture and provides all the financing cash flows. For discounting the cash flows, we use the Public Market Equivalent method in Kaplan and Schoar (2005) and the Generalized Public Market Equivalent method in Korteweg and Nagel (2016).

Our sample consists of US-based ventures in the SDC VentureXpert database. Our data consists of 16,396 ventures that raised \$448 billion through 57,884 funding rounds between 1980 and 2018. We first compute the ex post risk-adjusted "time to break-even" - that is, the minimum holding period such that the NPV of a venture's cumulative cash flows becomes positive. We find that venture investments are very illiquid. Even for a diversified portfolio of ventures, the time to break-even can be substantially long.

Suppose an investor holds a portfolio of all the ventures that had the first rounds in a given quarter, her average time to break-even will be between 5 and 60 quarters, depending on the calendar quarter of the first rounds. That is, even for such a diversified portfolio of ventures, money can be locked-in for as long as 15 years before breaking even. Most of the return comes from a few successful ventures, and more than 64% of ventures have negative NPVs.

The time series of normalized NPVs have an average of 1.56 – i.e., on average a dollar invested in the first round has a value of (2.56) dollars. For every dollar invested in the first round, on average 3.75 dollars were invested in the rounds that followed till exit. Further, the time series of realized normalized NPVs exhibits a structural break in the second quarter of 1999. This structural break follows the passage of the National Securities Markets Improvement Act (NSMIA). We hypothesize that this would have increased the supply of capital to ventures, especially from less sophisticated investors (VCs). To understand the effect of NSMIA, we develop a model characterizing the matching process of the ventures and the VCs, and the bargaining among VCs and founders.

Our empirical findings are consistent with the model's implications. First, the average normalized NPV of ventures declines after the structural break from 2.46 to 0.72. Second, ventures with participation by more experienced VCs have higher normalized NPVs and higher likelihood of successful exits, but this relationship weakened after the structural break. Third, ventures with participation by more experienced VCs are more innovative as measured by the number patent grants and citations. The relationship holds both before and after the structural break. Finally, founders with participation by more experienced VCs give up more ownership, but this relationship weakens after the structural break.

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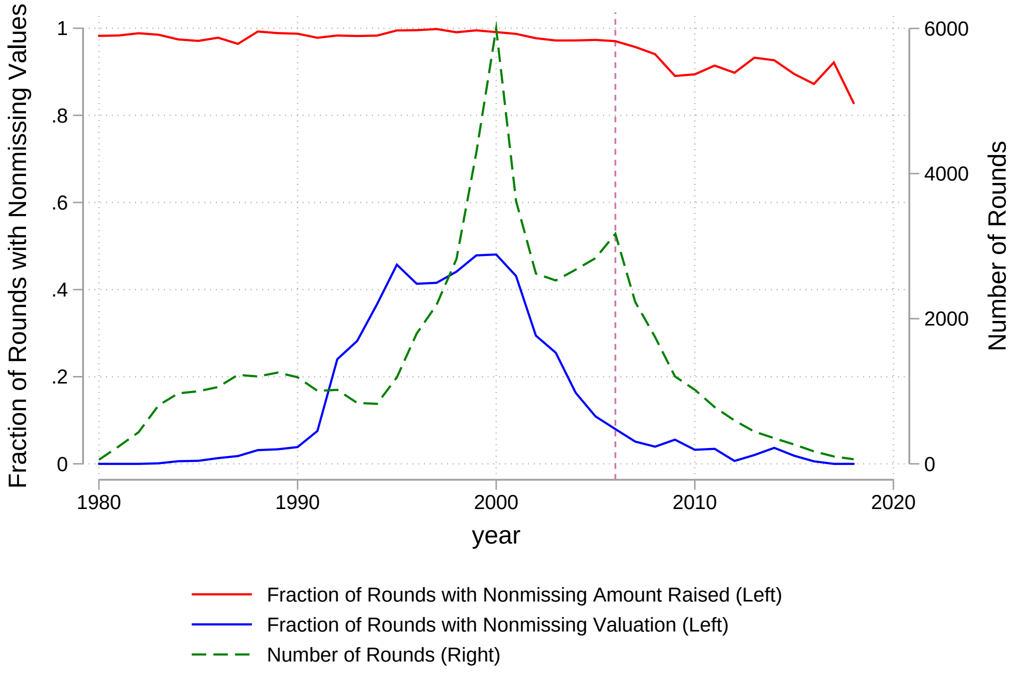


Figure 1: Fraction of Rounds with Nonmissing Data in Each Year

Note: Figure plots the number of funding rounds received by the ventures in each year, as well as the fraction of the funding rounds that have non-missing amount raised data and non-missing post-money valuation data. The sample includes all the US-based ventures in the SDC VentureXpert database that had the first funding round prior to 2006.

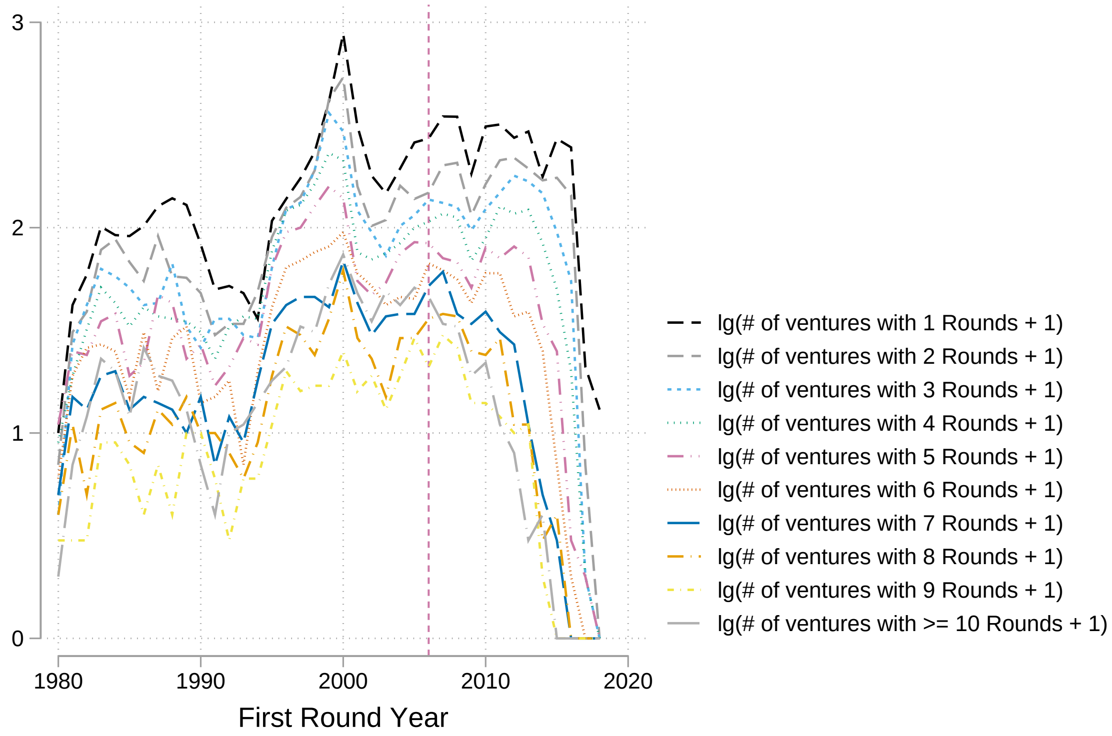
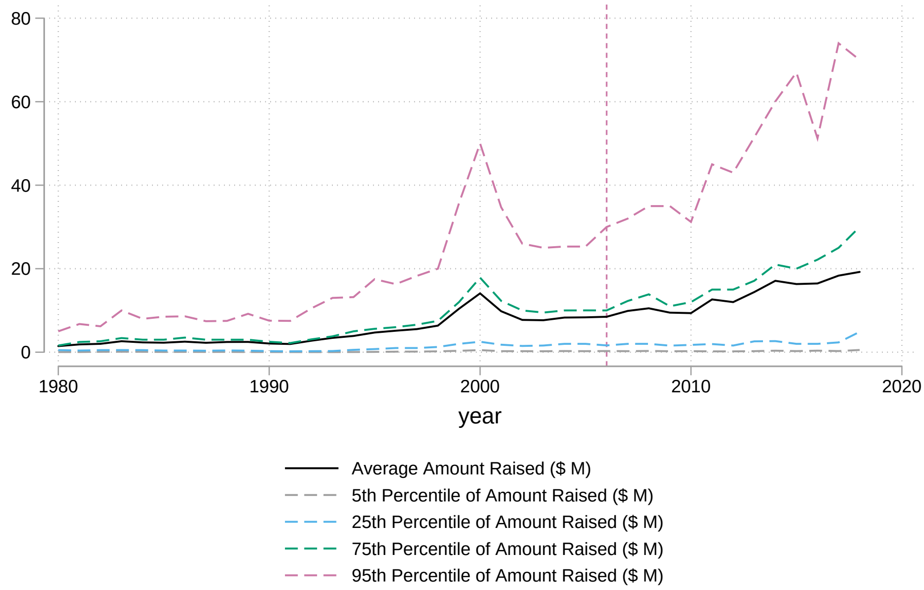


Figure 2: Ventures with Different Lifetime Total Funding Rounds by the First-Round Years

Note: Figure plots for each year from 1980 to 2018, the number of ventures whose first funding rounds are in that year, and ended up receiving 1,2,...,9 or 10 and more funding rounds in total over their life time. Figure uses the log-10 scale for the number of ventures. The vertical line is at year 2006. We see the number of ventures whose first funding round is after 2006 decreased abruptly, suggesting as it gets close to the sample end, there is a data censorship bias. The sample is the universe of ventures in the SDC VentureXpert database.



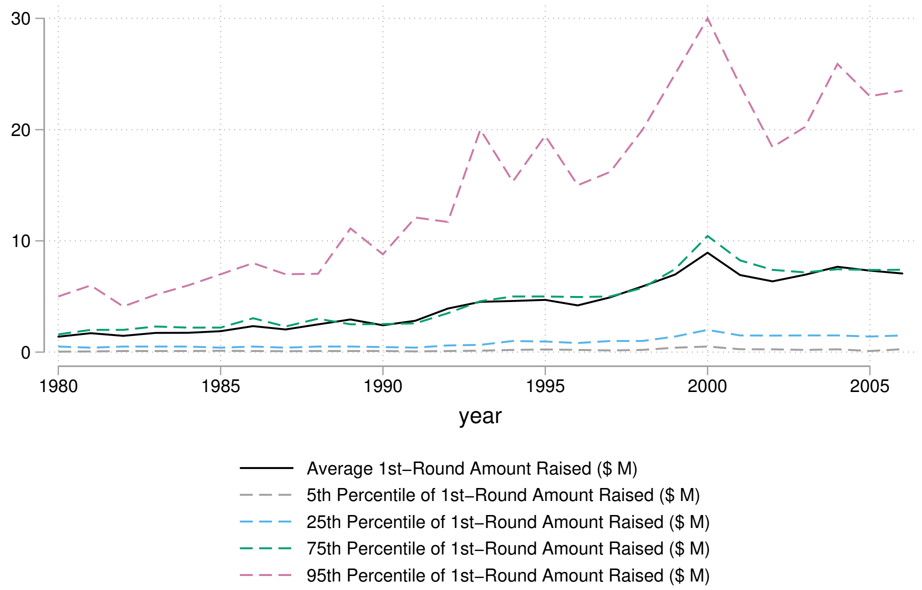


Figure 3: Amount Raised in the Funding Rounds by the Year of the Rounds

Note: The upper panel plots the average, 5th, 25th, 75th and 90th percentiles of the amount of funding raised by all the ventures in each year from 1980 to 2018. The bottom panel plots the average, 5th, 25th, 75th and 90th percentiles of the first-round amount of funding raised by all the ventures in each year from 1980 to 2006. The sample includes all the US-based ventures in the SDC VentureXpert database that had the first funding round prior to 2006. The vertical line is at year 2006.

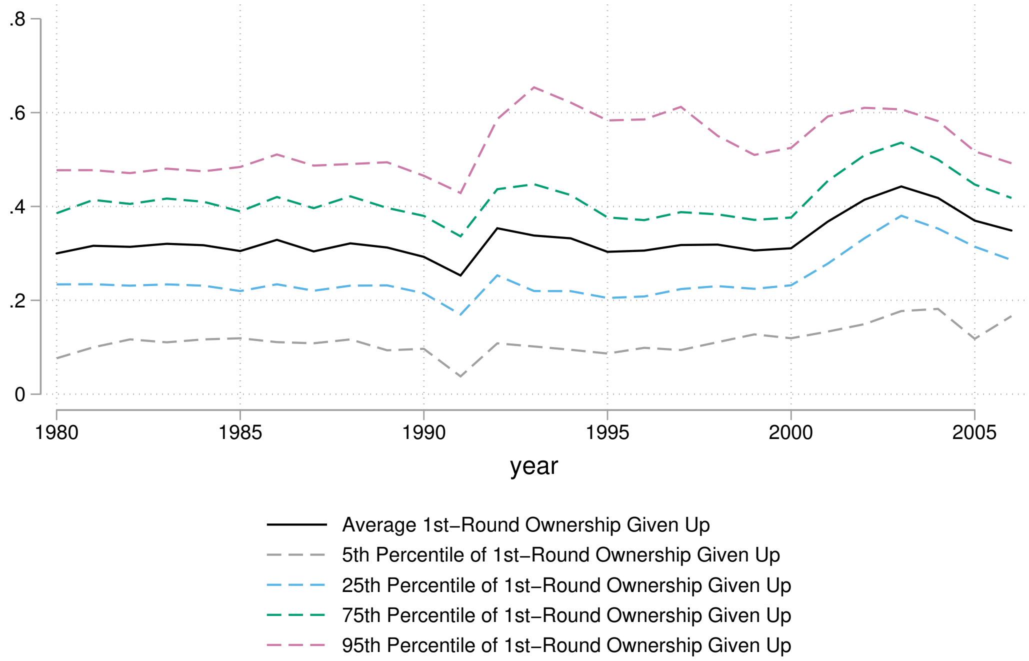
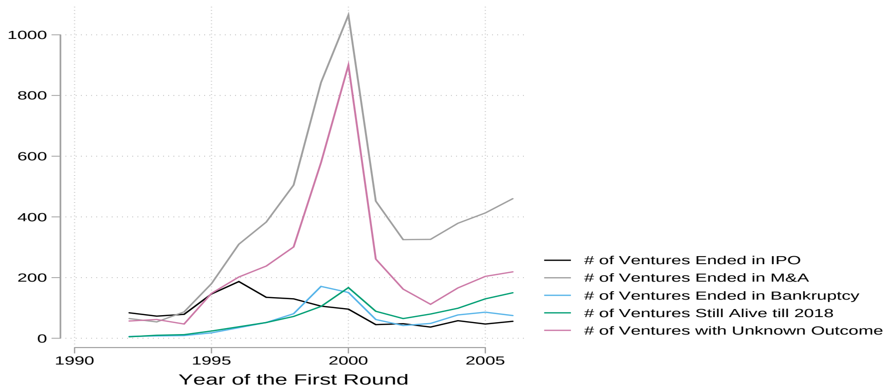
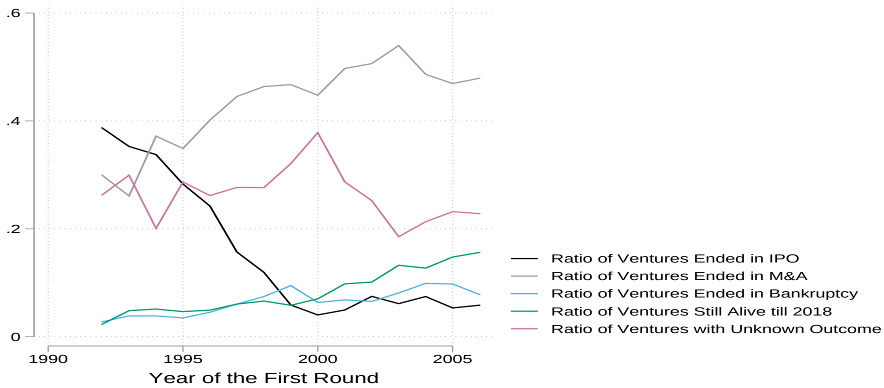


Figure 4: First-round Ownership Given Up by the Year of the Rounds

Note: Figure plots the average, 5th, 25th, 75th and 90th percentiles of the ownership given up in the first funding round by the ventures in each year from 1980 to 2006. The sample includes all the US-based ventures in the SDC VentureXpert database that had the first funding round prior to 2006. We calculate the ownership given up in the first funding round as the amount of the funding raised/the venture's post money valuation. If the ownership given up data is missing, we impute the ownership given up using the logit model described before.



(a) Number of Ventures



(b) Fraction of Ventures

Figure 5: Number of Ventures with Different Outcomes by the Year of the First Round

Note: For each year from 1992 to 2006, Panel (a) plots the number of ventures which had the first funding round in that year, and have different outcomes later in their life time. Panel (b) plots the fraction of ventures with different outcomes among those that had the first funding round in each year from 1992 to 2006. The ventures are US-based ventures in the SDC VentureXpert database. Five venture outcomes are considered – IPO, Merger/Acquisition, Bankruptcy, Still Active, and Unknown Outcomes. A venture is regarded as being bankrupted if its bankruptcy is recorded by VentureXpert, Pitchbook or Bloomberg. A venture is regarded as being still active if it still has operating activity according to Pitchbook or Bloomberg. Those ventures that we find no information on their outcomes are labeled here as having Unknown Outcomes.

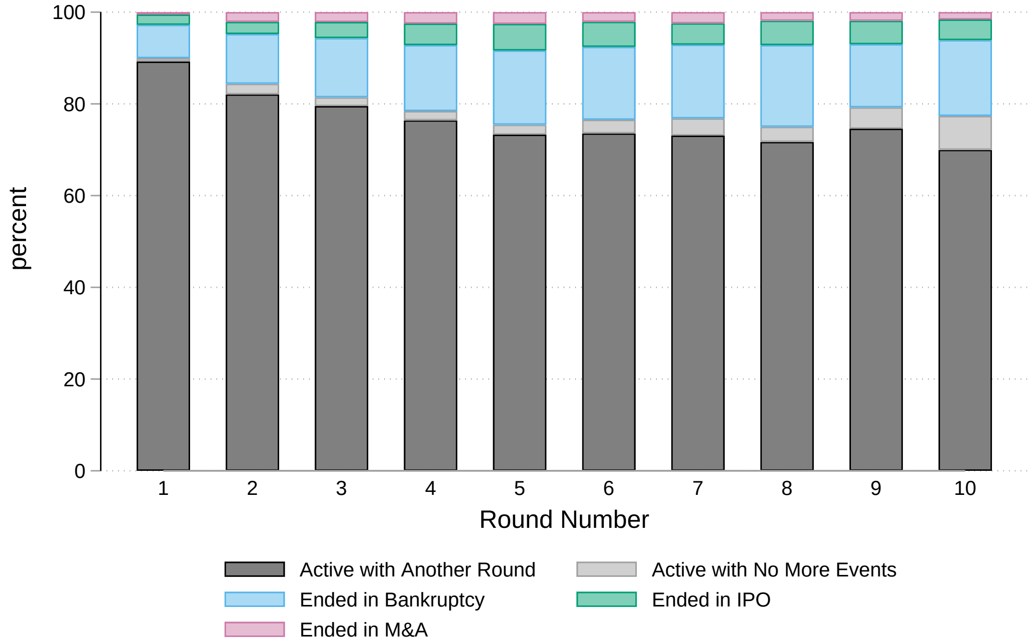
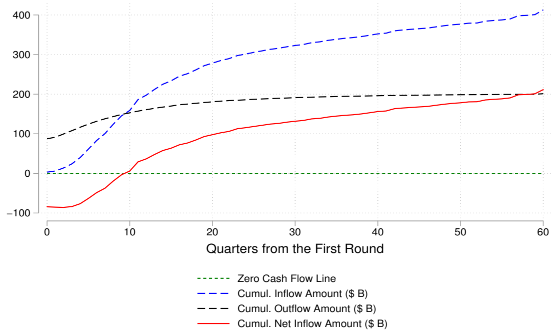
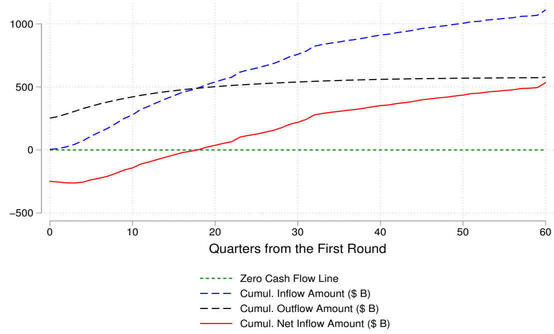


Figure 6: Distribution of Next Event by Round

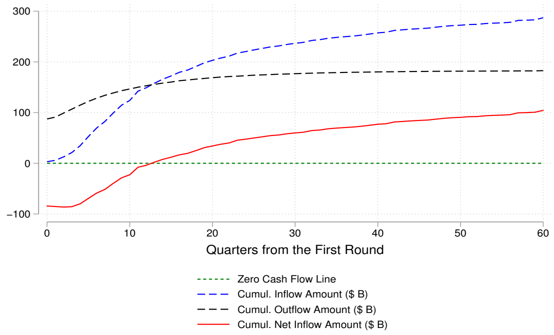
Note: When a venture receives a funding round, the next event that occurs is one of the following: (1) it remains active and receives another funding round, (2) it goes to bankruptcy, (3) it goes to MA, (4) it goes to IPO, and (5) it remains active but we observe no continued funding or exit events. Figure plots the fraction of ventures that experienced each of the above listed events after they receive their first, second, third funding round and so on. Those ventures receiving more than 10 funding rounds are top coded to have received 10 rounds when computing the fraction. The sample includes all US-based ventures in SDC VentureXpert database that had the first funding round prior to 2006.



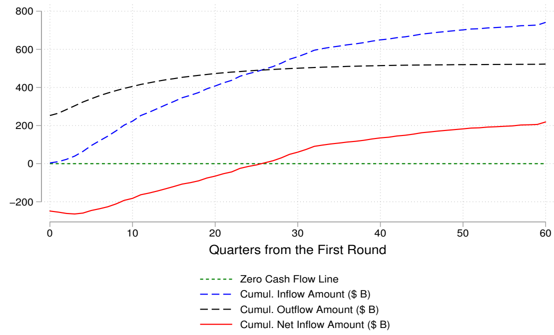
(a) No Discounting, Group A



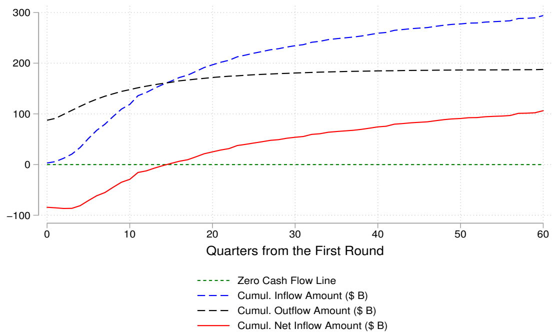
(b) No Discounting, Group AB



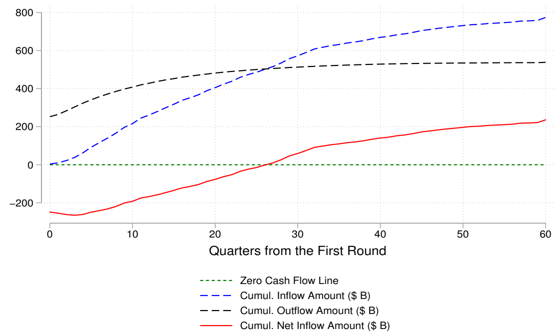
(c) PME, Group A



(d) PME, Group AB



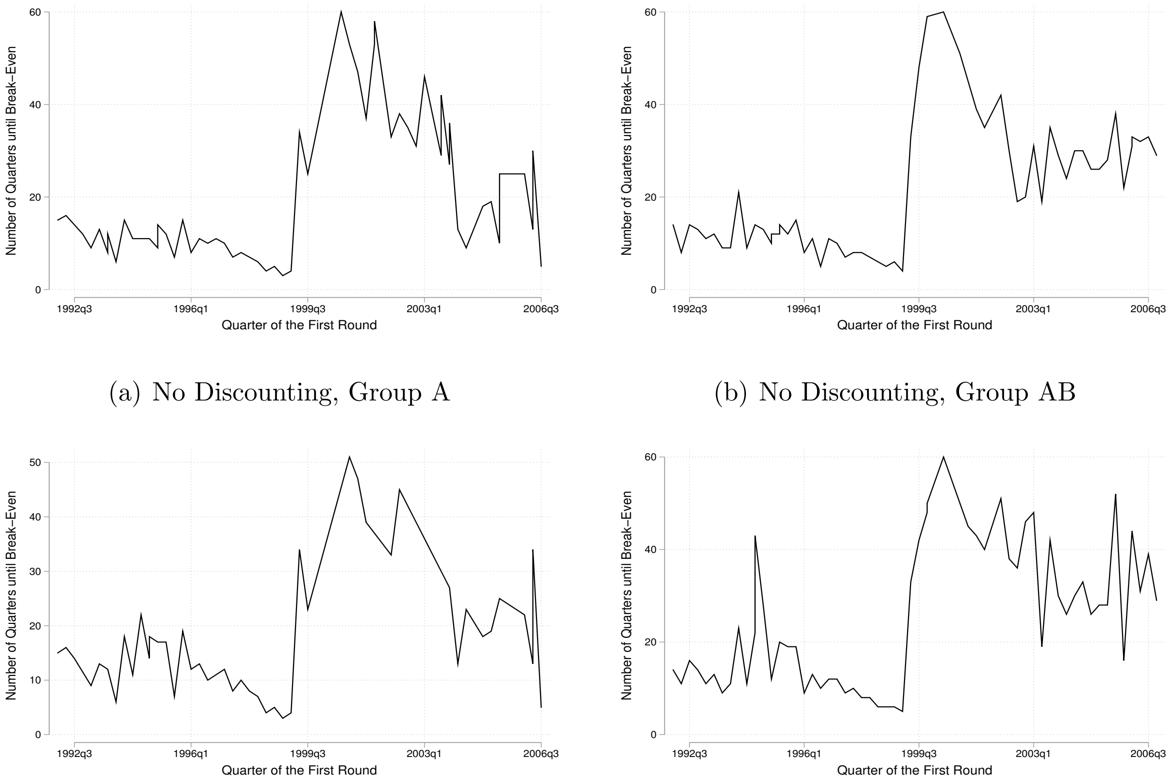
(e) GPMEround, Group A



(f) GPMEround, Group AB

Figure 7: Cumulative Cash Flows by Quarters from the First Round

Note: Over the life cycle of the venture, Figure plots the aggregate cumulative cash inflow, aggregate cumulative cash outflow and aggregate cumulative net cash flow for investors investing in the portfolio of US-based ventures in SDC VentureXpert database who had the first funding round prior to 2006. Cash outflows and inflows are either not discounted or discounted to the venture's first funding round date using the PME and GPME methods. Group A includes the ventures that have post-money valuation data for the first round. Group AB in addition includes the ventures that do not have post-money valuation data for the first round.



(a) No Discounting, Group A

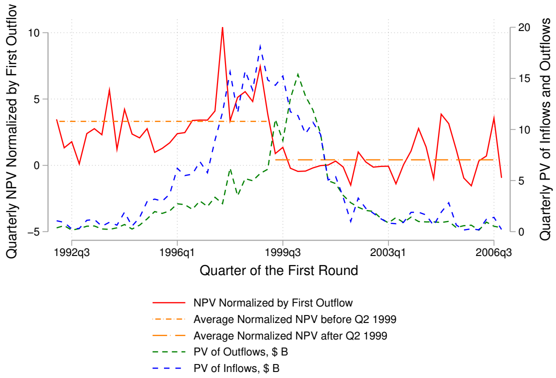
(b) No Discounting, Group AB

(c) GPMEround, Group A

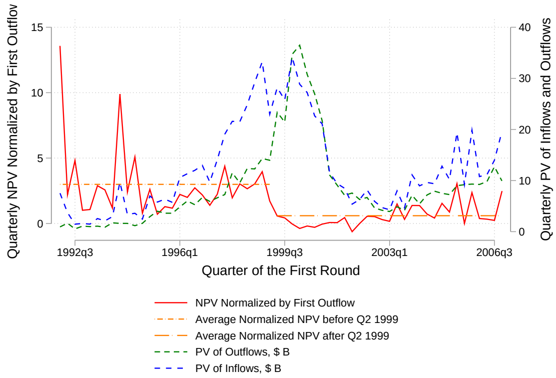
(d) GPMEround, Group AB

Figure 8: Break-even Time by the First-Round Time

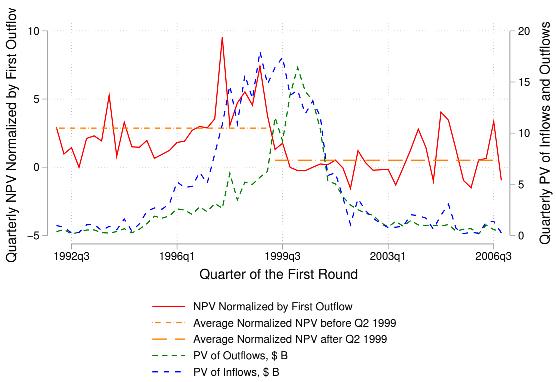
Note: For ventures that received the first funding round in each quarter, Figure plots the aggregate break-even time of investing in these ventures – i.e., the number of quarters from the the first round after which the aggregate cumulative net cash inflows from all these ventures becomes positive. Net cash inflows are either not discounted, or discounted to the venture's first funding round date using the GPMEround method, that is, the Generalized Public Market Equivalent method with parameters calibrated to round-to-round returns. We do not report the results with the PME method, since they show very similar patterns. The sample includes all US-based ventures in SDC VentureXpert database who had the first funding round prior to 2006. Group A includes the ventures that have post-money valuation data for the first round. Group AB in addition includes the ventures that do not have post-money valuation data for the first round.



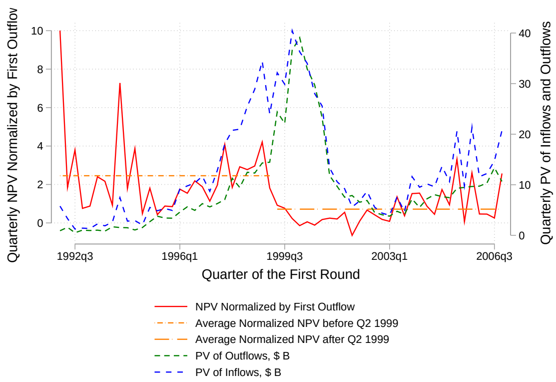
(a) PME, Group A



(b) PME, Group AB



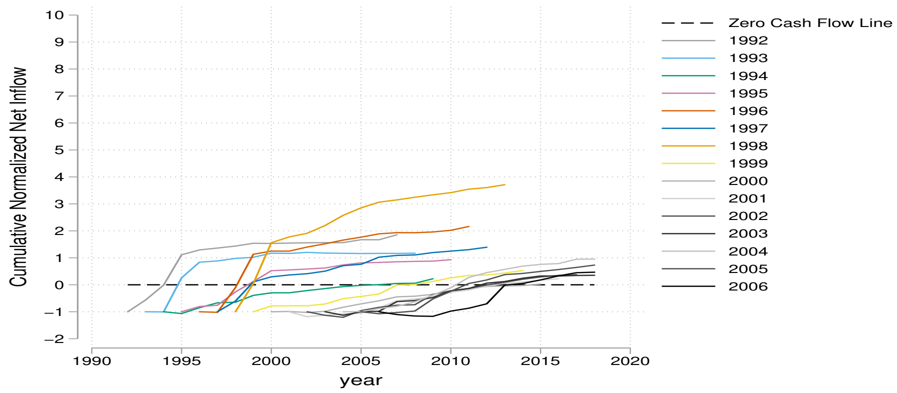
(c) GPMEround, Group A



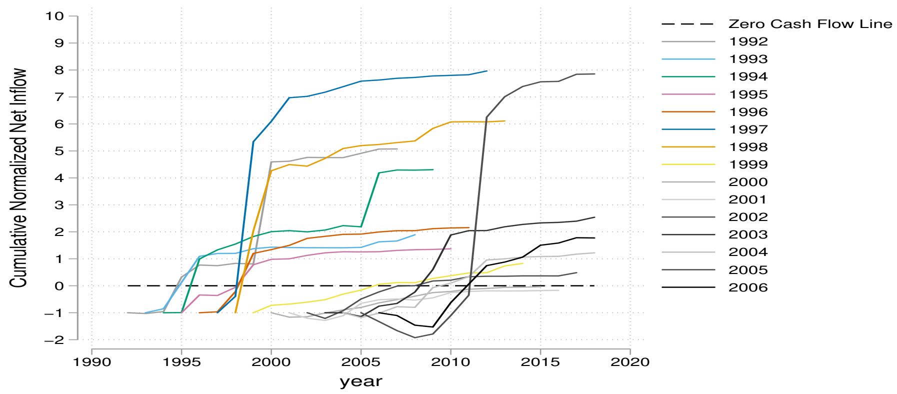
(d) GPMEround, Group AB

Figure 9: Normalized Inflow, Normalized Outflow, and Normalized NPV

Note: Figure plots the aggregate NPV normalized by first-round post-money valuation, aggregated cash inflow and aggregate cash outflow by the first-round time of ventures. The sample includes US-based ventures in SDC VentureXpert database that had the first funding round prior to 2006. Group A includes the ventures that have post-money valuation data for the first round. Group AB in addition includes the ventures that do not have post-money valuation data for the first round. Panel (a) and (b) use Public Market Equivalent method to discount the cash flows. Panel (c) and (d) use Generalized Public Market Equivalent method to discount the cash flows, with parameters calibrated to round-to-round returns.



(a) 1st-Round without Top 30 VC



(b) 1st-Round with Top 30 VC

Figure 10: Cumulative Discounted Cash Flows over Years, for Different 1st-round Year

Note: Figure plots the aggregate cumulative normalized cash flows of ventures that received the first funding round in different years, for any given years after the first round. Venture cash flows are dicounted using the GPMEround method, i.e., the Generalized Public Market Equivalent method with parameters calibrated to round-to-round returns. The sample includes all US-based ventures in SDC VentureXpert database that had the first funding round prior to 2006. Panel(a) uses the subsample of ventures whose first-round investor team does not include any Top 30 VC as defined before. Panel (b) uses the subsample of ventures whose first-round investor team includes at least one Top 30 VC.

Table 1: Analysis of Ventures Alive in VentureXpert

SDC Outcomes\Outcomes in Other Data	Alive	BR	IPO	MA	Total	Other Data
	48	440	8	389	885	PitchBook
	202	97	0	37	336	Bloomberg
Alive	0	0	4	0	4	Nasdaq
	30	16	1	6	53	Crunchbase
	673	51	1	23	748	Others
Total	953	604	14	455	2026	

Note: We collect information on ventures' outcomes from the universe of SDC VentureXpert, SDC Merger & Acquisition, and SDC Global New Issues data updated to 2019 June . Based on VentureXpert data, we classify a venture whose current situation is active or if we do not observe its current situation as Alive. Also, we classify a venture whose current situation is defunct or bankruptcy as Bankruptcy (i.e., BR). The ventures that are observed to exit through IPOs and mergers & acquisitions in any of the SDC databases are classified as IPO and MA, respectively. For US-based ventures that had the first funding round in 1992-2006, did not go bankrupt according to VentureXpert data, we cross-checked their outcomes with various other data sources including PitchBook, Bloomberg, Nasdaq, Crunchbase and other Internet sources. Table reports a tabulation of the ventures' outcomes based on the other data source, when classified as Alive based on VentureXpert data.

Table 2: Source of Venture Outcomes and Exit Values

A. Source of the Venture Outcomes			
# of Ventures \ Outcome	IPO	MA	BR
Total	1,229	5,070	2,228
Outcome recorded in SDC	937	4569	1315
Outcome solely from other sources	292	501	913

B. Exit Values		
# of Ventures \ Outcome	IPO	MA
Total	1,229	5,070
Outcomes recorded in SDC		
Exit values non-missing	796/937	2,194/4,569
Exit values complemented by other sources	122/937	396/4,569
Exit values conflicted with other sources	75/937	242/4,569
Outcomes solely from other sources		
Exit values non-missing	278/292	91/501
Total # of ventures with exit values	1,196/1,229	2,681/4,569

Note: We collect information on ventures' outcomes from the universe of SDC VentureXpert, SDC Merger & Acquisition, and SDC Global New Issues data updated to 2019 June . Based on VentureXpert data, we classify a venture whose current situation is active or if we do not observe its current situation as Alive. Also, we classify a venture whose current situation is defunct or bankruptcy as Bankruptcy (i.e., BR). The ventures that are observed to exit through IPO or mergers & acquisitions are classified as IPOs and MA, respectively. For US-based ventures that received the first funding round in 1992-2006, did not go bankrupt according to VentureXpert, we cross-checked their outcomes using PitchBook, Bloomberg, Nasdaq, Crunchbase and other Internet sources. Then we supplemented the SDC data with these other data sources. Restricted to the sample of ventures we cross-checked, Panel A of this table shows the number of ventures that were recorded to go to IPO, M&A and Bankruptcy in SDC databases, and the number of ventures that were identified to go to IPO, M&A and Bankruptcy only in other data sources. Panel B shows the number of ventures recorded to go to IPO and MA in SDC databases with exit values, the number of those without exit values but can be complemented by other sources, the number of those whose exit values in SDC databases and other sources have conflicts –i.e., differ by more than 5%. Panel B also shows the number of ventures that were identified to go to IPO and MA solely in other data sources and with exit values.

Table 3: Filter's Effect on the Number of Rounds and Ventures

Period	Group	# Rounds	# Ventures	# Rounds per Venture
Before Filtering	A	14,304	3,885	3.7
Before Filtering	B	45,203	13,357	3.4
After Filtering	A	14,304	3,885	3.7
After Filtering	B	43,580	12,511	3.5

Note: We first separate all the ventures to two groups. Group A includes ventures that have post-money valuation data for the first round. Group B includes ventures that do not have post-money valuation data for the first round. Then we apply a filtering process that excludes the rounds whose records are not informative. Our filtering process starts from the beginning of the venture's funding process, drops the rounds with neither amount raised nor post-money valuation data, and reclassify the round with the first appearance of either amount raised or post-money valuation available as the first round. The filter has effect only on Group B.

Table 4: Actual Data vs. Data Filled with Imputation Models

Amount Raised					
Group	Actual or Filled	# Rounds	% Rounds	Total Raised ($ B)	% Raised
A	Actual	14,029	98.1%	142.2	99.4%
	Filled	275	1.9%	0.9	0.6%
B	Actual	42,372	97.2%	300.9	98.8%
	Filled	1,208	2.8%	3.8	1.2%

First-Round Ownership Given Up				
Group	Actual or Filled	# Ventures	% Ventures	Avg. 1st-Round OGU
A	Actual	3,871	99.6%	37.1%
	Filled	14	0.4%	30.2%
B	Actual	112	0.9%	37.4%
	Filled	12,399	99.1%	32.3%

MA Value					
Group	Actual or Filled	# Ventures	% Ventures	Total Value($ B)	% Value
A	Actual	909	52.4%	142.8	77.9%
	Filled	826	47.6%	40.5	22.1%
B	Actual	2,244	50.2%	369.2	78.0%
	Filled	2,224	49.8%	104.4	22.0%

Pre-IPO Value					
Group	Actual or Filled	# Ventures	% Ventures	Total Value($ B)	% Value
A	Actual	697	98.7%	238.1	99.2%
	Filled	9	1.3%	1.9	0.8%
B	Actual	1,123	97.4%	311.1	99.0%
	Filled	30	2.6%	3.1	1.0%

Note: Table shows the fraction of data that is filled for four variables including the amount raised, the first-round ownership given up by the venture founders, the venture's MA value and the venture's pre-IPO value. Table also compares the filled data with the actual data. Group A includes ventures that have post-money valuation data for the first round. Group B includes ventures that do not have post-money valuation data for the first round.

Table 5: Test Statistics for Structural Break: Constant and AR(1) Models

Normalized NPV_t	(1)	(2)	(3)	(4)	(5)	(6)
Constant	1.817***	1.651***	1.558***	0.764**	0.760**	1.159***
	(0.296)	(0.275)	(0.229)	(0.328)	(0.311)	(0.238)
Normalized NPV_{t-1}				0.551***	0.513***	0.166
				(0.112)	(0.115)	(0.101)
Observations	60	60	60	59	59	59
R-squared	0.000	0.000	0.000	0.298	0.258	0.045
Sample	GroupA	GroupA	GroupAB	GroupA	GroupA	GroupAB
Discounting	PME	GPMEround	GPMEround	PME	GPMEround	GPMEround
Break Date	1999Q2	1999Q2	1999Q2	1999Q2	1999Q2	1999Q2
Chi-squared	39.77	26.01	18.77	14.64	10.49	18.67
DF	1	1	1	2	2	2
P Value	0.000	0.000	0.000	0.013	0.078	0.002

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Note: The Table shows the test statistics from the Supremum Wald tests of whether the parameters estimates of the time-series models of the aggregate normalized NPV are different before and after an unknown break date. Column (1)-(3) assumes the aggregate normalized NPV is a constant. Column (4)-(6) assumes the aggregate normalized NPV follows an AR(1) model. Different discounting method and different sample of ventures are used in each specification. Group A includes the ventures that have post-money valuation data for the first round. Group AB in addition includes the venture that do not have post-money valuation data for the first round. PME stands for the Public Market Equivalent method for discounting the venture cash flows. And GPMEround stands for the Generalized Public Market Equivalent method for discounting the venture cash flows, with parameters calibrated to round-to-round returns.

Table 6: Past Experience of 1st-Round VCs and Realized Normalized NPV

VARIABLES	NPV Normalized by First Outflow					
lg(1st-Round Amount Raised)	-1.684***	-1.617***	-1.779***	-1.042***	-1.029***	-1.139***
	(0.461)	(0.469)	(0.488)	(0.215)	(0.214)	(0.226)
Top 30 VC	3.455***	5.677***	4.497***	2.307***	3.672***	2.940**
	(0.993)	(1.746)	(1.569)	(0.573)	(1.179)	(1.148)
Top 30 VC $\times$ Post-1999		-3.943**	-4.174**		-2.100*	-2.349*
		(1.919)	(1.908)		(1.254)	(1.237)
WAVG VC Ratio of Exit			5.830**			4.860***
			(2.381)			(0.916)
WAVG VC Ratio of Next Round			-0.838			-0.426
			(1.091)			(0.582)
WAVG VC Ratio of Bankruptcy			-0.615			2.481
			(4.247)			(2.588)
lg(WAVG VC # Rounds)			0.688			0.279
			(0.568)			(0.296)
N	3608	3608	3608	11899	11899	11899
R^2	0.080	0.083	0.087	0.034	0.035	0.038
Sample	GroupA	GroupA	GroupA	GroupAB	GroupAB	GroupAB
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year $\times$ Industry FE	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: Table reports the estimation results from regressing NPV normalized by first round post money valuation on a set of experience measures of the VC team invested in the venture's first funding round, and control variables. The NPV uses the GPMEround discounting specification. Top 30 VC is a dummy variable that equals 1 if any VC that ranked in the top 30 according to the number of total funding rounds invested in the past 10 years, participated in the venture's first round. WAVG VC Ratio of Exit is the weighted average of the ratio of the funding rounds that are associated with successful exits in the past 10 year of all the VCs participated in the venture's first round, where the weight is the total funding rounds invested by the VCs in the past 10 years. Similarly defined are WAVG VC Ratio of Next Round and WAVG VC Ratio of Bankruptcy. They are the total-funding-rounds-weighted-average of the ratio of the funding rounds that are associated with continued financing and bankruptcy of the first-round VCs, respectively. WAVG VC # Rounds is the total-funding-rounds-weighted-average of the funding rounds invested in the past 10 years by the first-round VCs. Group A are ventures that have first-round post-money valuations. Group AB in addition includes the ventures that do not have first-round post-money valuations. In parenthesis are standard errors.

Table 7: Past Experience of 1st-Round VCs and Venture Successful Exits

VARIABLES	Exit through IPO or M&A		Exit through IPO		Exit through M&A	
lg(1st-Round Amount Raised)	0.0579***	0.0448***	0.0394***	0.0216***	0.0184**	0.0232***
	(0.00617)	(0.00392)	(0.00626)	(0.00278)	(0.00705)	(0.00421)
Top 30 VC	0.0585***	0.0326	0.0760***	0.0638***	-0.0175	-0.0312
	(0.0200)	(0.0200)	(0.0270)	(0.0207)	(0.0266)	(0.0208)
Top 30 VC × Post-1999	-0.0505**	-0.0407**	-0.0885***	-0.0473**	0.0381	0.00661
	(0.0214)	(0.0201)	(0.0295)	(0.0221)	(0.0301)	(0.0223)
WAVG VC Ratio of Exit	0.00658	0.0761**	0.128**	0.0452**	-0.121*	0.0309
	(0.0812)	(0.0353)	(0.0530)	(0.0185)	(0.0709)	(0.0359)
WAVG VC Ratio of Next Round	0.0180	-0.0134	-0.0763**	-0.0337**	0.0944*	0.0204
	(0.0537)	(0.0255)	(0.0350)	(0.0132)	(0.0510)	(0.0269)
WAVG VC Ratio of Bankruptcy	0.0432	0.0383	0.212	0.0310	-0.169	0.00729
	(0.325)	(0.175)	(0.240)	(0.0762)	(0.201)	(0.166)
lg(WAVG VC # Rounds)	0.0225	0.0381***	0.0000598	0.0104*	0.0224	0.0276***
	(0.0239)	(0.00950)	(0.0152)	(0.00560)	(0.0220)	(0.00995)
N	3608	11899	3608	11899	3608	11899
R^2	0.077	0.059	0.199	0.116	0.066	0.045
Sample	GroupA	GroupAB	GroupA	GroupAB	GroupA	GroupAB
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year × Industry FE	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: Table reports the estimation results from regressing dummies for venture successful exits on a set of experience measures of the VC team invested in the venture's first funding round, together with control variables. Top 30 VC is a dummy variable that equals 1 if any VC that ranked in the top 30 according to the number of total funding rounds invested in the past 10 years, participated in the venture's first round. WAVG VC Ratio of Exit is the weighted average of the ratio of the funding rounds that are associated with successful exits in the past 10 year of all the VCs participated in the venture's first round, where the weight is the total funding rounds invested by the VCs in the past 10 years. Similarly defined are WAVG VC Ratio of Next Round and WAVG VC Ratio of Bankruptcy. They are the total-funding-rounds-weighted-average of the ratio of the funding rounds that are associated with continued financing and bankruptcy of the first-round VCs, respectively. WAVG VC # Rounds is the total-funding-rounds-weighted-average of the funding rounds invested in the past 10 years by the first-round VCs. Group A are ventures that have first-round post-money valuations. Group AB in addition includes the ventures that do not have first-round post-money valuations. In parenthesis are standard errors.

Table 8: Past Performance of 1st-Round VCs and Realized Normalized NPV Conditional on Exit

VARIABLES	NPV Normalized by First Outflow (Only Exited Ventures)					
lg(1st-Round Amount Raised)	-5.143***	-5.065***	-5.372***	-4.536***	-4.518***	-4.690***
	(0.995)	(1.015)	(1.033)	(0.518)	(0.519)	(0.534)
Top 30 VC	5.845***	8.209***	5.537**	4.801***	6.464***	4.794**
	(1.580)	(2.702)	(2.491)	(0.986)	(1.970)	(2.006)
Top 30 VC × Post-1999		-4.572	-4.739		-2.697	-3.020
		(3.023)	(2.997)		(2.104)	(2.077)
WAVG VC Ratio of Exit			10.71**			8.091***
			(4.351)			(2.383)
WAVG VC Ratio of Next Round			-0.981			-0.107
			(1.918)			(1.304)
WAVG VC Ratio of Bankruptcy			-23.41			-1.228
			(14.77)			(6.878)
lg(WAVG VC # Rounds)			1.582			0.763
			(1.058)			(0.618)
N	2337	2337	2337	6932	6932	6932
R^2	0.132	0.134	0.141	0.095	0.096	0.100
Sample	GroupA	GroupA	GroupA	GroupAB	GroupAB	GroupAB
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year × Industry FE	Yes	Yes	Yes	Yes	Yes	Yes

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Note: Table reports the estimation results from regressing NPV normalized by first round post money valuation on a set of experience measures of the VC team invested in the venture's first funding round, and control variables. The NPV uses the GPMEround discounting specification. The sample includes only the successfully exited ventures. Top 30 VC is a dummy variable that equals 1 if any VC that ranked in the top 30 according to the number of total funding rounds invested in the past 10 years, participated in the venture's first round. WAVG VC Ratio of Exit is the weighted average of the ratio of the funding rounds that are associated with successful exits in the past 10 year of all the VCs participated in the venture's first round, where the weight is the total funding rounds invested by the VCs in the past 10 years. Similarly defined are WAVG VC Ratio of Next Round and WAVG VC Ratio of Bankruptcy. They are the total-funding-rounds-weighted-average of the ratio of the funding rounds that are associated with continued financing and bankruptcy of the first-round VCs, respectively. WAVG VC # Rounds is the total-funding-rounds-weighted-average of the funding rounds invested in the past 10 years by the first-round VCs. Group A are ventures that have first-round post-money valuations. Group AB in addition includes the ventures that do not have first-round post-money valuations. In parenthesis are standard errors.

Table 9: Past Performance of 1st-Round VCs and Performance: Regression by Periods

VARIABLES	Normalized NPV		IPO or M&A Exit		Normalized NPV (Exited)	
	(1)	(2)	(3)	(4)	(5)	(6)
lg(1st-Round Amount Raised)	-3.365**	-0.738	0.0484**	0.0626***	-8.100***	-3.032***
	(1.633)	(0.638)	(0.0219)	(0.0134)	(1.794)	(0.834)
Top 30 VC	4.611***	0.284	0.101*	-0.0116	5.699**	0.448
	(1.648)	(0.541)	(0.0538)	(0.0282)	(2.614)	(0.572)
WAVG VC Ratio of Exit	13.97**	1.709	0.194***	-0.0668	16.06	4.448
	(6.050)	(1.582)	(0.0556)	(0.0846)	(9.842)	(2.955)
WAVG VC Ratio of Next Round	-3.929*	0.573	-0.155**	0.121*	0.215	-1.155
	(2.093)	(1.273)	(0.0564)	(0.0615)	(4.014)	(2.146)
WAVG VC Ratio of Bankruptcy	-21.91	0.982	1.245	-0.0720	-61.49	-9.276
	(21.29)	(3.767)	(1.031)	(0.216)	(38.14)	(18.04)
lg(WAVG VC # Rounds)	0.793	0.363	0.00164	0.0297	1.353	1.278
	(1.324)	(0.515)	(0.0202)	(0.0287)	(2.444)	(0.840)
N	1355	2253	1355	2253	989	1348
R^2	0.076	0.041	0.081	0.057	0.133	0.103
Sample	GroupA	GroupA	GroupA	GroupA	GroupA	GroupA
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year × Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Period	Pre-Break	Post-Break	Pre-Break	Post-Break	Pre-Break	Post-Break

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Note: Table reports the estimation results from regressing NPV normalized by first outlow (Column (1) and (2)), dummies for successful exits (Column (3) and (4)) on a set of experience measures of the VC team invested in the venture's first funding round, and control variables. The NPV uses the GPMEround discounting specification. Column (5) and (6) have NPV normalized by first outlow as outcome variable as well, but restrict the sample to only the successfully exited ventures. Column (1), (3) and (5) are regression results for the pre-break period. Column (2), (4) and (6) are regression results for the post-break period. Top 30 VC is a dummy variable that equals 1 if any VC that ranked in the top 30 according to the number of total funding rounds invested in the past 10 years, participated in the venture's first round. WAVG VC Ratio of Exit is the weighted average of the ratio of the funding rounds that are associated with successful exits in the past 10 year of all the VCs participated in the venture's first round, where the weight is the total funding rounds invested by the VCs in the past 10 years. Similarly defined are WAVG VC Ratio of Next Round and WAVG VC Ratio of Bankruptcy. They are the total-funding-rounds-weighted-average of the ratio of the funding rounds that are associated with continued financing and bankruptcy of the first-round VCs, respectively. WAVG VC # Rounds is the total-funding-rounds-weighted-average of the funding rounds invested in the past 10 years by the first-round VCs. Group A are ventures that have first-round post-money valuations. In parenthesis are standard errors.

Table 10: Past Performance of 1st-Round VCs and Innovation

VARIABLES	Has Patent		lg(1 + # Patents)		lg(1 + # Citations)	
lg(1st-Round Amount Raised)	0.000178	-0.00484	0.0723	0.0974***	0.105	0.194***
	(0.00878)	(0.00610)	(0.0456)	(0.0254)	(0.0854)	(0.0465)
Top 30 VC	0.0902***	0.0531***	0.209*	0.196**	0.684**	0.446**
	(0.0280)	(0.0175)	(0.123)	(0.0945)	(0.284)	(0.196)
Top 30 VC × Post-1999	-0.0425	-0.00141	-0.0127	0.0406	-0.219	-0.0122
	(0.0337)	(0.0152)	(0.148)	(0.0878)	(0.320)	(0.170)
WAVG VC Ratio of Exit	0.0869	0.0335	0.0294	0.210	-0.654	0.139
	(0.0688)	(0.0358)	(0.239)	(0.207)	(0.812)	(0.277)
WAVG VC Ratio of Next Round	0.0853**	0.00120	-0.241	0.0123	-0.0733	0.173
	(0.0406)	(0.0227)	(0.214)	(0.135)	(0.446)	(0.304)
WAVG VC Ratio of Bankruptcy	0.294	-0.0446	0.204	0.167	-2.028	0.384
	(0.220)	(0.118)	(0.686)	(0.455)	(2.702)	(1.312)
lg(WAVG VC # Rounds)	0.0325*	0.0419***	0.183***	0.0698***	0.261	0.131
	(0.0188)	(0.00996)	(0.0599)	(0.0246)	(0.207)	(0.0819)
N	3608	11899	2039	6450	2039	6450
R^2	0.112	0.090	0.126	0.096	0.144	0.114
Sample	GroupA	GroupAB	GroupA	GroupAB	GroupA	GroupAB
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year × Industry FE	Yes	Yes	Yes	Yes	Yes	Yes

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Note: Table reports the estimation results from regressing venture's patents holding and patents citations on a set of experience measures of the VC team invested in the venture's first funding round, together with control variables. Top 30 VC is a dummy variable that equals 1 if any VC that ranked in the top 30 according to the number of total funding rounds invested in the past 10 years, participated in the venture's first round. WAVG VC Ratio of Exit is the weighted average of the ratio of the funding rounds that are associated with successful exits in the past 10 year of all the VCs participated in the venture's first round, where the weight is the total funding rounds invested by the VCs in the past 10 years. Similarly defined are WAVG VC Ratio of Next Round and WAVG VC Ratio of Bankruptcy. They are the total-funding-rounds-weighted-average of the ratio of the funding rounds that are associated with continued financing and bankruptcy of the first-round VCs, respectively. WAVG VC # Rounds is the total-funding-rounds-weighted-average of the funding rounds invested in the past 10 years by the first-round VCs. Group A are ventures that have first-round post-money valuations. Group AB in addition includes the ventures that do not have first-round post-money valuations. In parenthesis are standard errors.

Table 11: Past Performance of 1st-Round VCs and 1st-Round Ownership Given Up

VARIABLES	1st-Round Ownership Given Up					
lg(1st-Round Amount Raised)	0.0603***	0.0608***	0.0593***	0.0601***	0.0603***	0.0594***
	(0.00239)	(0.00241)	(0.00221)	(0.000890)	(0.000896)	(0.000862)
Top 30 VC	0.0285***	0.0434***	0.0207***	0.0203***	0.0343***	0.0148***
	(0.00379)	(0.00397)	(0.00533)	(0.00193)	(0.00292)	(0.00323)
Top 30 VC × Post-1999		-0.0263***	-0.0233***		-0.0215***	-0.0199***
		(0.00688)	(0.00680)		(0.00411)	(0.00402)
WAVG VC Ratio of Exit			-0.0495**			-0.0243**
			(0.0211)			(0.00918)
WAVG VC Ratio of Next Round			0.0439***			0.0235***
			(0.0165)			(0.00333)
WAVG VC Ratio of Bankruptcy			-0.148			-0.0641**
			(0.101)			(0.0311)
lg(WAVG VC # Rounds)			0.0174***			0.0149***
			(0.00642)			(0.00185)
N	3608	3608	3608	11899	11899	11899
R^2	0.207	0.208	0.214	0.466	0.467	0.474
Sample	GroupA	GroupA	GroupA	GroupAB	GroupAB	GroupAB
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year × Industry FE	Yes	Yes	Yes	Yes	Yes	Yes

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Note: Table reports the estimation results from regressing venture's first-round ownership given up to the VC investors on a set of experience measures of the VC team invested in the venture's first funding round, together with control variables. Top 30 VC is a dummy variable that equals 1 if any VC that ranked in the top 30 according to the number of total funding rounds invested in the past 10 years, participated in the venture's first round. WAVG VC Ratio of Exit is the weighted average of the ratio of the funding rounds that are associated with successful exits in the past 10 year of all the VCs participated in the venture's first round, where the weight is the total funding rounds invested by the VCs in the past 10 years. Similarly defined are WAVG VC Ratio of Next Round and WAVG VC Ratio of Bankruptcy. They are the total-funding-rounds-weighted-average of the ratio of the funding rounds that are associated with continued financing and bankruptcy of the first-round VCs, respectively. WAVG VC # Rounds is the total-funding-rounds-weighted-average of the funding rounds invested in the past 10 years by the first-round VCs. Group A are ventures that have first-round post-money valuations. Group AB in addition includes the ventures that do not have first-round post-money valuations. In parenthesis are standard errors.

A Appendix

A.1 Methodology for Imputing Missing Values

We utilize statistical models to impute the missing values in several key variables of our study. For the amount raised data, we impute the missing values using linear regression models. For each round number $r = 1, 2, ..., 9$ and separately for rounds which has round number > 9 , we estimate the model given below.

$$\log AmountRaised_{i,r} = \alpha + \beta \log AmountRaised_{i,r-1} + \gamma Z_{i,r} + \epsilon_{i,r} \tag{1}$$

where $AmountRaised_{i,r}$ is the amount raised by venture i in round r. $Z_{i,r}$ is a set of control variables: including fixed effects on the number of participating investors, industry, funding stage and time.

For the first-round ownership given up data, we impute the missing values using a logit model. Specifically, we estimate a logit model relating the ownership given up in each round to a rich set of observable variables as follows.

$$\begin{aligned}\log \frac{OwnershipGivenUp_{i,r}}{1 - OwnershipGivenUp_{i,r}} &= \alpha + \beta_1 \log AmountRaised_{i,r} + \beta_2 (\log AmountRaised)^2_{i,r} + \\ &\beta_3 \log CumulativeAmountRaised_{i,r} + \gamma Z_{i,r} + \epsilon_{i,r} \end{aligned} \tag{2}$$

where $OwnershipGivenUp_{i,r}$ is the ownership given up by venture i in round r to the outside investors. $AmountRaised_{i,r}$ is the amount raised by venture i in round r. $CumulativeAmountRaised_{i,r}$ is the cumulative amount raised by venture i from the first round to round r. $Z_{i,r}$ is a set of control variables, including fixed effects on the number of participating investors, industry fixed effects, funding stage fixed effects, round number fixed effects and time fixed effects.

For the pre-IPO valuations and pre-MA valuations, the imputation model is

$$\begin{aligned} Valuation_i = \alpha &+ \beta_1 \overline{Valuation}_i + \beta_2 lastPMVtoExit_i + \beta_3 \overline{Valuation}_i \times lastPMVtoExit_i \\ &+ \beta_4 \log FinalAmountRaised_i + \beta_5 FinalRoundtoExit_i \\ &+ \beta_6 NASDAQReturn_i + \epsilon_i \end{aligned} \tag{3}$$

where $Valuation_i$ is either pre-IPO valuation or pre-MA valuation of venture i. As for the independent variables, $\overline{Valuation}_i$ is the extrapolated valuation for venture i, which equals the last available post-money valuation multiplied by the cumulative NASDAQ stock return from the last post-money valuation date to the venture's exit. $lastPMVtoExit_i$ is the number of days from the last post-money valuation date to the venture's exit. $FinalAmountRaised_i$ is the amount raised by venture i in its last funding round. $FinalRound-toExit_i$ is the number of days from venture i's last funding round to the its exit. $NASDAQ-Return_i$ is the cumulative NASDAQ stock return from venture i's last funding round to its exit.

A.2 Example: Calculating the NPV of a Venture

In Table A.1, we show the life cycle of a hypothetical venture the complete funding round information. The venture raises one round per year and bankrupt at the end of the 4th year. In the example, the market return is 10% every year. With the amount raised and post-money valuation data in each round, we can easily calculate the pre-money valuation, ownership given up, and the three measures of returns: round-to-round return, round-to-exit return and normalized NPV.

$$\text{Ownership Given Up} = \frac{\text{Amount Raised}}{\text{Post-Money Valuation}}$$

$$\text{Round-to-Round Return}_t = \frac{\text{Pre-Money Valuation}_{t+1}}{\text{Post-Money Valuation}_t} - 1$$

$$\text{Round-to-Exit Return}_t = \frac{\text{Value of Founder's Equity}_T}{\text{Value of Founder's Equity}_t}$$

The Normalized NPV capturing the net return to all equity holders is calculated as:

$$\text{Normalized NPV} = \frac{1}{10} \times (-10 - \frac{5}{1.1} - \frac{8}{1.1^2} - \frac{20}{1.1^3} + \frac{8}{1.1^4}) = -3.07$$

Here, we use the first-round pre-money valuation as a proxy for the amount of money invested by the founder, and use PME for discounting.

Table A.2 illustrates how the calculation of round-to-round returns and round-to-exit returns is impacted by missing data. We still study this hypothetical venture, but assume the post-money valuation of the 3rd round is missing. We see that the round-to-round returns and round-to-exit returns could not be computed for multiple rounds. However, the Normalized NPV could still be calculated and is not affected by the missing data.

Table A.1: Computation of Return Measures with Complete Round Information

Year	0	1	2	3	4
Stage	Round 1	Round 2	Round 3	Round 4	Bankrupt
Amount Raised	2	5	8	20	n.a.
Post-Money Valuation	10	20	40	80	8
Market Return	10%	10%	10%	10%	10%
Pre-Money Valuation	8	15	32	60	n.a.
Ownership Given Up	20%	25%	20%	25%	n.a.
Round-to-Round Return	50%	60%	50%	-90%	n.a.
Round-to-Exit Return	-64%	-76%	-85%	-90%	n.a.
Normalizd NPV (PME)	-3.07				

Table A.2: Computation of Return Measures with Incomplete Round Information

Year	0	1	2	3	4
Stage	Round 1	Round 2	Round 3	Round 4	Bankrupt
Amount Raised	2	5	8	20	n.a.
Post-Money Valuation	10	20	.	80	8
Market Return	10%	10%	10%	10%	10%
Pre-Money Valuation	8	15	.	60	n.a.
Ownership Given Up	20%	25%	.	25%	n.a.
Round-to-Round Return	50%	.	.	-90%	n.a.
Round-to-Exit Return	.	.	.	-90%	n.a.
Normalizd NPV (PME)	-3.07				

A.3 Proofs of the Propositions

Proof of Proposition 1:

From the first order condition of the maximization problem in Equation (6), we get:

$$x = \frac{\mathbb{E}[s] - \bar{v} + m\theta\bar{v}}{2s}$$

Since $\mathbb{E}[s] = \mathbb{E}[\alpha v] = \alpha\bar{v} = \alpha V$, we have $x = \dfrac{\alpha + \theta m - 1}{2\alpha}$.

Since the average quality of VCs funding a venture $\alpha = \rho H + (1-\rho)L$ and the fraction of H-type VCs among VCs funding a given venture $\rho = p(1-\lambda) + \lambda Q$, we know that $\alpha = H(-\lambda p + p + \lambda Q) + (\lambda - 1)Lp - \lambda LQ + L$, and could then express x as:

$$x = \frac{H(-\lambda p + p + \lambda Q) + (\lambda - 1)Lp - \lambda LQ + L + \theta m - 1}{2(H(-\lambda p + p + \lambda Q) + (\lambda - 1)Lp - \lambda LQ + L)}$$

Then we could calculate the partial derivatives:

$$\frac{\partial x}{\partial \rho} = \frac{\partial x}{\partial Q}\frac{\partial Q}{\partial \rho} = -\frac{(H-L)(\theta m - 1)}{2(H(-\lambda p + p + \lambda Q) + (\lambda - 1)Lp - \lambda LQ + L)^2}$$

$$\frac{\partial^2 x}{\partial \rho \partial p} = \frac{\partial^2 x}{\partial Q \partial p}\frac{\partial Q}{\partial \rho} = -\frac{(\lambda - 1)(H-L)^2(\theta m - 1)}{(H(-\lambda p + p + \lambda Q) + (\lambda - 1)Lp - \lambda LQ + L)^3}$$

Assume that $1 - \theta m > 0$, since θ will in general be much smaller than 1, and m only slightly above 1. Then $\frac{\partial x}{\partial \rho} \geqslant 0$ and $\frac{\partial^2 x}{\partial \rho \partial p} \leqslant 0$.

Proof of Proposition 2:

(1) All equity holders

The NPV of the investment in a venture is $\alpha QV - (\theta \bar{v} + \bar{v})$, where Q indicates the quality of the venture. Normalize the NPV with the initial investment by both VCs and founder, we get the normalized NPV to all equity holders:

$$\gamma = \frac{\alpha QV}{\theta \bar{v} + \bar{v}} - 1$$

Since $\alpha = H(-\lambda p + p + \lambda Q) + (\lambda - 1)Lp - \lambda LQ + L$ and $\bar{v} = V/2$, we could express the normalized NPV as:

$$\gamma = -\frac{\theta - 2HQ(-\lambda p + p + \lambda Q) + 2LQ(-\lambda p + p + \lambda Q - 1) + 1}{\theta + 1}$$

With which we could calculate the partial derivatives:

$$\frac{\partial \gamma}{\partial p} = -\frac{2(\lambda - 1)Q(H-L)}{\theta + 1}$$

$$\frac{\partial \gamma}{\partial \rho} = \frac{\partial \gamma}{\partial Q}\frac{\partial Q}{\partial \rho} = \frac{2(2\lambda Q(H-L) + (1-\lambda)p(H-L) + L)}{(\theta + 1)\lambda}$$

$$\frac{\partial^2 \gamma}{\partial \rho \partial p} = \frac{\partial^2 \gamma}{\partial Q \partial p}\frac{\partial Q}{\partial \rho} = -\frac{2(\lambda - 1)(H-L)}{(\theta + 1)\lambda}$$

Since $Q \geqslant 0$, $H - L > 0$, and $-1 + \lambda \leqslant 0$, we know $\frac{\partial \gamma}{\partial p} \geqslant 0$, $\frac{\partial \gamma}{\partial \rho} \geqslant 0$ and $\frac{\partial^2 \gamma}{\partial \rho \partial p} \geqslant 0$.

(2) VCs The VCs get x fraction of the return, and the investment is $\theta \bar{v}$, so:

$$\gamma_{VC} = \frac{\alpha x Q V}{\theta \bar{v}} - 1 = \frac{2Qx(H(-\lambda p + p + \lambda Q) + (\lambda - 1)Lp - \lambda LQ + L)}{\theta} - 1$$

(3) Founder The founder get $1 - x$ fraction of the return, and the investment is $\bar{v}$, so:

$$\begin{aligned} \gamma_{FD} &= \frac{\alpha(1-x)QV}{\bar{v}} - 1 \\ &= 2Q(1-x)(H(-\lambda p + p + \lambda Q) + (\lambda - 1)Lp - \lambda LQ + L) - 1 \end{aligned} \tag{4}$$

Proof of Proposition 3:

From the first order condition of the maximization problem in Equation (6), we get:

$$x = \frac{\mathbb{E}[s] - QV + m\theta QV}{2s}$$

Since $\mathbb{E}[s] = s = \alpha QV$, we have $x = \dfrac{\alpha + \theta m - 1}{2\alpha}$.

Thus, the same as the case in Proposition 1, $x = \frac{H(-\lambda p + p + \lambda Q) + (\lambda - 1)Lp - \lambda LQ + L + \theta m - 1}{2(H(-\lambda p + p + \lambda Q) + (\lambda - 1)Lp - \lambda LQ + L)}$.

Proof of Proposition 4:

(1) All equity holders

All equity holders get αQV as the return, and the investment is $\theta QV + QV$, so:

$$\begin{aligned} \gamma &= \frac{\alpha QV}{\theta QV + QV} - 1 \\ &= \frac{-\theta + H(-\lambda p + p + \lambda Q) + (\lambda - 1)Lp - \lambda LQ + L - 1}{\theta + 1} \end{aligned}$$

With which we could calculate the partial derivatives:

$$\frac{\partial \gamma}{\partial p} = -\frac{(\lambda - 1)(H - L)}{\theta + 1}$$

$$\frac{\partial \gamma}{\partial \rho} = \frac{\partial \gamma}{\partial Q}\frac{\partial Q}{\partial \rho} = \frac{H - L}{\theta + 1}$$

$$\frac{\partial^2 \gamma}{\partial \rho \partial p} = \frac{\partial^2 \gamma}{\partial Q \partial p}\frac{\partial Q}{\partial \rho} = 0$$

Since $Q \geqslant 0$, $H - L > 0$, and $-1 + \lambda \leqslant 0$, we know $\frac{\partial \gamma}{\partial p} \geqslant 0$, $\frac{\partial \gamma}{\partial \rho} \geqslant 0$.

(2) VCs

The VCs get x fraction of the return, and the investment is θQV, so:

$$\gamma_{VC} = \frac{\alpha x QV}{\theta QV} - 1 = \frac{x(H(-\lambda p + p + \lambda Q) + (\lambda - 1)Lp - \lambda LQ + L)}{\theta} - 1$$

(3) High-ability VCs

The high-ability VCs contribute to ρ fraction of the amount raised, and get $\frac{H\rho}{H\rho+L(1-\rho)}$ fraction of the return to the VCs, then:

$$\gamma_{VC}^{H} = \frac{\alpha x QV \frac{H\rho}{H\rho+L(1-\rho)}}{\theta QV\rho} - 1 = \frac{Hx}{\theta} - 1$$

(4) Low-ability VCs

The low-ability VCs contribute to $1-\rho$ fraction of the amount raised, and get $\frac{L(1-\rho)}{H\rho+L(1-\rho)}$ fraction of the return to the VCs, then:

$$\gamma_{VC}^{L} = \frac{\alpha x QV \frac{L(1-\rho)}{H\rho+L(1-\rho)}}{\theta QV(1-\rho)} - 1 = \frac{Lx}{\theta} - 1$$

(5) Founder

The founder get $1 - x$ fraction of the return, and the investment is QV, so:

$$\gamma_{FD} = \frac{\alpha(1-x)QV}{QV} - 1 = (1-x)(H(-\lambda p + p + \lambda Q) + (\lambda - 1)Lp - \lambda LQ + L) - 1$$

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Internet Appendix

(Not Intended for Publication)

A. Data Sources and Data Cleaning

For 10,533 US-based ventures that received the first funding round between 1992 and 2006, and did not experience bankruptcy according to VentureXpert, we cross-checked their exit events with data from PitchBook, Bloomberg, NASDAQ, Crunchbase and other Internet sources. Among the 2,026 ventures thatare shown as being alive in VentureXpert, 604 exited through bankruptcy, 14 through IPO, and 455 through MA according to other sources. Table IA.1 below lists the 14 exits through IPOs.

Table IA.1: IPOs not recorded by VentureXpert

name	IPO exchange	IPO date	PERMCO
Ikano Communications Inc	NASDAQ	9/22/2005	47441
EXDS Inc	NASDAQ	3/19/1998	16018
Ivow Inc	NASDAQ	7/3/1997	15577
Jmxi Inc	NASDAQ	5/7/1999	16518
Rubio's Restaurants Inc	NASDAQ	5/21/1999	16543
Greenway Health Inc	NYSE	2/2/2012	53986
Ambicom Inc	OTC	3/4/2011	
Modular Space Corp	OTC	2/22/2017	
Infoteria Corp	TKS	6/22/2007	
Morpho Technologies	TOKYO SE	7/21/2011	
Crown Bioscience Inc	TPEX	12/12/2016	
CoadNA Photonics Inc	TWSE	9/9/2011	
Intelligent Epitaxy Technology Inc	TWSE	7/24/2013	
Netex Inc	MADRID SE	10/31/2017	

B. Estimation Results of the Imputation Models

We utilize statistical models described in Appendix A.1 to impute the missing values in the variables essential to our analysis – including first-round ownership given up, amount raised in the funding rounds, pre-IPO valuations and pre-MA valuations, based on observable information.

Table IA.2 reports the estimation results of the imputation models for the first-round ownership given up data. Table IA.3 below reports the estimation results of the imputation models for the amount raised data. Table IA.4 and Table IA.5 report the estimation results of the imputation model for the pre-MA and pre-IPO valuations.

Table IA.2: Estimation of the Imputation Models for the Ownership Given Up

	(1)	(2)	(3)
VARIABLES	Logit Ownership Given Up		
Log Amount	0.431***	2.355***	2.448***
	(0.008)	(0.097)	(0.090)
Log Amount Squared		-0.064***	-0.050***
		(0.003)	(0.003)
Log Cumulative Amount			-0.711***
			(0.015)
Observations	13,709	13,709	13,709
R-squared	0.384	0.402	0.489
Industry FE	Yes	Yes	Yes
Stage FE	Yes	Yes	Yes
Round Number FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Investor Number FE	Yes	Yes	Yes
CV Psuedo-R2 Mean	0.379	0.396	0.484
CV Psuedo-R2 Sd	0.025	0.029	0.026
Repeats of 10-fold CV	10	10	10

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Note: Table reports the regression results when estimating the imputation models for the ownership given up by the venture founders. The sample includes all the US-based ventures in the SDC VentureXpert database and had the first funding round prior to 2006. In parenthesis are standard errors.

Table IA.3: Estimation of the Imputation Model for the Amount Raised

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES					Log Amount Raised					
ROUND NUMBER	1	2	3	4	5	6	7	8	9	>9
Log Amount Raised$_{t-1}$		0.310***	0.333***	0.296***	0.289***	0.254***	0.286***	0.294***	0.267***	0.265***
		(0.008)	(0.010)	(0.011)	(0.013)	(0.016)	(0.019)	(0.024)	(0.028)	(0.023)
Constant	16.647***	13.865***	12.158***	14.175***	12.727***	14.824***	12.942***	13.316***	13.348***	13.684***
	(0.693)	(1.159)	(0.786)	(0.777)	(0.730)	(0.732)	(0.716)	(0.967)	(0.922)	(0.627)
Observations	16,371	11,643	8,624	6,303	4,413	2,996	2,013	1,375	912	1,751
R-squared	0.328	0.517	0.551	0.538	0.514	0.475	0.526	0.501	0.515	0.507
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stage FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Investor Number FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CV Psuedo-R2 Mean	0.320	0.488	0.505	0.505	0.496	0.484	0.483	0.479	0.449	0.465
CV Psuedo-R2 Sd	0.011	0.011	0.012	0.012	0.013	0.015	0.017	0.017	0.020	0.027
Repeats of 10-fold CV	10	10	10	10	10	10	10	10	10	10

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Note: Table reports the regression results when estimating the imputation models for the amount raised in each venture funding round. The sample includes all the US-based ventures in the SDC VentureXpert database that had the first funding round prior to 2006. In parenthesis are standard errors.

Table IA.4: Estimation of the Imputation Models for Mergers and Acquisitions Valuation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES			Log Mergers and Acquisitions Valuation					
Extrapolated Valuation		0.596***	0.764***	0.742***	0.738***	0.481***	0.824***	0.733***
		(0.028)	(0.039)	(0.043)	(0.044)	(0.104)	(0.057)	(0.095)
Days between Last PMV and Exit			0.002***	0.002***	0.002***	0.001	0.003***	0.003***
			(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)
Extrapolated Valuation × Days between Last PMV and Exit			-0.000***	-0.000***	-0.000***	-0.000	-0.000***	-0.000***
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log Amount of the Final Round				0.110***	0.112***	0.211***	0.092***	0.079*
				(0.021)	(0.021)	(0.050)	(0.029)	(0.043)
Days between Final Round and Exit				-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
				(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
NASDAQ Return from Final Round to Exit					0.037	0.072	0.088	-0.082
					(0.051)	(0.188)	(0.070)	(0.087)
Observations	3,436	3,433	3,433	3,433	3,433	628	1,972	833
R-squared	0.054	0.166	0.176	0.205	0.205	0.254	0.233	0.216
Industry FE	Yes	Yes	Yes	Yes	Yes	No	No	No
Stage FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Round Number FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CV Psuedo-R2 Mean	0.006	0.090	0.099	0.132	0.133	0.086	0.107	0.098
CV Psuedo-R2 Sd	0.004	0.013	0.014	0.016	0.016	0.015	0.014	0.013
Repeats of 10-fold CV	10	10	10	10	10	10	10	10
Industry	All	All	All	All	All	Health	IT	Others

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Note: Table reports the regression results when estimating the imputation models for the M&A valuations of ventures. The sample includes all the US-based ventures in the SDC VentureXpert database and had the first funding round prior to 2006. In parenthesis are standard errors.

Table IA.5: Estimation of the Imputation Models for the Pre-IPO Valuation

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Log Pre-IPO Valuation				
Extrapolated Valuation		0.508***	0.578***	0.527***	0.502***	0.423***	0.482***	0.575***
		(0.024)	(0.028)	(0.032)	(0.032)	(0.066)	(0.046)	(0.069)
Days between Last PMV and Exit			0.002***	0.001***	0.001***	0.001**	0.001***	0.002***
			(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)
Extrapolated Valuation × Days between Last PMV and Exit			-0.000***	-0.000***	-0.000***	-0.000**	-0.000***	-0.000**
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log Amount of the Final Round				0.052***	0.057***	0.088***	0.096***	-0.027
				(0.017)	(0.017)	(0.032)	(0.026)	(0.036)
Days between Final Round and Exit				-0.000**	-0.000***	-0.000***	-0.000**	-0.000
				(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
NASDAQ Return from Final Round to Exit					0.204***	0.305***	0.415***	-0.035
					(0.048)	(0.095)	(0.080)	(0.086)
Observations	1,833	1,833	1,833	1,833	1,833	555	873	405
R-squared	0.364	0.491	0.500	0.518	0.523	0.487	0.568	0.562
Industry FE	Yes	Yes	Yes	Yes	Yes	No	No	No
Stage FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Round Number FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CV Psuedo-R2 Mean	0.223	0.397	0.414	0.449	0.449	0.358	0.346	0.360
CV Psuedo-R2 Sd	0.030	0.038	0.037	0.034	0.035	0.035	0.038	0.037
Repeats of 10-fold CV	10	10	10	10	10	10	10	10
Industry	All	All	All	All	All	Health	IT	Others

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Note: Table reports the regression results when estimating the imputation models for the pre-IPO valuations of ventures. The sample includes all the US-based ventures in the SDC VentureXpert database and had the first funding round prior to 2006. In parenthesis are standard errors.

C. Calculating Robust Standard Errors

When testing the hypotheses implied by the matching model between ventures and VCs, we carried out a series of regression analyses. In these regression analyses, the outcome variables – for example, venture normalized NPV and successful exits, depend not only on the time of the venture's first round, but also the market conditions over the life cycle of the venture. The overlaps of life cycles of different ventures introduce correlations in the error term of the regression model among ventures. The dependent variables are also likely subject to serial correlation over time. These correlations make it necessary to calculate robust standard errors of the coefficient estimates of the regressions. Here, we provide robust standard errors using an Fama-MacBeth standard errors approach modified from Fama and MacBeth (1973).

We first run multiple cross-sectional regressions relating the venture's performance to the VC's experience, where each cross section consists of ventures receiving the first funding round in a given quarter. After collecting the cross-sectional regression coefficients, we adopt their average as the point estimate. Then we use three methods to calculate the standard errors of the point estimates. The first method is based on the sample standard deviation of the coefficients from the cross-sectional regressions. The second method uses Newey-West adjusted standard errors with 3 lags. The third method uses Bootstrap standard errors. Specifically, we first fit the best ARMA model to the time series of cross-sectional regression coefficients according to AICc (Akaike Information Criterion corrected for small sample). Then we bootstrap the error terms from the best ARMA model, construct the series of regression coefficients in each bootstrap iteration according to the ARMA model and calculate their average. Then the sample standard deviation of these averages is the bootstrap standard errors.

Hypothesis 2

We now test *Hypothesis 2* of the model, showing that ventures invested by high-ability VCs have higher NPV than the others, but the difference shrinks after the structural break. We regress the normalized NPV of venture or the likelihood of successful exits on the measure of VC experience. In order to compare the relationship between before and after the structural break, we conduct the Fama-MacBeth regressions for the pre-break and the post-break period separately. Also, since the sample size for some cross sections is small, we minimize the number of right hand side variables to avoid bias caused by too many regressors. That is, we use only the Top 30 VC variable as the VC experience measure, but control variables including the first round's raised amount, and year-industry fixed effects are still added.

Table IA.6 and IA.7 report the regression results for Group A ventures and Group AB ventures separately. In Column (1) and (2) of both tables, we see that having a Top 30 VC in the first round is significantly positively related to the venture's NPV normalized by the first-round raised amount before the structural break in 1999. This reflects that good ventures are matched with more experienced VCs. However, after the structural break, the relationship between VC experience and venture's performance becomes smaller and insignificant. The results are robust regardless of whether the regression uses Group A ventures (ventures with first funding round post-money valuation data) or Group AB ventures (the sample of all ventures).

Column (3) and (4) of both tables report the estimation results when we use successful exits including IPO and MA to proxy for the performance of the ventures – that is, we regress the indicator variable for successful exits on the variable Top 30 VC, together with control variables including the first round's raised amount, and year-industry fixed effects. We find that having a Top 30 VC in the first round is significantly positively related to the venture's successful exits both before and after the structural break in 1999. The results are robust regardless of whether our sample includes Group A ventures or Group AB ventures.

Column (5) and (6) of both tables report the Fama-MacBeth regression results studying the intensive margin. We see that having a Top 30 VC in the first round is significantly positively related to the venture's NPV normalized by the first-round amount raised before the structural break in 1999. This reflects that experienced VCs is associated with higher NPVs even conditional on the ventures having successful exits. However, after the structural break, the relationship becomes insignificant for Group A ventures and becomes much weaker for Group AB ventures. These results are consistent with what we find using the double clustered standard errors.

Table IA.6: Past Experience of 1st-Round VCs and Performance: Fama-MacBeth Regression by Period on Group A Ventures

VARIABLES	Normalized NPV		IPO or MA Exit		Normalized NPV (Exited)	
	(1)	(2)	(3)	(4)	(5)	(6)
log(1st Round Amount Raised)	-2.486***	-0.901*	0.037**	0.083***	-5.086***	-2.714***
F-M p-value	0.002	0.058	0.067	0.000	0.001	0.002
N-W p-value	0.010	0.065	0.064	0.000	0.003	0.002
Bootstrap p-value	0.006	0.063	0.026	0.000	0.000	0.005
ARMA(p,q)	ARMA(1,0)	ARMA(0,1)	ARMA(0,0)	ARMA(0,0)	ARMA(0,0)	ARMA(0,1)
Top 30 VC	5.688***	2.071	0.069***	0.053**	8.188***	2.682
F-M p-value	0.001	0.195	0.037	0.087	0.000	0.120
N-W p-value	0.000	0.305	0.034	0.161	0.000	0.161
Bootstrap p-value	0.000	0.137	0.007	0.031	0.000	0.184
ARMA(p,q)	ARMA(1,0)	ARMA(0,1)	ARMA(0,0)	ARMA(0,0)	ARMA(0,0)	ARMA(0,2)
Sample	GroupA	GroupA	GroupA	GroupA	GroupA	GroupA
Discounting	GPMEround	GPMEround	GPMEround	GPMEround	GPMEround	GPMEround
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Period	Pre-Break	Post-Break	Pre-Break	Post-Break	Pre-Break	Post-Break

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$ according to Bootstrap p-value

Note: Table reports the Fama-MacBeth estimation results from regressing NPV normalized by first outlow (Column (1) and (2)), dummies for successful exits (Column (3) and (4)) on the experience measure of the VC team invested in the venture's first funding round, together with control variables. Column (5) and (6) have NPV normalized by first outlow as outcome variable as well, but restrict the sample to only the successfully exited ventures. Column (1), (3) and (5) are regression results for the pre-break period. Column (2), (4) and (6) are regression results for the post-break period. Top 30 VC is a dummy variable that equals 1 if any VC that ranked in the top 30 according to the number of total funding rounds invested in the past 10 years, participated in the venture's first round. Group A are ventures that have first-round post-money valuations.The average of Fama-MacBeth cross-sectional coefficient estimates, where each cross section includes ventures having the first funding rounds in a specific quarter, is reported as the point estimate. F-M p-value is the p-value based on the sample standard deviation of the cross-sectional coefficient estimates.N-W p-value is the p-value based on Newey-West standard errors with 3 lags of the cross-sectional coefficient estimates. We then select the best ARMA model for the cross-sectional coefficient estimates based on AICc information criterion. Then Bootstrap p-value based on bootstrapping the errors from the best ARMA model is reported.

Table IA.7: Past Experience of 1st-Round VCs and Performance: Fama-MacBeth Regression by Period on Group AB Ventures

VARIABLES	Normalized NPV		IPO or MA Exit		Normalized NPV (Exited)	
	(1)	(2)	(3)	(4)	(5)	(6)
log(1st Round Amount Raised)	-2.040***	-0.531***	0.046***	0.055***	-6.221***	-3.116***
F-M p-value	0.000	0.014	0.000	0.000	0.000	0.000
N-W p-value	0.000	0.015	0.000	0.000	0.000	0.000
Bootstrap p-value	0.000	0.004	0.000	0.000	0.000	0.000
ARMA(p,q)	ARMA(0,0)	ARMA(0,0)	ARMA(0,0)	ARMA(0,0)	ARMA(0,0)	ARMA(0,0)
Top 30 VC	3.834***	0.802	0.082***	0.036**	6.432***	2.095**
F-M p-value	0.000	0.120	0.000	0.033	0.000	0.004
N-W p-value	0.000	0.248	0.001	0.004	0.000	0.025
Bootstrap p-value	0.000	0.135	0.000	0.012	0.000	0.014
ARMA(p,q)	ARMA(0,0)	ARMA(1,0)	ARMA(0,0)	ARMA(0,0)	ARMA(0,0)	ARMA(1,0)
Sample	GroupAB	GroupAB	GroupAB	GroupAB	GroupAB	GroupAB
Discounting	GPMEround	GPMEround	GPMEround	GPMEround	GPMEround	GPMEround
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Period	Pre-Break	Post-Break	Pre-Break	Post-Break	Pre-Break	Post-Break

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$ according to Bootstrap p-value

Note: Table reports the Fama-MacBeth estimation results from regressing NPV normalized by first outflow (Column (1) and (2)), dummies for successful exits (Column (3) and (4)) on the experience measure of the VC team invested in the venture's first funding round, together with control variables. Column (5) and (6) have NPV normalized by first outlow as outcome variable as well, but restrict the sample to only the successfully exited ventures. Column (1), (3) and (5) are regression results for the pre-break period. Column (2), (4) and (6) are regression results for the post-break period. Top 30 VC is a dummy variable that equals 1 if any VC that ranked in the top 30 according to the number of total funding rounds invested in the past 10 years, participated in the venture's first round. Group A are ventures that have first-round post-money valuations. Group AB in addition includes the ventures that do not have first-round post-money valuations. The average of Fama-MacBeth cross-sectional coefficient estimates, where each cross section includes ventures having the first funding rounds in a specific quarter, is reported as the point estimate. F-M p-value is the p-value based on the sample standard deviation of the cross-sectional coefficient estimates.N-W p-value is the p-value based on Newey-West standard errors with 3 lags of the cross-sectional coefficient estimates. We then select the best ARMA model for the cross-sectional coefficient estimates based on AICc information criterion. Then Bootstrap p-value based on bootstrapping the errors from the best ARMA model is reported.

Hypothesis 3

We now test *Hypothesis 3* of the model, showing that ventures invested by more high-ability (H-type) VCs tend to be high-quality (h-type) ventures, both before and after the structural break. In this test, we proxy the quality of a venture by the number of innovations it creates. We regress the venture's lifetime number of patents and patent citations on the experience measures of the VC team invested in the venture's first funding round, together with control variables including the first round's amount raised, year fixed effects, industry fixed effects and year-industry fixed effects.

Table IA.8 and Table IA.9 report the Fama-MacBeth regression results for Group A and Group AB ventures separately. We see that VC's past experience is highly correlated with venture's innovation ability, either measured by lifetime number of patents or by patent citations, and this relationship holds both before and after the structural break. This means that although after the structural break experienced VCs are not more likely to invest in high NPV ventures in the first round, they still tend to invest in the more innovative ventures. The results are robust regardless of whether the regression uses Group A ventures or Group AB ventures.

Table IA.8: Past Experience of 1st-Round VCs and Innovation: Fama-MacBeth Regression by Period on Group A Ventures

VARIABLES	Has Patent		log(1 + # Patents)		log(1 + # Citations)	
	(1)	(2)	(3)	(4)	(5)	(6)
log(1st-Round Amount Raised)	−0.016	0.047	0.005	0.123**	0.016	0.234**
F-M p-value	0.493	0.001	0.979	0.060	0.936	0.146
N-W p-value	0.384	0.007	0.977	0.036	0.899	0.077
Bootstrap p-value	0.236	0.451	0.516	0.013	0.406	0.050
ARMA(p,q)	ARMA(0,0)	ARMA(0,0)	ARMA(0,0)	ARMA(0,0)	ARMA(0,1)	ARMA(0,0)
Top 30 VC	0.180***	0.088***	0.253	0.393***	0.684**	0.797**
F-M p-value	0.000	0.001	0.584	0.000	0.150	0.009
N-W p-value	0.000	0.000	0.561	0.000	0.109	0.046
Bootstrap p-value	0.000	0.000	0.317	0.000	0.048	0.012
ARMA(p,q)	ARMA(0,0)	ARMA(0,0)	ARMA(0,0)	ARMA(0,0)	ARMA(0,0)	ARMA(0,1)
Sample	GroupA	GroupA	GroupA	GroupA	GroupA	GroupA
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Period	Pre-Break	Post-Break	Pre-Break	Post-Break	Pre-Break	Post-Break

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$ according to Bootstrap p-value

Note: Table reports the Fama-MacBeth estimation results from regressing venture's patents holding and patents citations on the experience measure of the VC team invested in the venture's first funding round, together with control variables. Top 30 VC is a dummy variable that equals 1 if any VC that ranked in the top 30 according to the number of total funding rounds invested in the past 10 years, participated in the venture's first round. Group A are ventures that have first-round post-money valuations. Group AB in addition includes the ventures that do not have first-round post-money valuations. The average of Fama-MacBeth cross-sectional coefficient estimates, where each cross section includes ventures having the first funding rounds in a specific quarter, is reported as the point estimate. F-M p-value is the p-value based on the sample standard deviation of the cross-sectional coefficient estimates. N-W p-value is the p-value based on Newey-West standard errors with 3 lags of the cross-sectional coefficient estimates. We then select the best ARMA model for the cross-sectional coefficient estimates based on AICc information criterion. Then Bootstrap p-value based on bootstrapping the errors from the best ARMA model is reported.

Table IA.9: Past Experience of 1st-Round VCs and Innovation: Fama-MacBeth Regression by Period on Group AB Ventures

VARIABLES	Has Patent		log(1 + # Patents)		log(1 + # Citations)	
	(1)	(2)	(3)	(4)	(5)	(6)
log(1st-Round Amount Raised)	−0.007	0.006	0.079**	0.124***	0.023	0.251***
F-M p-value	0.341	0.400	0.050	0.000	0.696	0.000
N-W p-value	0.107	0.470	0.009	0.000	0.668	0.001
Bootstrap p-value	0.147	0.191	0.025	0.000	0.342	0.000
ARMA(p,q)	ARMA(0,0)	ARMA(0,0)	ARMA(0,0)	ARMA(0,0)	ARMA(0,0)	ARMA(0,1)
Top 30 VC	0.103***	0.113***	0.293***	0.318***	0.652***	0.695***
F-M p-value	0.000	0.000	0.015	0.000	0.001	0.000
N-W p-value	0.000	0.000	0.008	0.000	0.000	0.000
Bootstrap p-value	0.000	0.000	0.006	0.000	0.000	0.000
ARMA(p,q)	ARMA(1,0)	ARMA(0,1)	ARMA(0,0)	ARMA(1,0)	ARMA(0,0)	ARMA(0,0)
Sample	GroupAB	GroupAB	GroupAB	GroupAB	GroupAB	GroupAB
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Period	Pre-Break	Post-Break	Pre-Break	Post-Break	Pre-Break	Post-Break

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$ according to Bootstrap p-value

Note: Table reports the Fama-MacBeth estimation results from regressing venture's patents holding and patents citations on the experience measure of the VC team invested in the venture's first funding round, together with control variables. Top 30 VC is a dummy variable that equals 1 if any VC that ranked in the top 30 according to the number of total funding rounds invested in the past 10 years, participated in the venture's first round. Group A are ventures that have first-round post-money valuations. Group AB in addition includes the ventures that do not have first-round post-money valuations. The average of Fama-MacBeth cross-sectional coefficient estimates, where each cross section includes ventures having the first funding rounds in a specific quarter, is reported as the point estimate. F-M p-value is the p-value based on the sample standard deviation of the cross-sectional coefficient estimates. N-W p-value is the p-value based on Newey-West standard errors with 3 lags of the cross-sectional coefficient estimates. We then select the best ARMA model for the cross-sectional coefficient estimates based on AICc information criterion. Then Bootstrap p-value based on bootstrapping the errors from the best ARMA model is reported.

Hypothesis 4

We now test *Hypothesis 4* of the model, showing that ventures invested by more high-ability (H-type) VCs give up more ownership to VCs than the others, but the difference shrinks after the structural break. Specifically, we regress the venture founder's first-round ownership given up on the experience measures of the VC team invested in the venture's funding round, together with control variables including the first round's amount raised, year fixed effects, industry fixed effects and year-industry fixed effects.

Table IA.10 reports the Fama-MacBeth regression results. The Fama-MacBeth regression results are consistent with the regression results based on double clustered standard errors. We see that VC's past experience is significantly correlated with the venture's first-round ownership given up before the structural break in 1999, suggesting that more experienced VC is able to acquire more ownership from the venture in the first round. However, this relationship weakens after the structural break.

Table IA.10: Past Experience of 1st-Round VCs and 1st-Round Ownership Given Up: Fama-MacBeth Regression by Period

VARIABLES	1st-Round Ownership Given Up			
	(1)	(2)	(3)	(4)
log(1st-Round Amount Raised)	0.075***	0.071***	0.066	0.064
F-M p-value	0.000	0.000	0.000	0.000
N-W p-value	0.000	0.000	0.000	0.000
Bootstrap p-value	0.000	0.000	0.472	0.435
ARMA(p,q)	ARMA(0,0)	ARMA(0,0)	ARMA(0,0)	ARMA(1,0)
Top 30 VC	0.039***	0.015**	0.034***	0.014***
F-M p-value	0.023	0.141	0.000	0.000
N-W p-value	0.002	0.029	0.000	0.000
Bootstrap p-value	0.000	0.040	0.000	0.000
ARMA(p,q)	ARMA(0,1)	ARMA(0,0)	ARMA(0,0)	ARMA(0,0)
Sample	GroupA	GroupA	GroupAB	GroupAB
Industry FE	Yes	Yes	Yes	Yes
Period	Pre-Break	Post-Break	Pre-Break	Post-Break

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$ according to Bootstrap p-value

Note: Table reports the Fama-MacBeth estimation results from regressing venture's first-round ownership given up to the VC investors on the experience measure of the VC team invested in the venture's first funding round, together with control variables. Top 30 VC is a dummy variable that equals 1 if any VC that ranked in the top 30 according to the number of total funding rounds invested in the past 10 years, participated in the venture's first round. Group A are ventures that have first-round post-money valuations. Group AB in addition includes the ventures that do not have first-round post-money valuations. The average of Fama-MacBeth cross-sectional coefficient estimates, where each cross section includes ventures having the first funding rounds in a specific quarter, is reported as the point estimate. F-M p-value is the p-value based on the sample standard deviation of the cross-sectional coefficient estimates. N-W p-value is the p-value based on Newey-West standard errors with 3 lags of the cross-sectional coefficient estimates. We then select the best ARMA model for the cross-sectional coefficient estimates based on AICc information criterion. Then Bootstrap p-value based on bootstrapping the errors from the best ARMA model is reported.

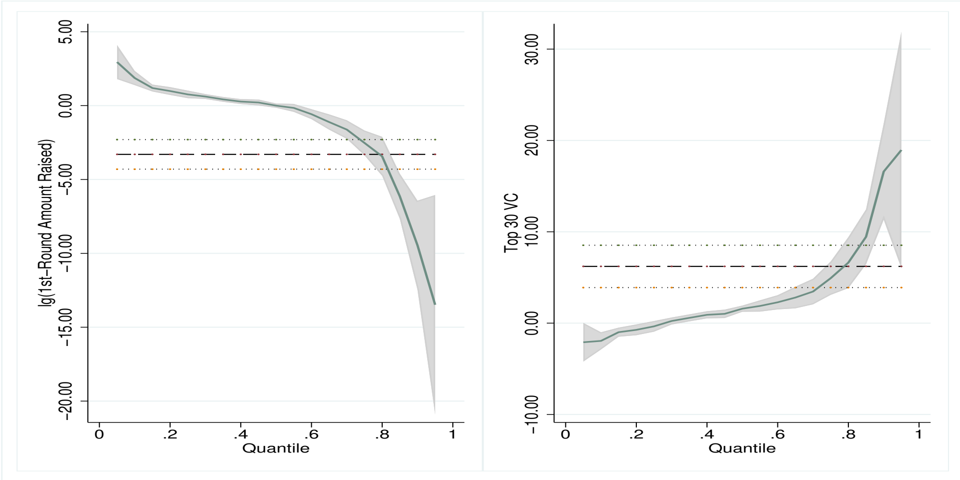
D. Quantile Regessions

The quantile regressions study the relationship between any quantile of the outcome variable with explanatory variables. We conduct quantile regressions to study the heterogeneity of the relationship between VC experience and venture performance, across ventures with different levels of normalized NPVs.

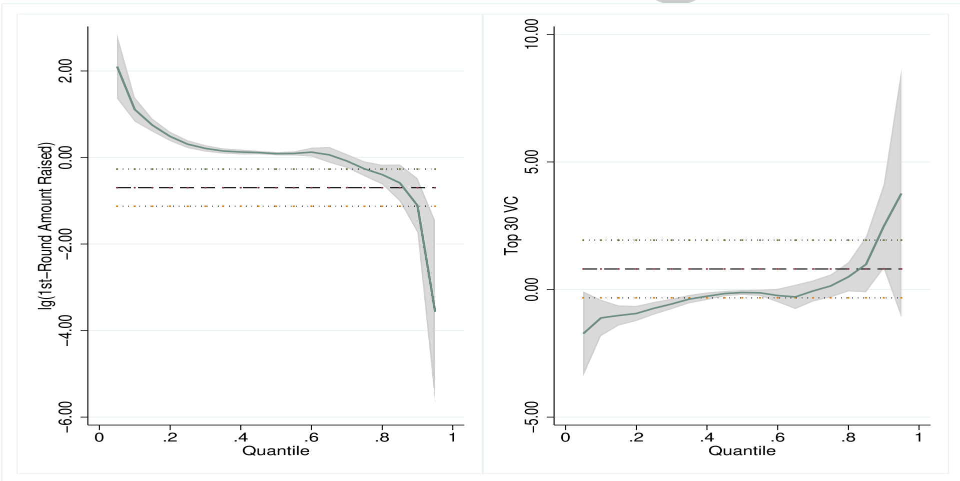
Figure IA.1 plots the coefficients on the explanatory variables from the quantile regressions of venture's normalized NPV on VC experience (Top 30 VC) and control variables. The regressions are conducted for the pre-break and post-break periods separately. We see from the figure that before the structural break, although having a Top 30 VC in the first round is on average positively related to venture's normalized NPV, this "average effect" is mainly driven by and concentrated at the high end of the distribution of normalized NPV. The coefficient on the Top 30 VC dummy is close to zero for ventures with normalized NPVs below the 30% percentile, meaning that experienced VC is not so good at keeping away from the "bad" ventures. Instead, the coefficient has a sharp increase for ventures with normalized NPVs above the 70% percentile, meaning that experienced VC is very good at cherry-picking the best ventures. The coefficients on the other explanatory variables from the quantile regressions are also plotted, and also show strong heterogeneity across the distribution of venture's normalized NPV.

Similarly, on the intensive margin, the relationship between venture's normalized NPV and VC experience shows strong heterogeneity across the ventures. Figure IA.2 plots the coefficients on explanatory variables from the quantile regressions of venture's normalized NPV on VC experience, after restricting to the sample of ventures with successful exits. We see from the figure that both before and after the structural breakthe strong correlation between venture normalized NPV and VC experience concentrates at the high end of the distribution of normalized NPV.

When conducting the quantile regressions in the pooled sample of both pre-break and post-break periods, the results are similar. Figure IA.3 plots the coefficients on explanatory variables from the quantile regressions of venture's normalized NPV on VC experience. And Figure IA.4 studies the intensive margin, that is it plots the coefficients on explanatory variables from the quantile regressions of venture's normalized NPV on VC experience, after restricting to the sample of ventures with successful exits.



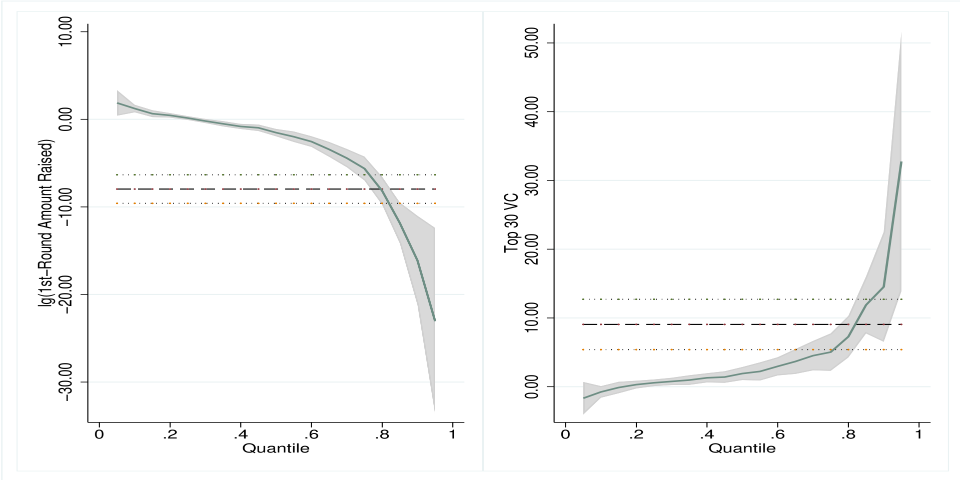
(a) Before the Structural Break



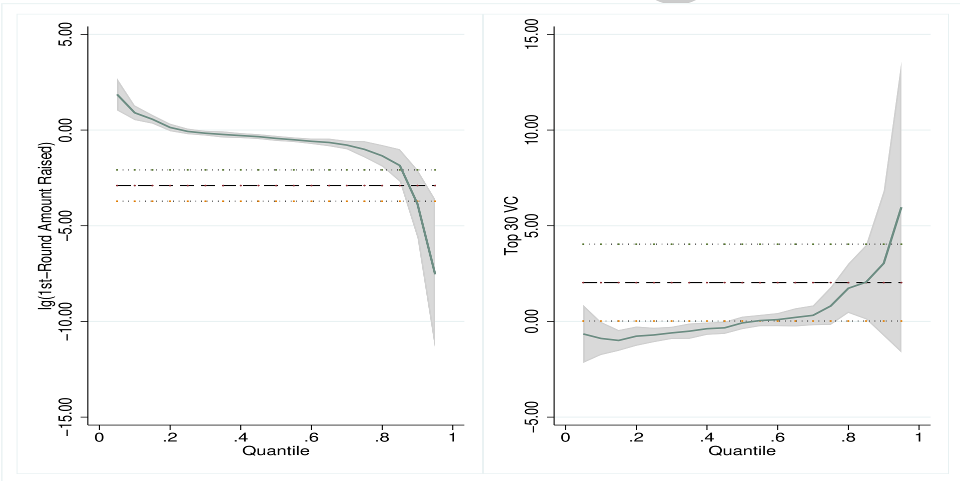
(b) After the Structural Break

Figure IA.1: Quantile Regression of Normalized NPV

Note: Different panels plot the point estimates and 95% confidence intervals (the curves and shaded areas) of the coefficients on explanatory variables – log(1st-Round Amount Raised) and Top30 VC, from the quantile regressions fitting different quantiles of the outcome variable – normalized NPV. The sample includes Group A ventures (those with first-round post-money valuation data). Dotted horizontal lines are point estimates and 95% confidence intervals of the coefficients from OLS. When calculating the normalized NPV, the cash flows are discounted using the GPMEround method, i.e., Generalized Public Market Equivalent method with parameters calibrated to round-to-round returns.



(a) Before the Structural Break



(b) After the Structural Break

Figure IA.2: Quantile Regression of Normalized NPV Conditional on Successful Exits

Note: Different panels plot the point estimates and 95% confidence intervals (the curves and shaded areas) of the coefficients on explanatory variables – log(1st-Round Amount Raised) and Top30 VC, from the quantile regressions fitting different quantiles of the outcome variable – normalized NPV. The sample is restricted to Group A ventures (those with first-round post-money valuation data) that eventually successfully exited. Confidence intervals are based on OLS standard errors. Dotted horizontal lines are point estimates and 95% confidence intervals of the coefficients from panel OLS regression. When calculating the normalized NPV, the cash flows are discounted using the GPMEround method, i.e., Generalized Public Market Equivalent method with parameters calibrated to round-to-round returns.

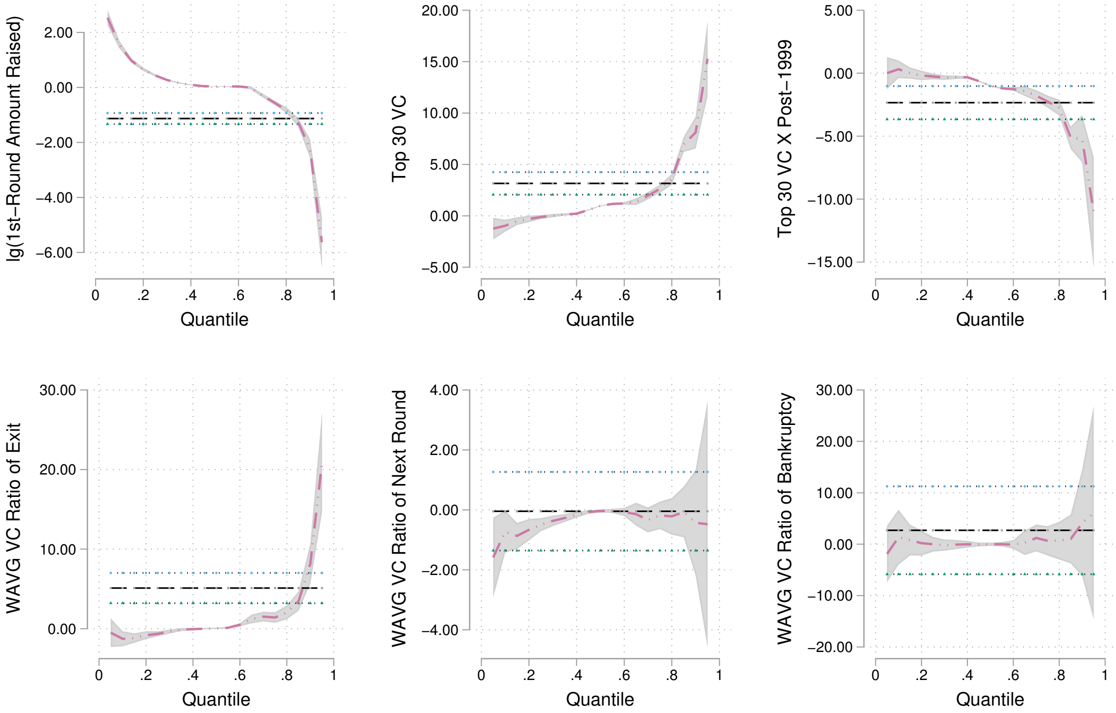


Figure IA.3: Quantile Regression of Normalized NPV

Note: Different panels plot the point estimates and 95% confidence intervals (the curves and shaded areas) of the coefficients on different explanatory variables, from the quantile regressions fitting different quantiles of the outcome variable – normalized NPV. Dotted horizontal lines are point estimates and 95% confidence intervals of the coefficients from OLS. When calculating the normalized NPV, the cash flows are discounted using the GPMEround method, i.e., Generalized Public Market Equivalent method with parameters calibrated to round-to-round returns. Top 30 VC is a dummy variable that equals 1 if any VC that ranked in the top 30 according to the number of total funding rounds invested in the past 10 years, participated in the venture's first round. WAVG VC Ratio of Exit is the weighted average of the ratio of the funding rounds that are associated with successful exits in the past 10 year of all the VCs participated in the venture's first round, where the weight is the total funding rounds invested by the VCs in the past 10 years. Similarly defined are WAVG VC Ratio of Next Round and WAVG VC Ratio of Bankruptcy. They are the total-funding-rounds-weighted-average of the ratio of the funding rounds that are associated with continued financing and bankruptcy of the first-round VCs, respectively. The sample of ventures includes both Group A (those with first-round post-money valuation data) and Group B (those without).

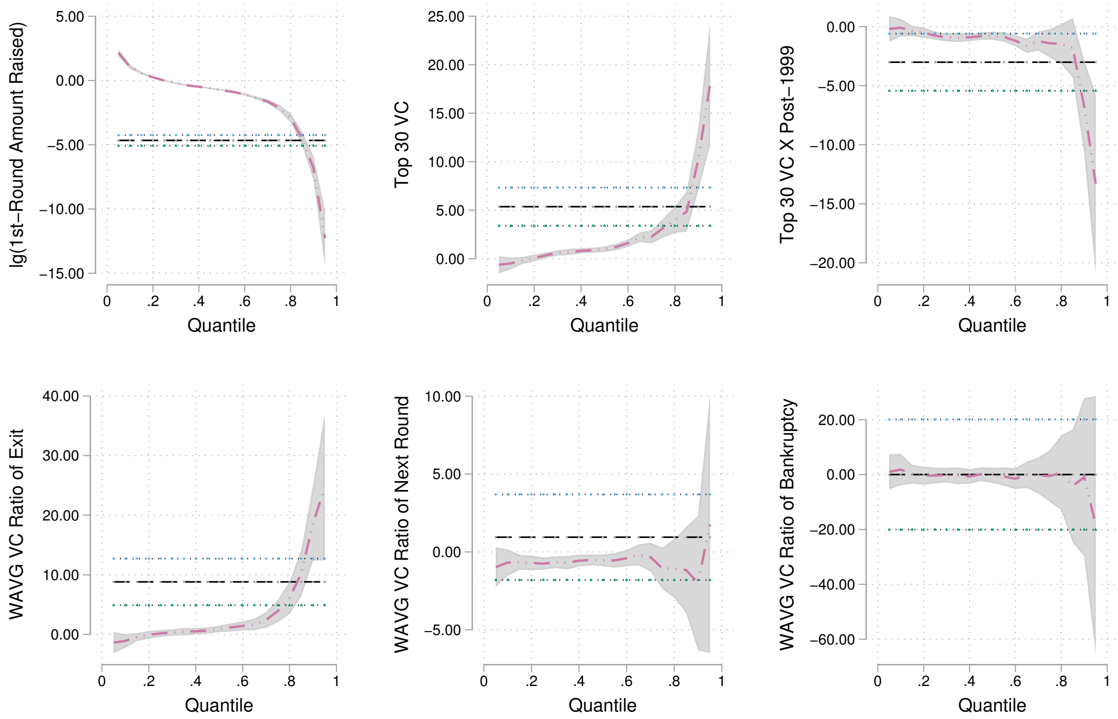


Figure IA.4: Quantile Regression of Normalized NPV of Exited Ventures

Note: Different panels plot the point estimates and 95% confidence intervals (the curves and shaded areas) of the coefficients on different explanatory variables, from the quantile regressions fitting different quantiles of the outcome variable – normalized NPV. Dotted horizontal lines are point estimates and 95% confidence intervals of the coefficients from OLS. When calculating the normalized NPV, the cash flows are discounted using the GPMEround method, i.e., Generalized Public Market Equivalent method with parameters calibrated to round-to-round returns. Top 30 VC is a dummy variable that equals 1 if any VC that ranked in the top 30 according to the number of total funding rounds invested in the past 10 years, participated in the venture's first round. WAVG VC Ratio of Exit is the weighted average of the ratio of the funding rounds that are associated with successful exits in the past 10 year of all the VCs participated in the venture's first round, where the weight is the total funding rounds invested by the VCs in the past 10 years. Similarly defined are WAVG VC Ratio of Next Round and WAVG VC Ratio of Bankruptcy. They are the total-funding-rounds-weighted-average of the ratio of the funding rounds that are associated with continued financing and bankruptcy of the first-round VCs, respectively. The sample includes the ventures eventually have successful exits from both Group A (those with first-round post-money valuation data) and Group B (those without first-round post-money valuation data).