Life Cycle Cash Flows of Ventures

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December 28, 2019

Abstract

We compute the collective return to investors in all the funding rounds of a venture by examining the net present value (NPV) of its life time cash flows. We use data for 16,396 ventures funded by venture capitalists (VC), with 57,884 funding rounds from 1980 to 2018 from VentureXpert. Post-money valuation is missing for more than 76% of the funding rounds, making it difficult to compute the return to investing in any given funding round. However, the amount raised is missing for only 3% of the funding rounds, making it feasible to estimate the collective return to all investors based on cash flows over the life cycle of ventures. While the realized NPV per dollar invested in the first round of funding – normalized NPV – is positive on average, there is large cross sectional variation. More than 64% of ventures have negative normalized NPV. In the aggregate, a hypothetical investor who holds all the ventures that had the first funding round in a specific quarter had to wait 5 to 60 quarters for the realized NPV to become positive – depending on the quarter of the first rounds. There is a structural break – ventures that started after 1999 tend to be less profitable. Before the structural break, ventures that had participation by more experienced VCs in the first round were more successful, and had more patent grants over their life cycle.

We thank Marco Sammon for valuable comments, Honghao Wang and Tiange Ye for excellent research assistance. We thank Lintong Li for sharing his codes for analyzing 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

As Rin, Hellmann, and Puri (2013) document, most of the studies in the literature examine the return to investing in ventures based on the return to limited partners in venture capital (VC) funds. In part this is because most investors access ventures through VC funds. There is another reason: venture level valuation information that is critical for examining the returns to investing in individual ventures at different rounds is sparse. To address this issue, Cochrane (2005) and Korteweg and Nagel (2016) use data from Sand Hill Econometrics, which employs proprietary valuation models to fill in missing valuations data. While these studies greatly enhance our understanding of the returns to investing in ventures, there is a 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 requires publicly available information only. 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 we discount the cash flows to calculate the realized 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), which use the equity market returns to construct risk-adjusted discount rate for the ventures. 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 the ventures' life cycle.

The advantage of our approach is that it circumvents the funding-round-level data limitations like selection bias, incomplete financing information, infrequent cash flows, and incomplete valuation information. Also, it avoids the need for analyzing complex contracting details on cash flow rights allocations between entrepreneurs and outside investors in each funding round, which is a challenging issue when calculating the returns to outside investors. The shortcoming is that we only examine the return to all investors as a group and not investors in any particular funding round.

The selection bias in the funding-round-level data, especially for post-money valuation, is well recognized in the literature. As Korteweg and Sorensen (2010) point out, consistent estimation of risk and return requires correcting for the selection bias arising from the fact that ventures that are performing better are more likely to report their valuations. To address the selection bias, 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. He estimates the parameters of the selection function and eventually corrects for the selection 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 uses the post-money valuation information only for the first round. By focusing on the sample of ventures with first-round post-money valuation data, our approach avoids the selection bias critique of Korteweg and Sorensen (2010) without the need of a selection model.

The incompleteness of financing information in the widely used commercial databases is discussed by Lerner (1995), Kaplan, Strmberg, and Sensoy (2002), and more recently by Maats, Metrick, Yasuda, Hinkes, and Vershovski (2011). Cochrane (2005) deals with the incomplete data issue for the round-level variables by classifying the round-level observations into six categories, based on the quality of data, the quality of return, and the type of exits. Assuming that data quality is independent from firm value, he then calculates the probability that each round falls into each category.

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. Our NPV measure which relies mainly on the amount raised data is less subject to the incomplete data problem. The only valuation data used in our analysis is the post-money valuation in the first round. 24.3% of the first rounds have post-money valuations available, and they account for about 29.3% of the total amount raised in the first rounds. For the ventures without first-round valuations data, we impute the valuations using a statistical model, then separately examine their NPVs and compare with the ventures with first-round valuations.

Since the cash flows occur infrequently at random unknown times in the future: when evaluating the returns we cannot directly apply the risk-adjusting tools often used for liquid assets. The Public Market Equivalent (PME) method in Kaplan and Schoar (2005) addresses this issue by matching 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. 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. Korteweg and Nagel (2016) develop a more general SDF framework– the Generalized Public Market Equivalent (GPME) method, for computing the risk adjusted return on venture investments, where the PME emerges as a special case. We consider both the PME method and the GPME method when computing the risk-adjusted discount rate to overcome the infrequent cash flows at random future times, and valuations issues.

Gornall and Strebulaev (2017) point out that the financial structures of the VC-backed companies are complex. Based on legal filings data, cash flow rights are allocated unequally for shares issued in different stage of the venture's life cycle. Ignoring this will lead to a significant upward bias in round-to-round and round-to-exit venture level returns. Besides, according to Ewens, Gorbenko, and Korteweg (2018a), the way the interest is split between entrepreneurs and VCs are usually complex, heterogeneous, and generally not observable. Thus measuring the return to investing in a venture requires additional information than cash flows, which is typically unavailable in common VC datasets. Our NPV measure is not subject to this problem, because it does not measure the return to any specific group of equity holders. Instead, the NPV measure represents the return to all the equity holders taken together as a group.

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 – that exited through an IPO or acquisition, or had no recorded exit events, 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.

Our NPV measure reveals several interesting patterns in the data. The variation of the break-even time is substantially large across different first funding round quarters. 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. Regardless of the first funding round time, a hypothetical investor holding all ventures will take approximately 5 years for the present value of cash flows to become positive, which is consistent with the stylized facts in Ramsinghani (2014). We also find substantial variation in the profitability of ventures that had their first round of funding at different points in time. 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 the aggregate first-round amount raised) in the second quarter of 1999. After the break, the aggregate normalized NPV drops from significantly positive to weakly positive and fluctuates around zero.

Ewens and Farre-Mensa (2019) argue that the National Securities Markets Improvement Act (NSMIA) of 1996 increased the supply of capital to ventures. This could explain the lower return of venture investments after the structural break in 1999. Ewens and Farre-Mensa (2019) also argue that the bargaining power of the venture founders increased after the regulation change. This is consistent with our finding that the relationship between VC experience and ownership given up by the venture founders in the first round declines after the structural break in 1999.

We find that first round participation by more experienced VCs, i.e., those who have invested in more ventures in the past, signals better performance by the venture as measured by its NPV as well as the likelihood of successful exit. The relationship measured by venture NPV significantly weakens after the structural break in 1999, 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. 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. Kaplan and Schoar (2005); Korteweg and Nagel (2016) develop methods for risk-adjusting venture capital cash flows and returns based on the stochastic discount factor framework. We build on Kaplan and Schoar (2005); Korteweg and Nagel (2016) to account for data limitations when using venture level data. Cochrane (2005) and Korteweg and Sorensen (2010) study the selection bias and information incompleteness in venture's disclosure. Ang, Chen, Goetzmann, and Phalippou (2018) develop a Bayesian Markov Chain Monte Carlo method for private equity (PE) returns using cash flows accruing to limited partners and factor returns from public capital markets. 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 investing in the public equity market, which potentially compensates for the illiquidity of PE investments. In contrast, Moskowitz and Vissing-Jrgensen (2002) find that the return to investing in PE is no higher than the return to investing in public equity. 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. Using Burgiss data, 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. A positive value for our NPV measure indicates a return premium to investing in ventures, and our finding of a structural break in 1999 contributes to this literature.

There is some consensus in the literature that the experience of VCs matter (Sorensen, 2007). Further, age (Gompers, 1996; Ramsinghani, 2014) , network connections (Hochberg, Ljungqvist, and Lu, 2007; Du and Hellmann, 2019), reputation (Nahata, 2008; Hsu, 2004), and active involvement by VCs (Bottazzi, Da Rin, and Hellmann, 2008; Bernstein, Giroud, and Townsend, 2016; Akcigit, Dinlersoz, Greenwood, and Penciakova, 2019) help. Harris, Jenkinson, Kaplan, and Stucke (2014b) analyze Burgiss data and find some evidence of performance persistence for VC funds but little evidence of persistence for buyout funds. Our finding that VC experience matters before the structural break in 1999 but matters less after the break, contributes to this literature.

Some caveats about our NPV measure should be mentioned. Since we do not take into account employee stocks and stock option grants, our measure may have an upward bias. Further, focusing on the subsample of the ventures with non-missing first-round post-money valuations may introduce a reporting bias, since these ventures may have systematically better relative performance. However, we argue that the reporting bias is likely to be small. As documented by Kerr, Nanda, and Rhodes-Kropf (2014) and Ewens, Nanda, and Rhodes-Kropf (2018b), the spray and pray investment approach is common among VCs in the early stages due to unreliable early-stage valuations. Hence the reporting bias in the first round is likely to be small. Even though there is a reporting bias, there is no forward-looking bias in our approach, and the strategy of investing in the ventures with non-missing first-round valuation is realizable for investors with access.

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 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 the data on funding rounds and exit events of these ventures from multiple data sources. In our final analysis we limit attention to ventures that had their first funding round in 2006. This allows for a minimum life cycle length of 12 years, since our data ends in 2018.

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 an IPO, MA, or bankruptcy. The VentureXpert status of ventures that exited through IPOs is "Went Public". We classify a venture whose VentureXpert status is "LBO", "Merger", "Acquisition" or "Pending Acquisition" as exiting through MA. We classify a venture whose VentureXpert status is "Defunct", "Bankruptcy – Chapter 7" or "Bankruptcy – Chapter 11" as 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 on their IPOs and MAs 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 betweeen 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, we find that a number of ventures with no recorded exit events in VentureXpert experienced Bankruptcies or MAs according to the other data sources. Only a few of those with no exit events recorded in VentureXpert exited through IPOs (mainly on foreign exchanges and OTC market). For those IPOs, we list the ventures' names, IPO exchanges, IPO dates and CRSP PERMCO in Table 21 in the appendix.

[Table 1 about here]

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 example, in our cross-checked sample of ventures, 4,569 ventures exited through MA according to VentureXpert, out of which 2,194 have pre MA venture valuation data in SDC databases, and the other data sources are able to provide valuation data for another 396 ventures. Besides, for 242 ventures their pre MA valuations in SDC databases conflict with those given by other data sources[1]. For these cases, we adopted the data that appears more reliable. Also, an additional 501 ventures exited through MA according to other sources, out of which 91 have valuation data.

[Table 2 about here]

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 there were 15.2 million pre-IPO shares and its offering price was $10 per share, giving a pre-IPO market value of about 152 million dollars.

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 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.

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

2.2 Sample Selection

As mentioned earlier, we restrict our sample to the US-based ventures that received the first funding round before 2006. We do this for two reasons. First, notice that the our data ends in 2018. So we are not yet able to observe the full life cycle of ventures that started their life closer to 2018. Looking at the total number of funding rounds we observe in data of ventures receiving their first funding round 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, when we look at distribution of the time from the first funding round to successful exits – IPOs and MAs, the majority falls within 10 years[2]. This suggests that it would be safe to treat a venture that had its first funding round before 2006 as dead if had not exited by 2018. In terms of estimating the return of investing in this venture, it is less problematic to regard its exit value as zero.

[Figure 1 about here]

[Figure 2 about here]

We further exclude the rounds and ventures whose initial funding round records are not informative. Specifically, from the beginning of the ventures funding process, we sequentially drop the funding rounds with neither amount raised nor post-money valuation data until a funding round recorded with either of these two variables is met. After this procedure, we label the first remaining funding round of a venture as its first funding round, the second remaining as its second funding round, etc. As shown in Table 3 below, less than 6.4% of the ventures are affected by this procedure. We also separate the ventures to two groups. Group A includes ventures that have post-money valuation data for the actual first funding round. Group B includes ventures that do not have post-money valuation data for the actual first round. Due to concerns that these two groups may have distinct natures from each other, we conduct our analysis on these two groups separately.

[Table 3 about here]

[2] 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 the ventures that went to MA

2.3 Imputation of Missing Values

We utilize statistical models described in Section A.2 in the appendix to impute the missing values in the variables essential to our analysis – amount raised in the funding rounds, first-round ownership given up, pre-IPO valuations and pre-MA valuations, based on observable information. First-round ownership given up is calculated as the ratio of first-round amount raised to first-round post-money valuation, measuring the ownership given up by the venture founders to the first rounds investors. Table 4 summarizes the data that were missing and imputed. As can be seen, imputed values are mainly used for the pre-MA valuation data and the first-round ownership given up data. We filled in about 50% of the pre-MA valuation data, and 99.1% of the first-round ownership given up data for Group B ventures. The filled pre-MA valuations are on average less than the actual data[3], and the average filled first-round ownership given-up is similar to the actual data.

[Table 4 about here]

For the amount raised data, we impute the missing data using linear regression models. We first estimate the relationship between the amount raised in a funding round and the number of investors who participated, the amount raised in previous round, as well as the industry fixed effects, funding stage fixed effects and time fixed effects, for the first, second,...,ninth rounds separately. For the first round, there is no previous round, so the model relates the amount raised to a set of fixed effects. For funding rounds after the ninth round, amount raised is frequently missing, so instead of relating the amount raised in these rounds to the previous funding rounds amount, we relate them to the ninth funding rounds amount. The fitted values from the model are the imputed values for the missing data. Table 5 shows the estimation results of the imputation model.

To measure the fitness of the models to the data, 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^2s 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.

[3]This may suggest those MA with no valuation records tend to have lower valuations.

[Table 5 about here]

For the first-round ownership given up data, we use logit models to impute the missing values. 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 (utilizing only original amount raised data instead of the interpolated values) and its square, log cumulative amount raised starting from the first round as independent variables, at the same time controlling for fixed effects on industry, funding stage, the number of rounds that have occurred, time and the number of investors. As is shown in Table 6, adding in all the aforementioned variables results in the highest cross-validation Pseudo-R^2 of 0.484, which is the specification we adopt for the imputation.

[Table 6 about here]

For the pre-IPO and pre-MA valuations, we also impute the missing values using linear regression models. For these, we estimate the relationship between the pre-MA or pre-IPO valuation, and a rich set of observables including extrapolated valuations based on last available post-money valuation and NASDAQ stock return[4], 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. Again the fitted values from the models are imputed values for the missing data. Table 7 and Table 8 report the estimation results of the imputation models.

[Table 7 about here]

[Table 8 about here]

2.4 Summary of the Data

Figure 3 shows the number of ventures in our final sample by the year of their first funding rounds. Before 1995, on average 300 new ventures had their first funding rounds each year. During the dot com bubble, the number peaks to almost 2,300. After that it decreases significantly, yet still remains higher than the pre-1995 time period.

[4] Extrapolated valuation 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.

[Figure 3 about here]

Figure 4 plots the amount raised by the ventures against the year of the funding rounds. Before 2000, there is an upward trend in the average amount raised by a venture in each year. This number peaked at \$14.4 million in 2000. After 2000, the average amount raised by a venture first dropped significantly and then stabilized between \$7.7 million and \$9.8 million before 2006. After 2006, the average amount raised in a round trended upward to as high as \$19.2 million, due to the fact that our sample includes ventures receiving the first round before 2006, and hence the rounds after 2006 are more likely to be later rounds. From the plot of the percentiles of the distribution of the amount raised by ventures, we see there is wide dispersion among ventures.

[Figure 4 about here]

Figure 5 plots the amount raised in the ventures first funding rounds against the year of the first funding rounds. Before 2000, there is an upward trend in the average first-round amount raised by a venture. The number peaked at \$8.9 million in 2000. After 2000, this number first dropped and remained stable.

[Figure 5 about here]

Figure 6 shows the fraction of ownership given up in the first round by the year of the first round. The ownership given up is based on our imputed data. We see on average the venture founders give up 30% of the ownership to investors in the first funding round, and this fraction remains generally constant over time except for possible structural breaks.

[Figure 6 about here]

Figure 7 shows the number and fraction of ventures that went to different outcomes by the year of the ventures first round years. Ventures in our data eventually reach one of the four final outcomes: IPO, merger and acquisition, bankruptcy, or alive[5] by 2018. As the first-round year increases, the fraction of ventures that eventually went to IPO decreases, and remains stable between 2000 and 2006 at around 6%. The fraction of ventures that exit through M&A increases before 2000 and then remains relatively stable at around 45%. The fraction of ventures that eventually declared bankruptcy remains stable at around 8%.

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

[Figure 7 about here]

Figure 8 shows the fractions of ventures that experienced another funding round, IPO, MA, bankruptcy, or no further observed events directly after receiving a funding round, and how the fractions change by the funding round number. We see that after receiving the first or second round, most ventures continue to have additional funding rounds and the probability of directly going to IPO, MA or bankruptcy is low. After about 5 rounds, the probability of a venture directly going to IPO, MA or bankruptcy peaks.

[Figure 8 about here]

3 Present Value of Life Cycle Cash Flows of Ventures

3.1 An Investment Performance Measure Based on Venture Cash Flows

The most commonly used measures of the VC investment performance are the round-to-round return and the round-to-exit return to the VCs. However, these measures are hard to construct accurately because we often do not observe how much equity the entrepreneurs hold in their start-ups, and how much equity they give up to the venture capital firms in each funding round, without access to proprietory models that use additional information. According to Ewens et al. (2018a), the way the interest is split between entrepreneurs and VCs are usually complex, heterogeneous, and generally not observable. Given the difficulties in the aforementioned return measure, we propose a new performance measure. Instead of measuring the round-to-round or round-to-exit returns to the equity investment by the venture capital firms, we measure the NPVs to all equity holders taken together.

This measure is based on the cash flows that the venture received from all the equity holders in the various funding rounds, and the cash (or value) received by all equity holders upon the venture's exit. Essentially the measure represents the return to a hypothetical investor who participate in all the funding rounds of a venture.

The amount raised in each funding round gives only the collective investment by all VCs [6]. In addition, we also need to know the fraction of the venture that VCs collectively received for their investment, and for that we need to know the investment of the entrepreneurs. An entrepreneur

[6] We use the term VCs to denote all the outside investors

would have invested money and put in efforts over time in her venture before the venture's first round, before the VC investments come in. We use the pre-money valuation of a venture in the first round as a proxy for the amount of money invested by the entrepreneurs. We utilize data on the ownership given up by the entrepreneurs to calculate the value of equity they hold before the first funding round.

The value received by equity holders who have invested in a venture at the terminal date is measured by its equity value at exit. If a venture's exit event is MA, then the equity value at exit is computed using data on the fraction of equity transacted and the transaction value. If the venture's exit event is IPO, the equity value at exit is the pre-IPO equity value. If a venture is neither acquired nor listed, we assume its exit equity value is zero. This assumption leads to a conservative measure of the returns to the equity holders. Our measure treating investors and founders as a whole.

To evaluate the present value of the cash flows of ventures, we need to adjust the risk of the cash flows and discount them in a proper way. As mentioned earlier, apart from the PME, we use the Generalized Public Market Equivalent (GPME) method developed by Korteweg and Nagel (2016). In the GPME specification, the stochastic discount factor (SDF) M_{t+1} is an exponentially affine function given in Equation (1)[7].

$$M_{t+1} = exp(a - br_{m,t+1}) \tag{1}$$

where $r_{m,t+1}$ is the log return on the publicly traded equity market index portfolio, and the key parameters are a and b.

Korteweg and Nagel (2016) estimate the parameters for both the VC funds and the round-to-round returns. In the following analysis, we use their estimated parameters, and calculate the present value of cash flows using four specifications: NoDisc, PME, and GPMEround. NoDisc takes the nominal cash flows without any discounting. PME is the classic Public Market Equivalent approach, which is the case that $a = 0$ and $b = 1$. GPMEround is the Generalized Public Market Equivalent approach with SDF parameters estimated for round-to-round returns: $a = 0.033$ and $b = 1.444$.

[7]This is Equation (1) in Korteweg and Nagel (2016)

3.2 Cash Flows over the Life Cycle of the Ventures

Based on the investment performance measure for individual ventures – the present value of the life-cycle cash flows, we examine how the NPV changes with the holding period. In particular, we are interested in knowing the time to break even for the investors holding a portfolio of all ventures that had their first funding round at a given point in time. For each venture, we first discount the cash flows that occur within a given length of time, starting from the time of its first funding round. 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. Then we construct the cumulative discounted cash flows for each individual venture, for various holding periods during its life cycle. After that we aggregate the cumulative discounted cash flows of the ventures that had the first funding round in the same quarter. Based on that, for each quarter from 1992Q1 to 2006Q4, we calculate the break-even time of a hypothetical investor who invests in all the ventures that received the first funding round in the quarter. The break-even time is defined as the first time from the first funding round when the aggregate cumulative discounted cash inflows exceeds that of cash outflows. Figure 9 shows the break-even time series. We see that the break-even time varies from 5 quarters to 60 quarters, which depends substantially on the quarter of the first funding round. When the investor invests in the ventures receiving the first funding rounds after the second quarter of 1999 rather than before the second quarter of 1999, the break-even time is significantly longer .

After constructing the cumulative discounted cash flows for each individual ventures over their life cycles, we also aggregate the cumulative discounted cash flows across all the ventures, regardless of their first funding round time. Figure 10 plots the aggregate cumulative cash inflows, cash outflows and net cash inflows against the number of quarters from the first funding round. We have three observations. First, the aggregate cumulative cash flows does not show abrupt changes around the 15th year from the first funding round, confirming that treating cash flows after 15 years from the first round as occurring in the 15th year does not introduce abnormal impact. In fact, few ventures still receive funding or successfully exit after 15 years from the first round. Second, the cash outflows from investors is on average larger during the initial funding stages. In the aggregate, around 70% of the total funding is invested within 8 quarters from the first round. Third, 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, depending on the discounting method used. That is, VCs' investments will be locked in the ventures for a significantly long period of time.

The break-even time is different between our Group A ventures and Group AB ventures. Group A ventures are those with disclosed post-money valuation data, while Group B are those without. Consistent with the view that better ventures are more likely to release valuation information, 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 which in addition includes ventures without post-money valuation data. We note that the shapes of the curves of average cumulative cash flows and hence the break-even times are robust to the choice of discounting methods. The results using no discounting, PME discounting, and GPMEround discounting methods are all very similar.

[Figure 9 about here]

[Figure 10 about here]

3.3 Time Series of NPVs of Ventures' Aggregate Cash Flows

Based on the investment performance measure for individual ventures – the present value of the life-cycle cash flows, we also study the time variation of the NPV of ventures in the aggregate. In this subsection, for each venture, we first calculate its NPV. Then for each quarter, we aggregate the NPV of ventures that received the first funding round in that quarter. Then we normalize the aggregate NPV for that quarter, by the aggregate first-round post-money valuation in that quarter. NPV is normalized by the first-round post-money valuation because larger ventures usually have higher NPV, and the normalization prevents the profitability measure from being mechanically higher when the size of the venture sector is larger. If post-money valuation is missing, we substitute it with the first-round amount raised.

Figure 11 plots the time series of the aggregate NPV of ventures normalized by the aggregate first-round post-money valuation. In addition, it plots the time series of the two components of aggregate NPV – present value of cash inflows and present value of cash outflows. We have three observations. First, the profitability of investing in ventures, as measured by the aggregate normalized NPV, is volatile. This implies that investing in the ventures is risky even in the aggregate. Second, the time series of the present value of cash inflows and outflows reflect the spike of the venture investment around 2000. This is in part due to the boom of ventures. As shown in Figure 12, there were significantly more ventures receiving their first-round financing around 2000, compared to other time. Figure 12 also plots the time series of average NPV per venture by the first funding round's quarter. We see that the average NPV per venture shows similar patterns as that of the aggregate normalized NPV.

Third, Figure 11 show that the aggregate normalized NPV of ventures significantly declined after 1999. The aggregate normalized NPV of ventures that had their first-round of funding before 1999 is always positive, regardless of the discounting method and sample of ventures we use. However, after 1999 the aggregate normalized NPV fluctuates around zero if we focus on the sample of ventures that have first-round post-money valuation data (i.e., Group A ventures). The decline in the aggregate normalized NPV is significant when we focus on all the ventures (i.e., Group A& B ventures) as well. The plots seem to indicate there is a structural break in the time series of the aggregate normalized NPV around 1999. This is consistent with the findings reported in the literature based on other data. For example, using Burgiss data, Harris et al. (2014a) show that VC funds outperformed public equities in the 1990s, but under-performed in the 2000s. We examine whether there is a structural break in the data using statistical tests in the next section. As we show in a later section, the structural change is consistent with the observations in Ewens and Farre-Mensa (2019) that a regulatory event could have increased the supply of capital available for ventures.

[Figure 11 about here]

[Figure 12 about here]

4 Hypotheses and Tests

4.1 Structural Break in NPV Time Series

We start by assuming the aggregate normalized NPV follows a basic time series model. 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 date. The method involves a series of Wald tests over all the possible break dates in our sample horizon, where each individual Wald test compares the parameters estimates from the sample before and after the break date. Not all sample observations can be tested as break dates because there are insufficient observations to estimate the parameters for dates 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 to solve the structural break date identification problem.

Table 9 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. 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. We also conducted the test assuming that the aggregate normalized NPV follows an ARMA model, and used the Bayesian Information Criterion (BIC) to select the appropriate ARMA model. Then the Supremum Wald test is applied to the most appropriate ARMA model. The test also suggest a structural break in NPV time series around the end of the second quarter of 1999.

[Table 9 about here]

4.2 VC Experience and Venture Performance

Utilizing our measure of the investment performance for individual ventures – the normalized present value of the life-cycle cash flows, 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, consistent with related findings in the literature. A natural question that arises is whether it is possible to identify ventures that are more likely to be successful. We find that more than 64% of ventures have negative normalized NPV. [8] A large body of literature already shows that, among many factors, VC characteristics like experience, age, network, and reputation are associated with the performance of venture investments [9].

We study the relationship between VC experience and the performance of investing in ventures from a slightly different perspective. Specifically, we study whether experienced VC fund managers have the ability to differentiate the high-NPV ventures from the others in as early as the first round.

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

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

From an investor's perspective, this is the same as examining whether the first-round VC team's past experience can predict a venture's NPV.

We have two main results. First, VCs' past experience is highly correlated with the venture's performance before the structural break in 1999. Second, after the structural break, VCs' past experience is not significantly correlated with the venture's performance. The experience gained by the VCs from their past investments before the structural break seems to less relevant afterwards, which could be a reflection of the structural change in the composition of the ventures and the business environment.

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 within all the VCs based on the number of total funding rounds each 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 and we assign the indicator variable Top 30 VC = 1, otherwise we assign the venture the indicator variable Top 30 VC = 0. Using this measure, we study the relationship between the performance of investing in ventures and our measures of VC experience.

We examine whether the cumulative discounted cash flows is different when investing in a venture whose first round involves a Top 30 VC, compared to investing in a venture whose first round doesn't. Figure 13 compares the aggregate normalized cumulative cash flows of ventures whose first-round VC team includes TOP 30 VC and those whose does not, along their life cycles. We first 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. Then we also see that for both groups of ventures - those with Top 30 VC in the first rounds and those without, their cumulative cash flows curves exhibit a downward change if the first rounds are received after the structural break in 1999 rather than before the structural break.

[Figure 13 about here]

Further, we regress the venture's NPV normalized by the first round's raised amount 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 raised amount, year fixed effects, industry fixed effects and year-industry fixed effects. The cash flows are discounted using the Generalized Public

Market Equivalent method when calculating the NPVs, with parameters calibrated to round-to-round returns. We measure VC experience by checking whether the first round VCs include a top 30 VC ranked by the number of rounds invested in the past 10 years. 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 successful exits, continued financing in the next round, and bankruptcy, using information observed up to that time. 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 first round , where the weight is individual VC's total number of rounds invested in the past 10 years. We use the weighted average, in order that we do not over-emphasize the investment performance of small VCs which is noisily measured using information from only a few rounds they invested. Table 10 reports the regression results. 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 insignificant (as indicated by results in Column (3) and Column (6)), meaning that VC's experience from past investments seem to become obsolete after the structural break. The results are robust regardless of whether the regression uses the sample of all ventures (GroupAB), or the subsample of ventures whose first funding round post-money valuation data is non-missing (GroupA). 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.

[Table 10 about here]

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. Specifically, the quantile regressions study the relationship between any quantile of the outcome variable with explanatory variables. Figure 14 plots the coefficients on the explanatory variables from the quantile regressions fitting different quantiles of the outcome variable - venture's normalized NPV. Focusing on the period 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 the strong correlation at the high end of the distribution of normalized NPV. We see from the figure that the coefficient on the Top 30 VC dummy is close zero for ventures with normalized NPVs below the 30% quantile, meaning that experienced VC is not less likely to invest in the "bad" ventures. Instead, the coefficient has a sharp increase for ventures with normalized NPVs above the 70% quantile, meaning that experienced VC is much more likely to invest in the top 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.

[Figure 14 about here]

When we use successful exits including IPO and MA to proxy for the performance of the ventures instead of using our NPV measure, the results confirm the analysis above using the NPV measure. Specifically, we regress the venture's performance measure – an indicator variable for successful exits on a set of experience measures of the VC team invested in the venture's first funding round, together with control variables. Table 11 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.

[Table 11 about here]

We showed that first-round VCs' experience is positively related to the probability of a venture's successful exit including IPO and MA. However, VC can influence the venture's exit decisions, either by making the exit process easier[10] or by persuading the entrepreneurs directly. If there is conflict of interest between VC and other venture shareholders, or if the VC simply makes 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. We therefore study the relationship between VC experience and venture performance at the intensive margin, namely whether experienced VC is positively associated with ventures with higher 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

[10]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.

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 Generalized Public Market Equivalent method when calculating the NPVs, with parameters calibrated to round-to-round returns. Table 12 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 disappears (as indicated by results in Column (3) and Column (6)). This confirms with our previous finding that VC's past experience seems to become obsolete after the structural break. The results are robust regardless of whether the regression is based on the GroupAB sample, or the GroupA sample. Quantile regressions results shown in Figure 15

[Table 12 about here]

[Figure 15 about here]

We showed that the estimated relationship between VC experience and the venture's normalized NPV is vastly different before the structural break and after the structural break. The previous regressions were conducted on the whole sample period, while the control variables include industry fixed effects. 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 also conduct the regressions separately on the pre-break and post-break sample period. Table 13 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, normalized NPV conditional on successful exit. But these relationships disappear after the structural break. The results in Table 13 is based on regressions on the Group A sample. Although not shown here in the paper, the results are robust when we use the Group AB sample.

[Table 13 about here]

As we mentioned, the outcome variables – 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 issues make it hard to calculate appropriate standard errors of the coefficient estimates of the regressions. The double clustered standard errors partially address these issues. We further address this issue by using Fama-MacBeth regressions.

In the Fama-MacBeth regression, we run multiple cross-sectional regressions relating the venture performance measure to the VC experience measure, where each cross section is defined by ventures receiving the first funding round in a specific 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 we compute the Bootstrap standard errors.

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. Specifically, we use only the Top 30 VC variable as the VC experience measure, together with control variables including the first round's raised amount, and year-industry fixed effects.

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. Table 14 and 15 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, meaning that VC's experience from past investments seem to become obsolete after the structural break. 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 Table 14 and 15 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 Table 14 and 15 report the Fama-MacBeth regression results studying this 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. This confirms with our previous finding that VC's past experience seems to become obsolete after the structural break. These results are consistent with what we find using the double clustered standard errors.

[Table 14 about here]

[Table 15 about here]

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. Specifically, the quantile regressions study the relationship between any quantile of the outcome variable with explanatory variables. Figure 16 plot the coefficients on the explanatory variables from the quantile regressions fitting different quantiles of the outcome variable – venture's normalized NPV, where the explanatory variables are Top 30 VC and control variables including the first round's raised amount, and year-industry fixed effects. Both before and after 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 the strong correlation at the high end of the distribution of normalized NPV. We see from the figure that the coefficient on the Top 30 VC dummy is close zero for ventures with normalized NPVs below the 40% quantile, meaning that experienced VC is not less likely to invest in the "bad" ventures. Instead, the coefficient has a sharp increase for ventures with normalized NPVs above the 70% quantile, meaning that experienced VC is much more likely to invest in the top ventures. Figure 16 plots the results for Group A ventures. The results are very similar for Group AB ventures, and are omitted.

We also plot the coefficients on explanatory variables from the quantile regressions restricted to ventures with successful exits, to study the heterogeneity in the intensive margin. Figure 17 plots the results for Group A ventures, and results for Group AB ventures are similar. We see that conditional on exit, still the strong correlation between venture normalized NPV and VC experience concentrates at the high end of the distribution of normalized NPV, both before and after the structural break.

[Figure 16 about here]

[Figure 17 about here]

4.3 VC Experience and Venture Innovation

One criteria that the VCs use to select the ventures to invest is whether the venture is innovative enough. Innovative ventures tend to have niche in the industry, and have higher profitability. Having documented that VC experience is closely related to the venture's performance measured by NPV and successful exits, we now study the relationship between VC experience and the venture's innovation activity. Specifically, we study whether experienced VC fund managers have the ability to differentiate innovative ventures from the others in as early as the first round. For this purpose we use the number of patent grants and patent citations during the life time of a venture as the measure of innovation. We regress the venture's lifetime number of patents and patent citations 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. Table 16 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 the innovative ventures. The results are robust regardless of whether the regression uses Group A ventures or Group AB ventures.

[Table 16 about here]

We also adopt the Fama-MacBeth regressions to address the complicated correlations in the model's error terms among ventures, similarly as before. To compare the relationship before and after the structural break, we conduct the Fama-MacBeth regressions for the pre-break and post-break period separately. Table 17 and Table 18 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 innovative ventures. The results are robust regardless of whether the regression uses Group A ventures or Group AB ventures.

[Table 17 about here]

[Table 18 about here]

4.4 VC Experience and Venture Founder's Bargaining Power

The structural break in the time series of the aggregate normalized NPV of ventures is an intriguing phenomenon. The drop in the aggregate normalized NPV after the structural break may reflect the fact that fewer startups go public in the recent decades, and those that do are older. More ventures are able to continue receive funding from private capital for a longer period of time in their late stage and thereby delaying their exit events. Ewens and Farre-Mensa (2019) studies this issue and finds that the deregulation of securities laws – in particular the National Securities Markets Improvement Act (NSMIA) of 1996 – increased the supply of private capital to late-stage private startups. According to the paper, the increased supply of financing increased the bargaining power of the venture founders. And venture founders are using their increased bargaining power relative to investors to stay private longer.

We study the venture founder's bargaining power before and after the structural break, by studying the relationship between VC experience and 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 a set of 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 19 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 take more shares from the venture in the first round. However, this relationship disappears after the structural break. This seems to imply the experienced VCs (usually large in size as well) lost their bargaining power relative to the venture founders after the structural break. Our result is consistent with the findings of Ewens and Farre-Mensa (2019), where the founders have more bargaining power after the regulation change in 1996, and also shows that the change in bargaining power occurs also in the early stage.

[Table 19 about here]

Table 20 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 take more shares from the venture in the first round. However, this relationship weakens after the structural break.

[Table 20 about here]

5 Conclusion

In this paper, we examine the return to venture investments based on funding round information for each venture. A major difficulty in the use of funding round level data is that valuation information is missing for many of the rounds. We address this issue by examining the return to the group of all equity investors in a venture during its entire life time. For computing the net present value (NPV) of all investments in a venture, we use the Public Market Equivalent method in Kaplan and Schoar (2005) and the Generalized Public Market Equivalent method in Korteweg and Nagel (2016).

We examine all US-based ventures in VentureXpert that had their first funding rounds before 2006. Since our data covers the period ending in December 2018, ventures had at least 12 years to exit, giving us sufficient confidence that we are measuring venture returns right. The data consists of 16,396 ventures and 57,884 funding rounds between 1980 and 2018. We find that for an investor in a portfolio of all ventures that had their funding rounds in a given quarter, the average holding period for breaking even (i.e., the NPV to become positive) is between 5 and 60 quarters – depending on the calendar quarter of the first rounds. That is, even for an investor who holds a diversified portfolio of all ventures that originated at a given quarter, money can be be locked in for as long as 15 years before breaking even.

We also find that the profitability of investing in ventures varies substantially over time even in the aggregate. Further, we find a structural break in the second quarter of 1999. After which ventures are less profitable on average – ventures that had the first rounds before 1999 have positive NPV in the aggregate, i.e., there was a return premium to investing in the ventures over investing in the public market. Ventures that had the first rounds between 1999 and 2006 were no more profitable in the aggregate than investing in the stock index portfolio.

We find that experienced VCs tend to invest in the ventures that have better future performance on average, as early as in the first funding round. We measure venture performance by its NPV and whether it had a successful exit. Among ventures with successful exits, experienced VCs tend to invest in high-NPV ventures in the first funding round. These relationships are pronounced before the structural break in 1999, and weaken after the break. This suggests that VCs' experience measured based on the participation on past ventures became less relevant after the structural break in 1999. It appears that the more experienced VCs have less bargaining power after the break. Founders give less shares of their firms to such VCs. This is consistent with Ewens and Farre-Mensa (2019)'s argument that the National Securities Markets Improvement Act in 1996 increased the supply of funding to ventures.

We also find that ventures that had more experienced VC investors in their first round on average have larger number of patent-grants and citations during their life cycle. This relationship holds both before and after the structural break in 1999.

Table 1: Analysis of Ventures Alive in VentureXpert

SDC Outcomes\Outcomes in Other Data	Alive	BR	IPO	MA	Total	Outcomes Based on
	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 M&A 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 M&A solely in other data sources and with exit values.

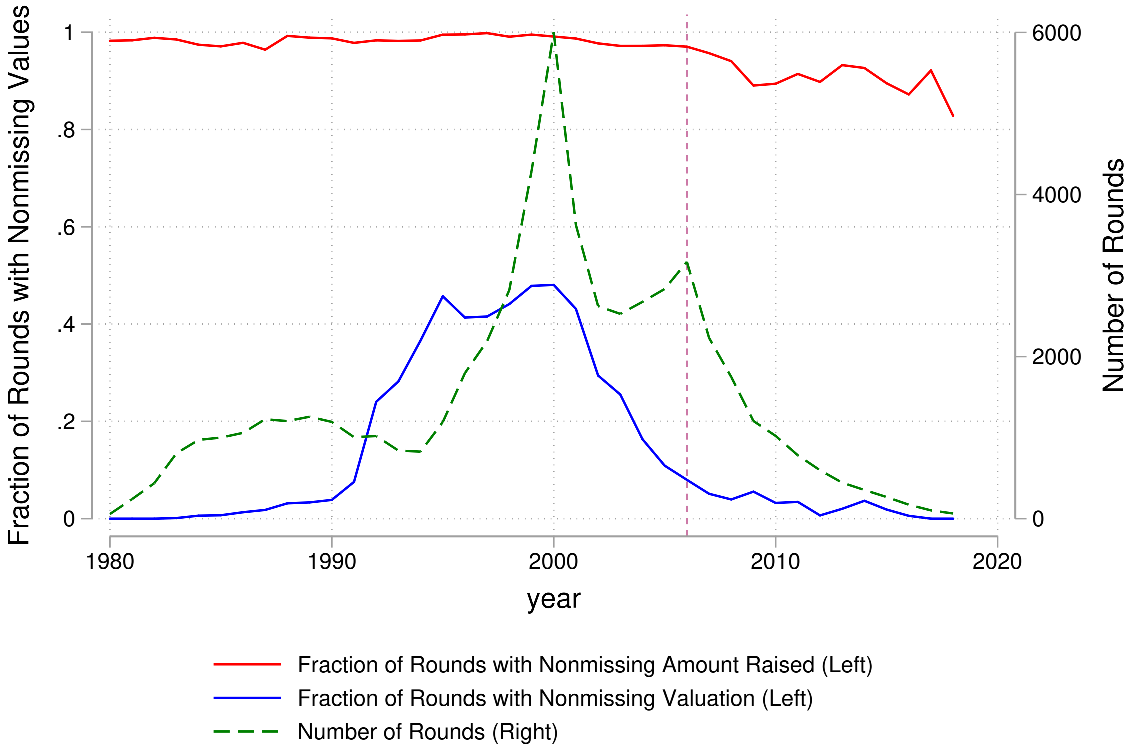


Figure 1: Fraction of Rounds with Nonmissing Data in Each Year

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.

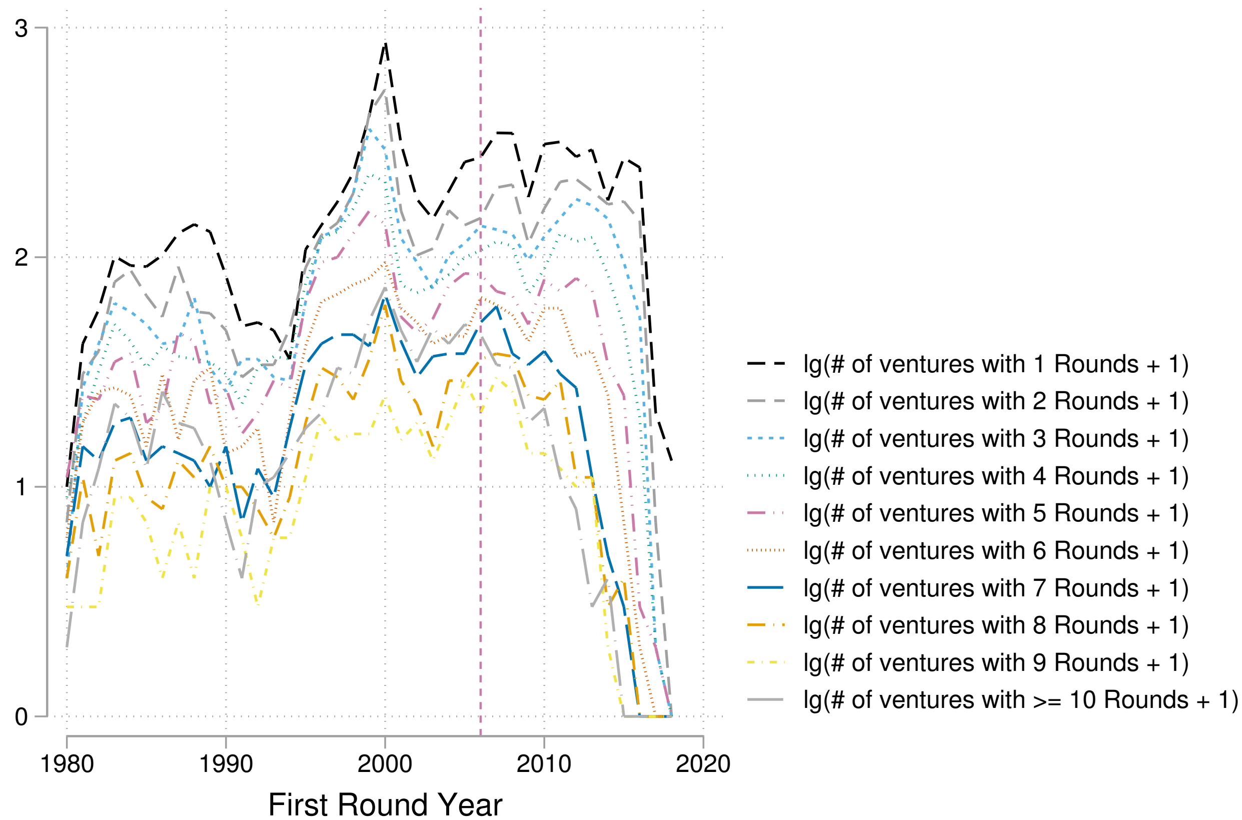


Figure 2: Ventures with Different Lifetime Total Funding Rounds by the First-Round Years

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 and receive in total more than one round 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.

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%

M&A 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 M&A 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 6: 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 5: 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 7: 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 8: 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

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

In parenthesis are standard errors.

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.

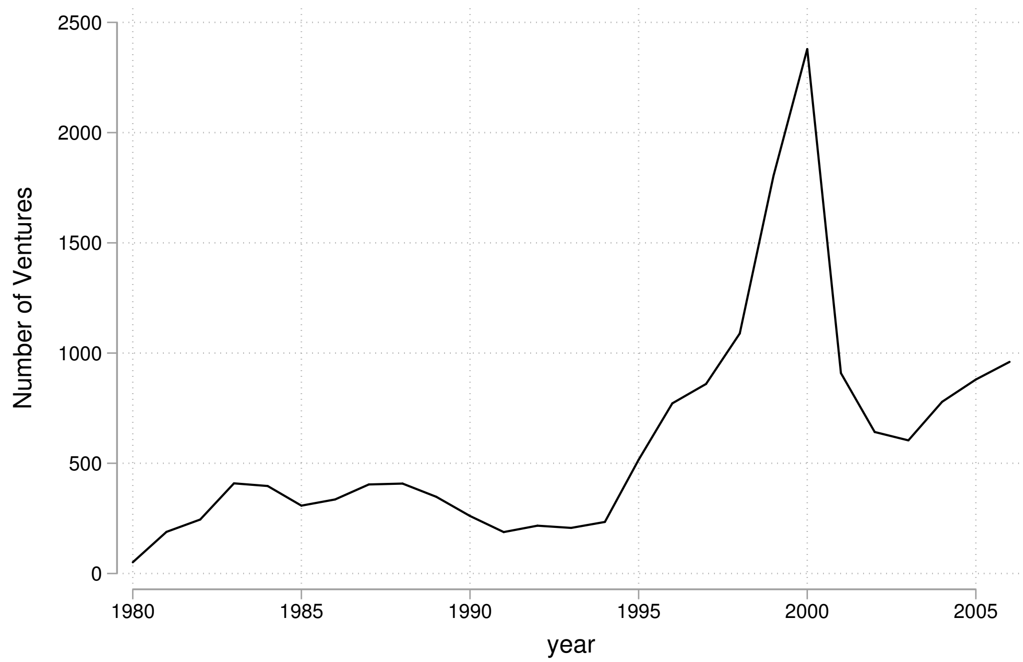


Figure 3: Number of Ventures by the Year of the First Round

Note: Figure plots for each year from 1980 to 2006, the number of ventures whose first funding rounds are in that year. The sample includes all the US-based ventures in the SDC VentureXpert database that had the first funding round prior to 2006.

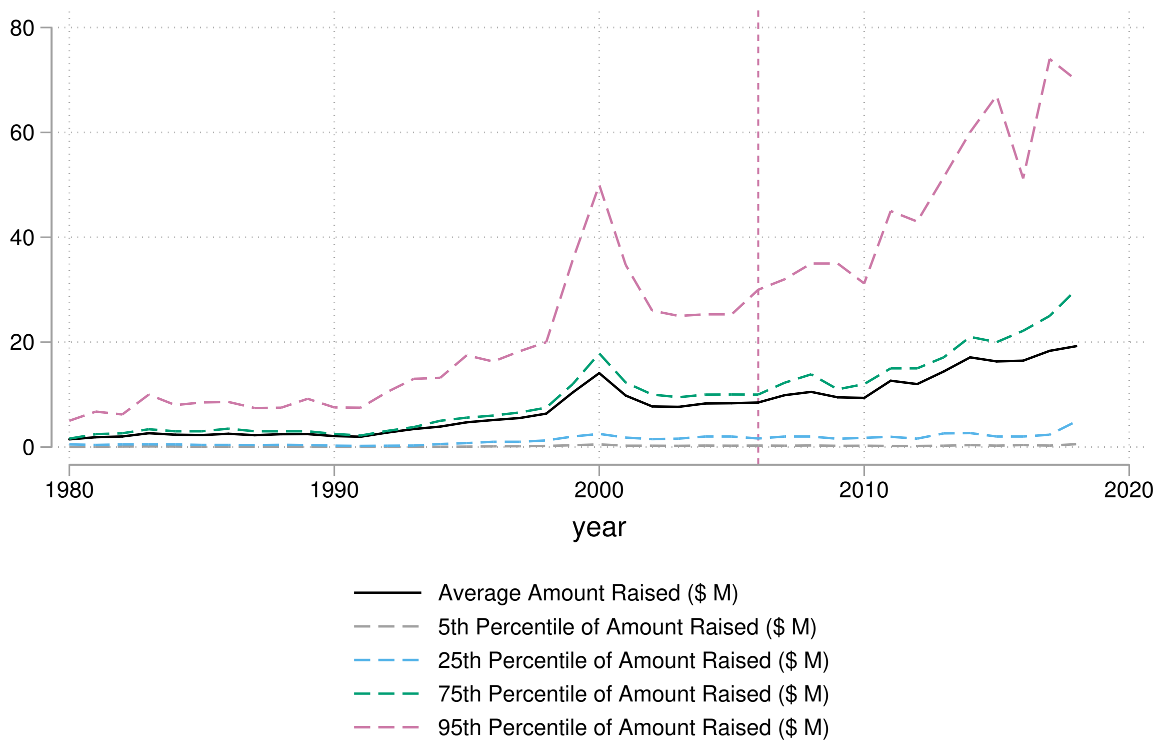


Figure 4: Amount Raised in the Funding Rounds by the Year of the Rounds

Note: Figure 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 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.

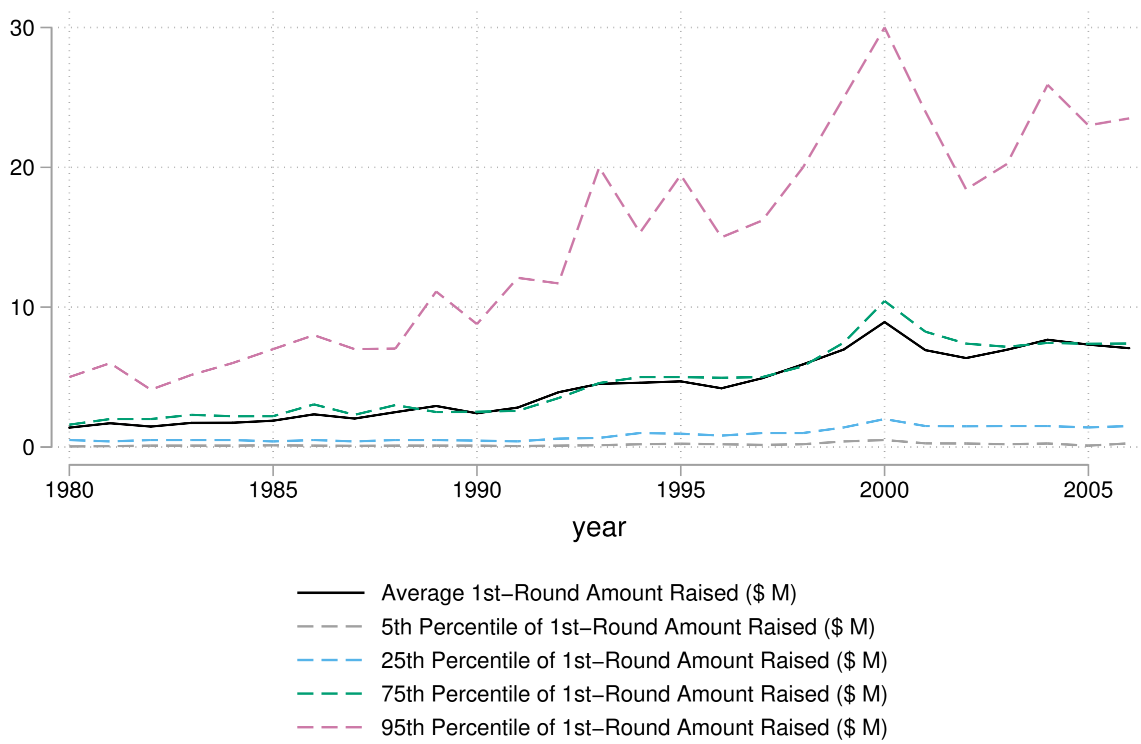


Figure 5: First-round Amount Raised by the Year of the Rounds

Note: Figure 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.

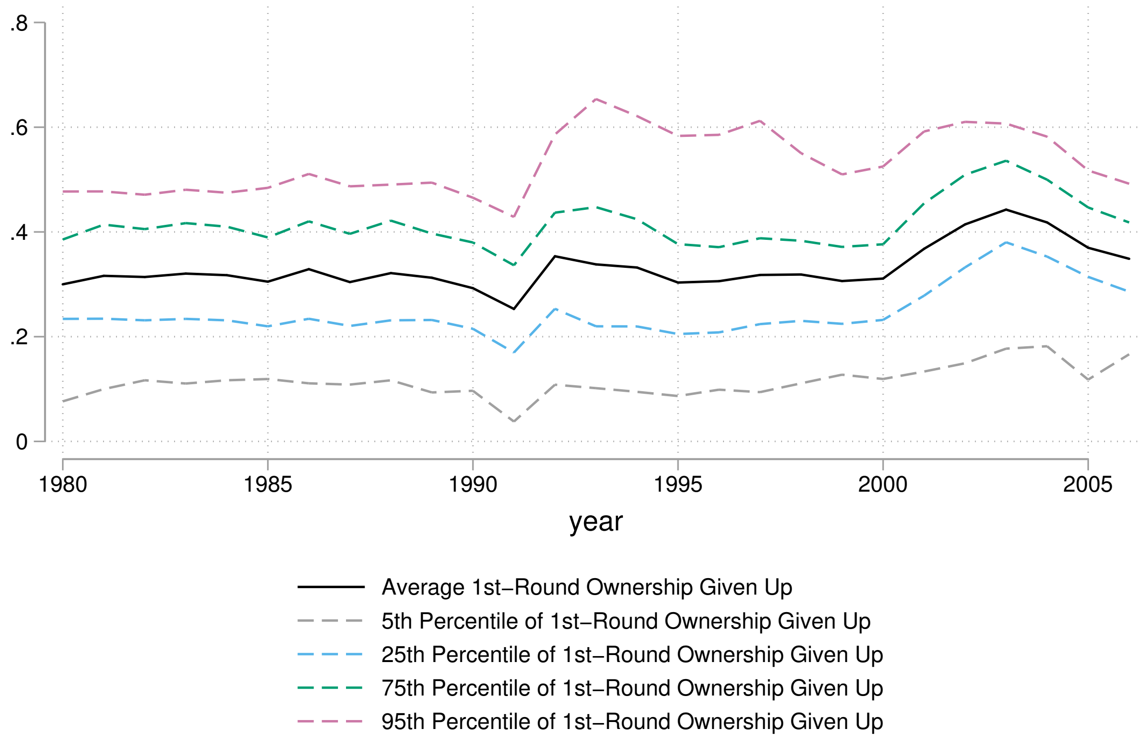
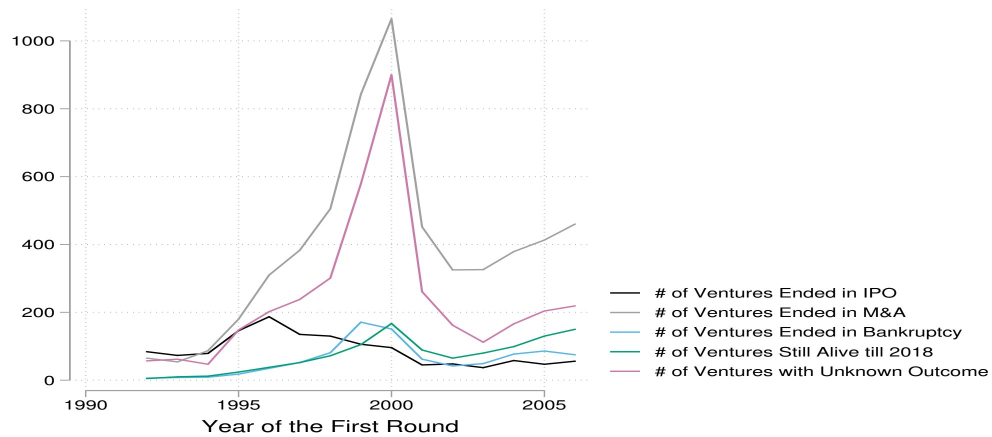
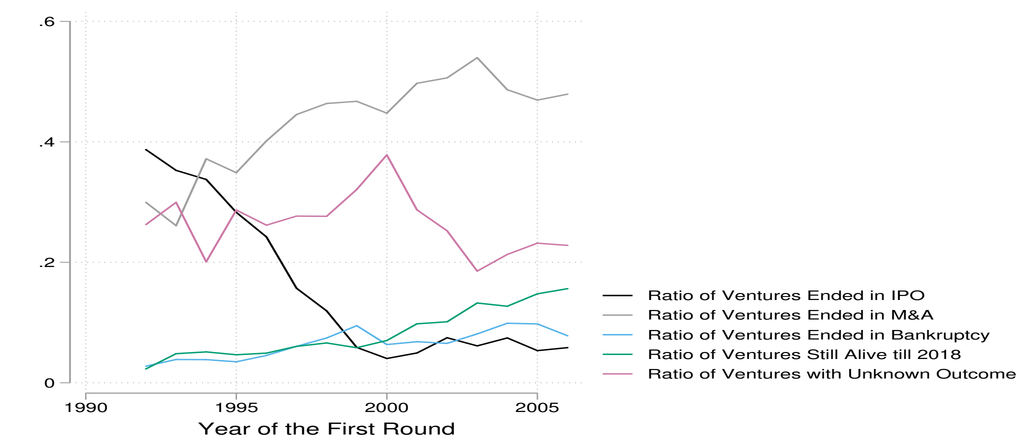


Figure 6: First-round Ownership Given Up by the Year of the Rounds

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. As for the ventures for which data for the ownership given up calculation is missing, we impute their ownership given up using the logit model described before.



(a) Number of Ventures



(b) Fraction of Ventures

Figure 7: 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 those US-based ventures in the SDC VentureXpert database, and their outcome information comes mainly from IPO and M&A databses in SDC Platinum, but supplemented by various other sources including Pitchbook and Bloomberg. 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 as having Unknown Outcomes.

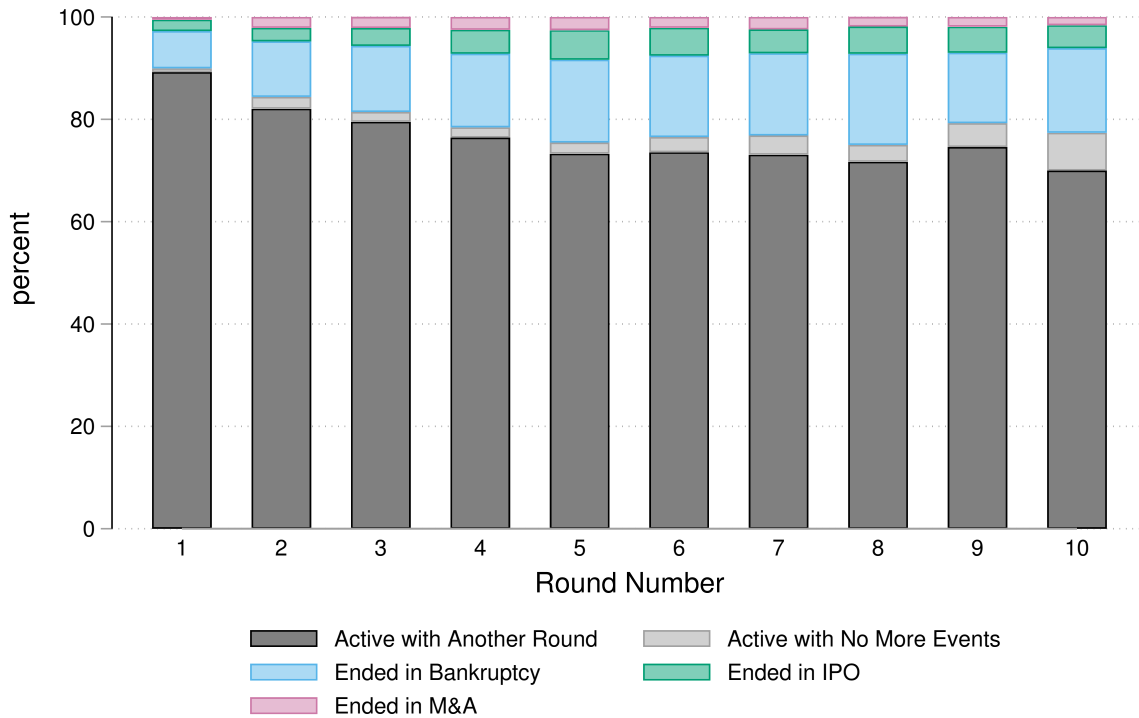
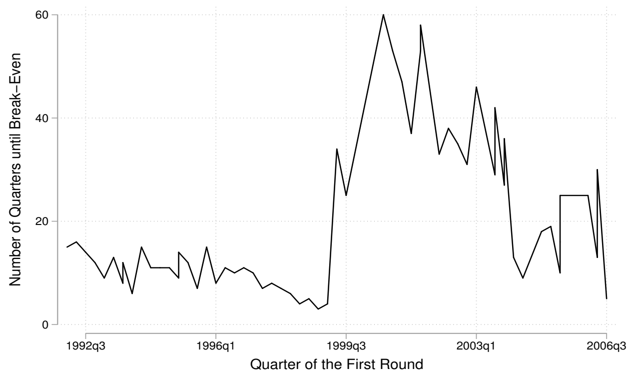
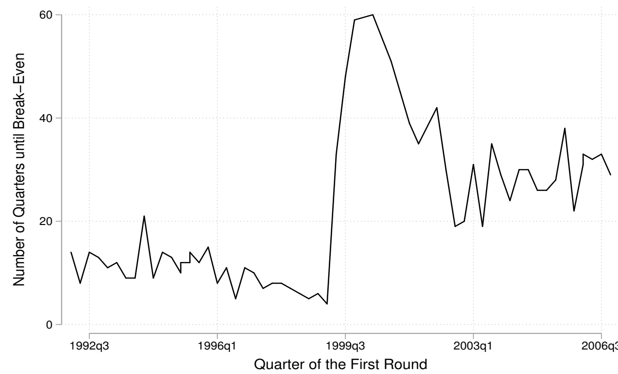


Figure 8: Distribution of Next Event by Round

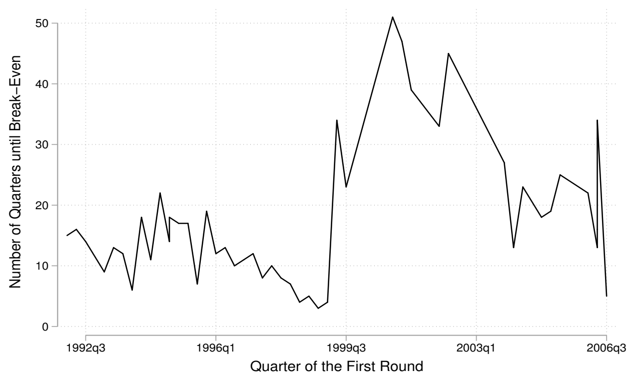
Note: When a venture receives a funding round, the next event that occurs is one of the following: (1) it remains active and receives another funding round, (2) it goes to bankruptcy, (3) it goes to M&A, (4) it goes to IPO, and (5) it remains active but we observe no continued funding or exit events. 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 ventures are those US-based ventures in SDC VentureXpert database that had the first funding round prior to 2006.



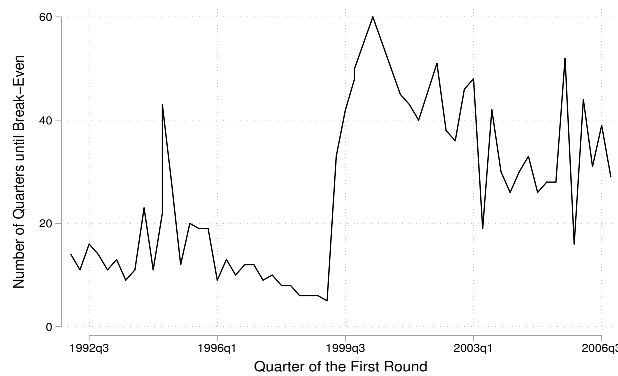
(a) No Discounting, Group A



(b) No Discounting, Group AB



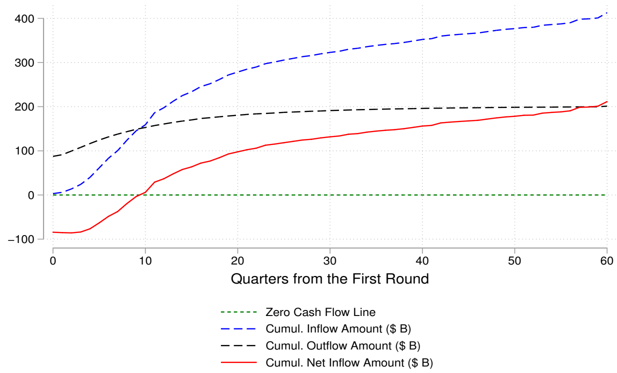
(c) GPMEround, Group A



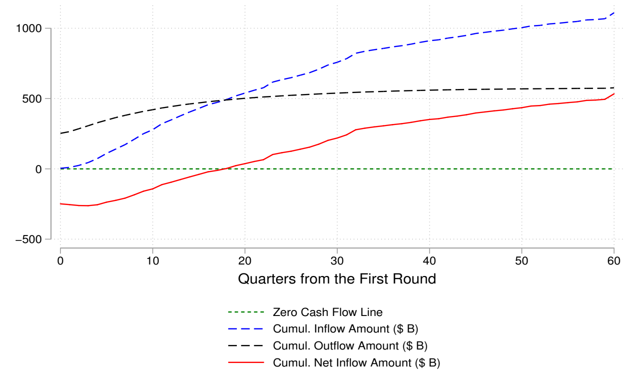
(d) GPMEround, Group AB

Figure 9: Break-even Time by the First-Round Time

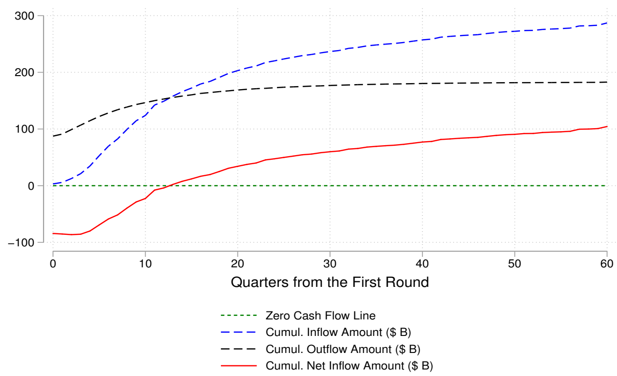
Note: For ventures that received the first funding round in each quarter, Figure plots the aggregate break-even time of investing in these ventures – i.e., the number of quarters from the the first round after which the aggregate cumulative net cash inflows from all these ventures becomes positive. Net cash inflows are either not discounted, or discounted to the venture's first funding round date using the GPMEround method. 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. The left panels restrict the sample to Group A ventures, and the right panels restrict the sample to Group AB ventures.



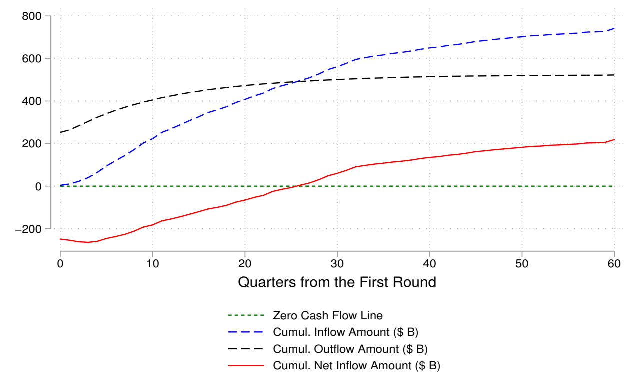
(a) No Discounting, Group A



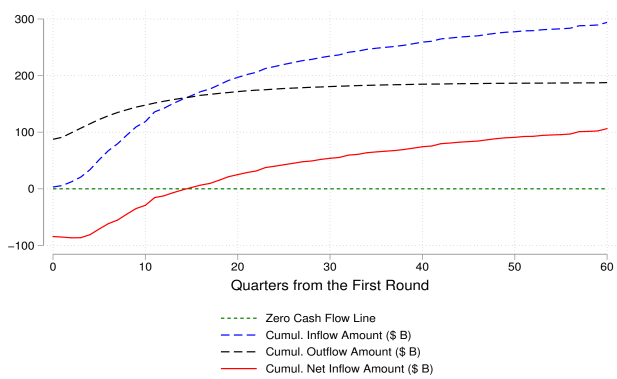
(b) No Discounting, Group AB



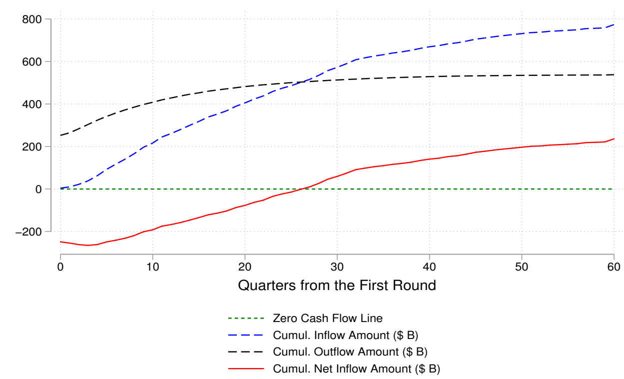
(c) PME, Group A



(d) PME, Group AB



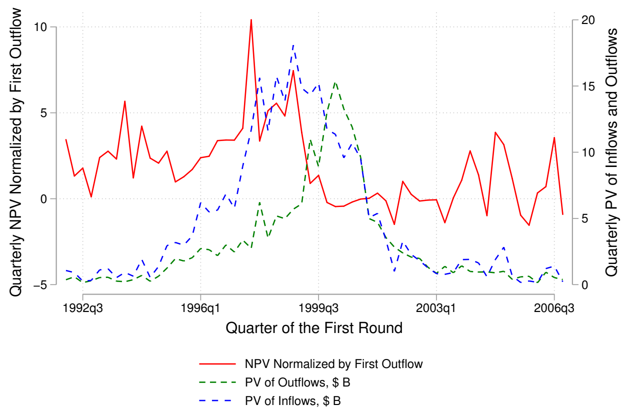
(e) GPMEround, Group A



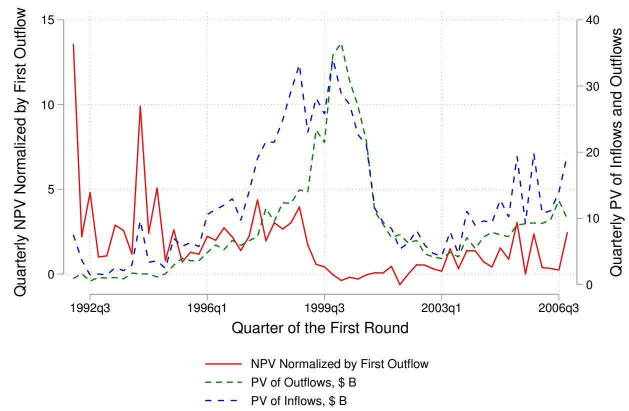
(f) GPMEround, Group AB

Figure 10: Cumulative Cash Flows by Quarters from the First Round

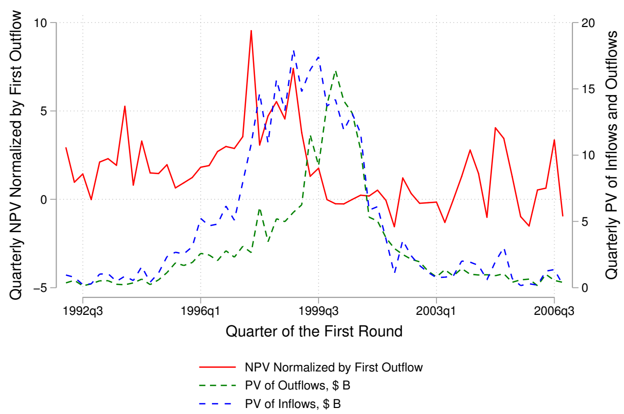
Note: Over the life cycle of the venture, Figure plots the aggregate cumulative cash inflow, aggregate cumulative cash outflow and aggregate cumulative net cash flow for investors investing in the portfolio of US-based ventures in SDC VentureXpert database who had the first funding round prior to 2006.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



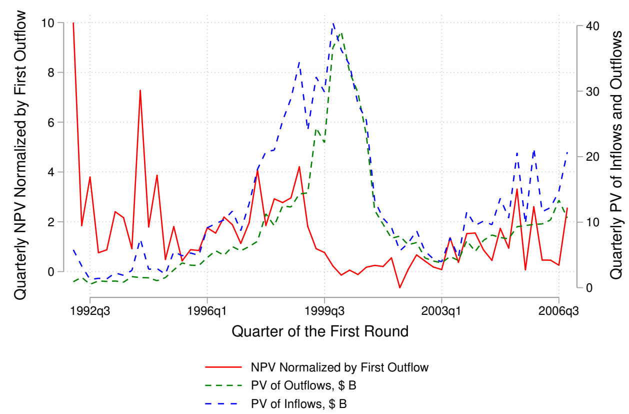
(a) PME, Group A



(b) PME, Group AB



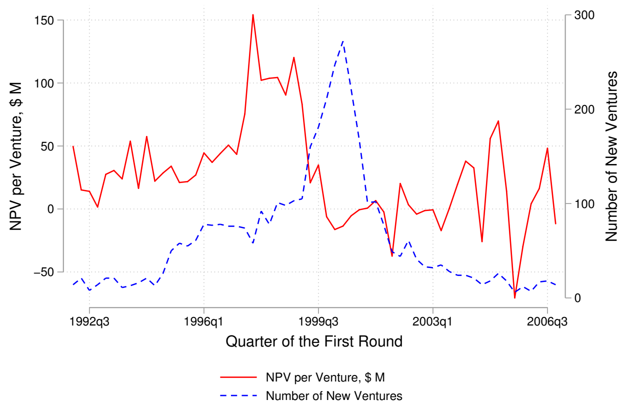
(c) GPMEround, Group A



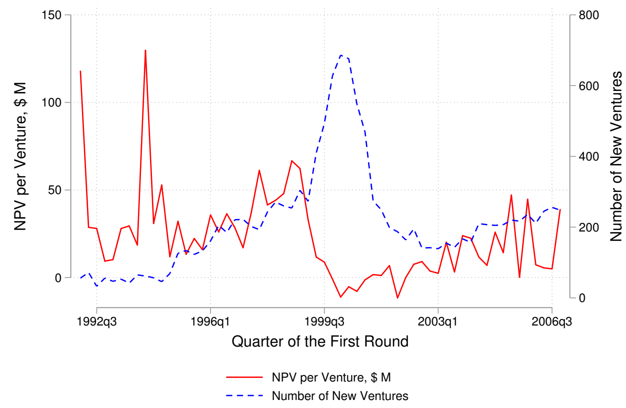
(d) GPMEround, Group AB

Figure 11: Normalized Inflow, Normalized Outflow, and Normalized NPV

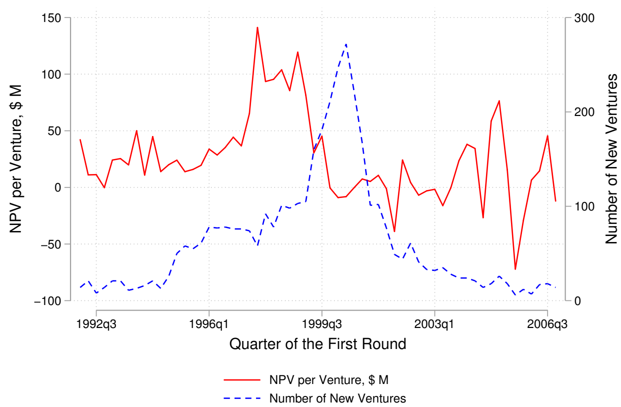
Note: Figure plots the aggregate NPV normalized by first-round post-money valuation, aggregated cash inflow and aggregate cash outflow by the first-round time of ventures. The sample includes US-based ventures in SDC VentureXpert database that had the first funding round prior to 2006. Group A includes 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.



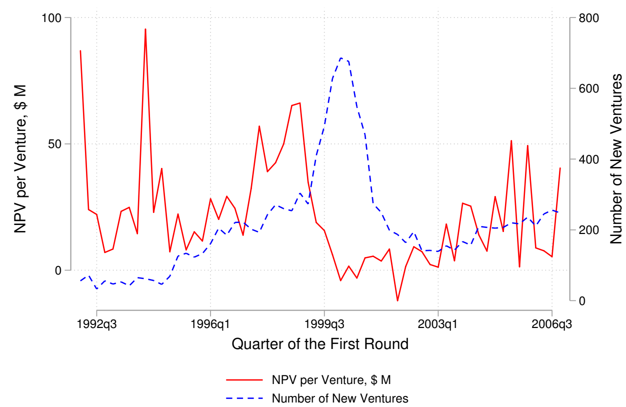
(a) PME, Group A



(b) PME, Group AB



(c) GPMEround, Group A



(d) GPMEround, Group AB

Figure 12: Number of Ventures and NPV

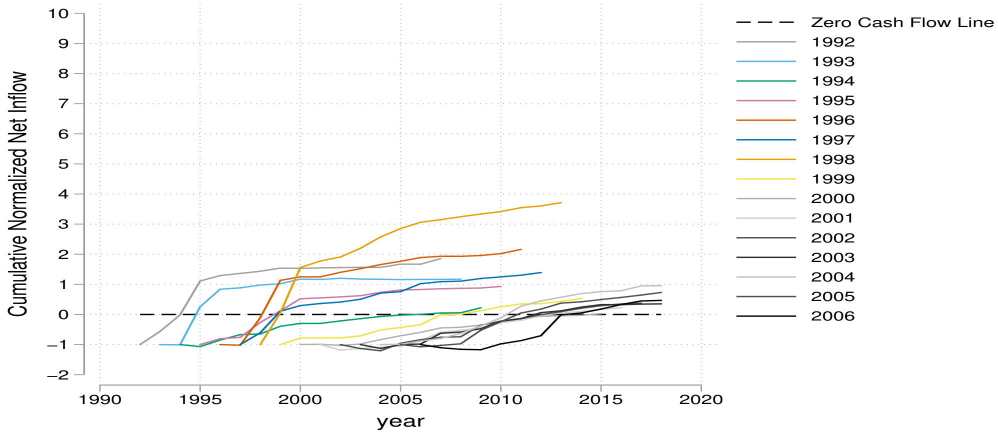
Note: Figure plots the average NPV per venture and the number of ventures by the first-round time of ventures. The sample includes US-based ventures in SDC VentureXpert database that had the first funding round prior to 2006. Group A includes the ventures that have post-money valuation data for the first 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.

Table 9: Test Statistics for Structural Break: Constant and AR(1) Models

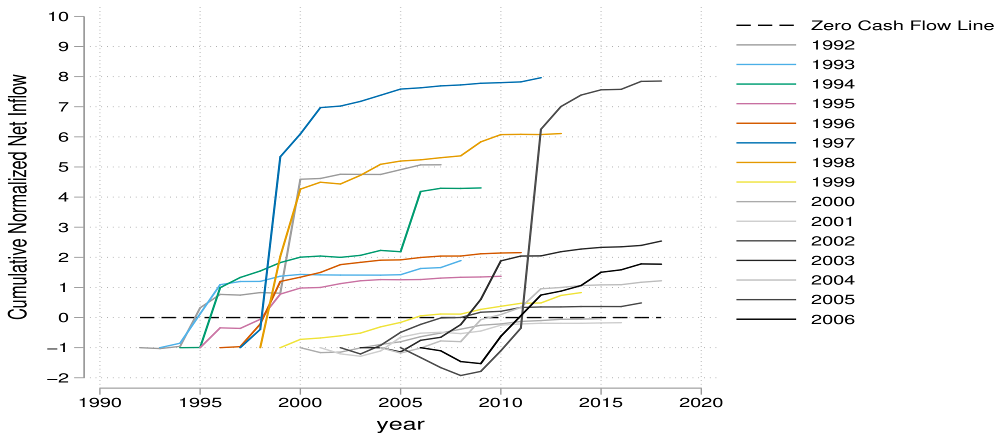
Normalized NPV_t	(1)	(2)	(3)	(4)	(5)	(6)
Constant	2.029***	1.864***	1.875***	0.901**	0.897***	1.483***
	(0.295)	(0.276)	(0.228)	(0.346)	(0.330)	(0.261)
Normalized NPV_{t-1}				0.533***	0.499***	0.135
				(0.113)	(0.116)	(0.102)
Observations	60	60	60	59	59	59
R-squared	0.000	0.000	0.000	0.282	0.246	0.030
Sample	GroupA	GroupA	GroupAB	GroupA	GroupA	GroupAB
Discounting	PME	GPMEround	GPMEround	PME	GPMEround	GPMEround
Break Date	1999Q2	1999Q2	1999Q2	1999Q2	1999Q2	1999Q2
Chi-squared	35.04	22.08	15.49	13.21	9.12	15.53
DF	1	1	1	2	2	2
P Value	0.000	0.000	0.002	0.025	0.134	0.009

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

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.



(a) 1st-Round without Top 30 VC



(b) 1st-Round with Top 30 VC

Figure 13: 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 under study includes both Group A (ventures that have post-money valuation data for the first round) and Group B(ventures that do not have post-money valuation for the first round). 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 10: 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 × 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
Discounting	GPMEround	GPMEround	GPMEround	GPMEround	GPMEround	GPMEround
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 NPV normalized by first outflow 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.

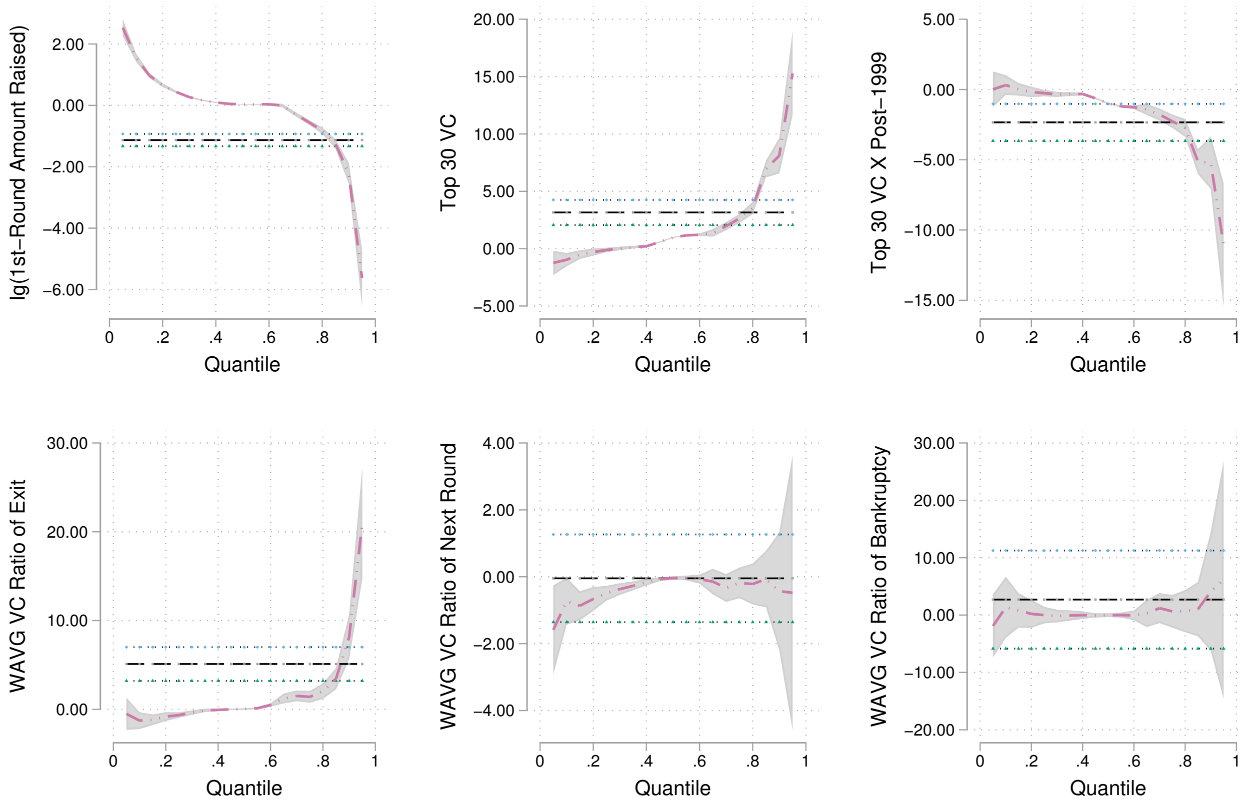


Figure 14: Quantile Regression of Normalized NPV

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. The sample of ventures includes both Group A (those with first-round post-money valuation data) and Group B (those without).

Table 11: 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 12: 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
Discounting	GPMEround	GPMEround	GPMEround	GPMEround	GPMEround	GPMEround
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 outlow on a set of experience measures of the VC team invested in the venture's first funding round, together with control variables. 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.

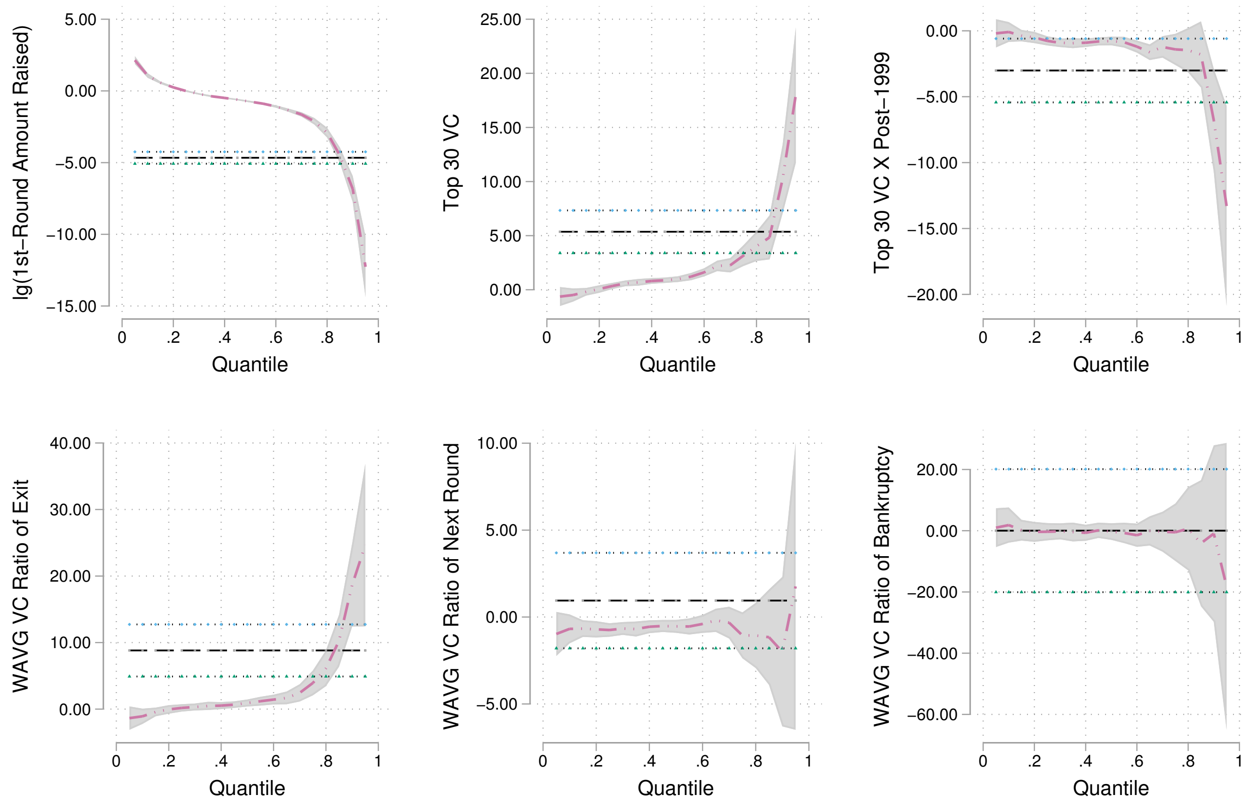


Figure 15: Quantile Regression of Normalized NPV of Exited Ventures (GPMEround, Group AB)

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. 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).

Table 13: 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
Discounting	GPMEround	GPMEround	GPMEround	GPMEround	GPMEround	GPMEround
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, 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. 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 14: Past Experience of 1st-Round VCs and Performance: Fama-MacBeth Regression by Period on Group A Ventures

VARIABLES	Normalized NPV		IPO or M&A 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.

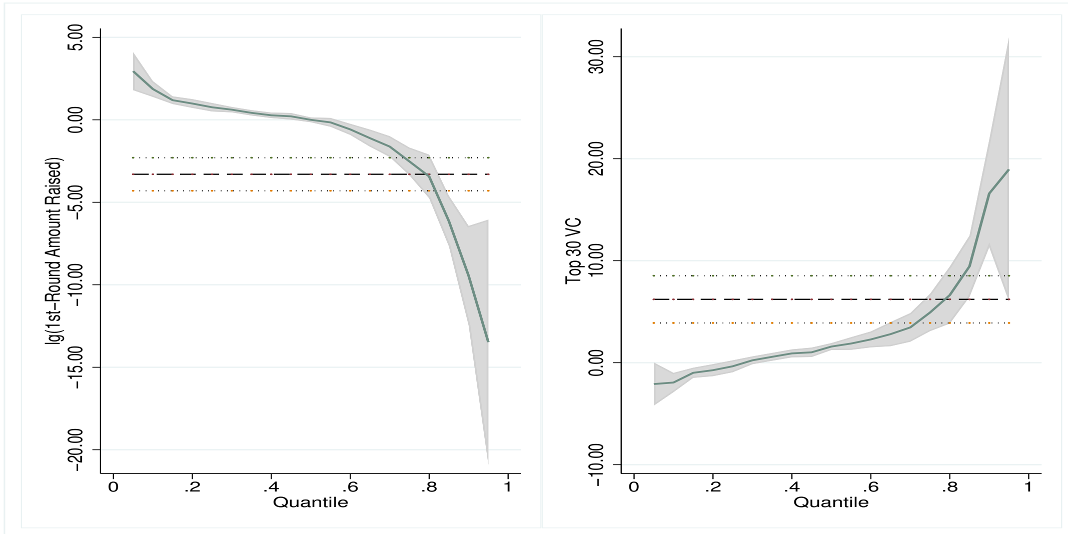
Table 15: Past Experience of 1st-Round VCs and Performance: Fama-MacBeth Regression by Period on Group AB Ventures

VARIABLES	Normalized NPV		IPO or M&A 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

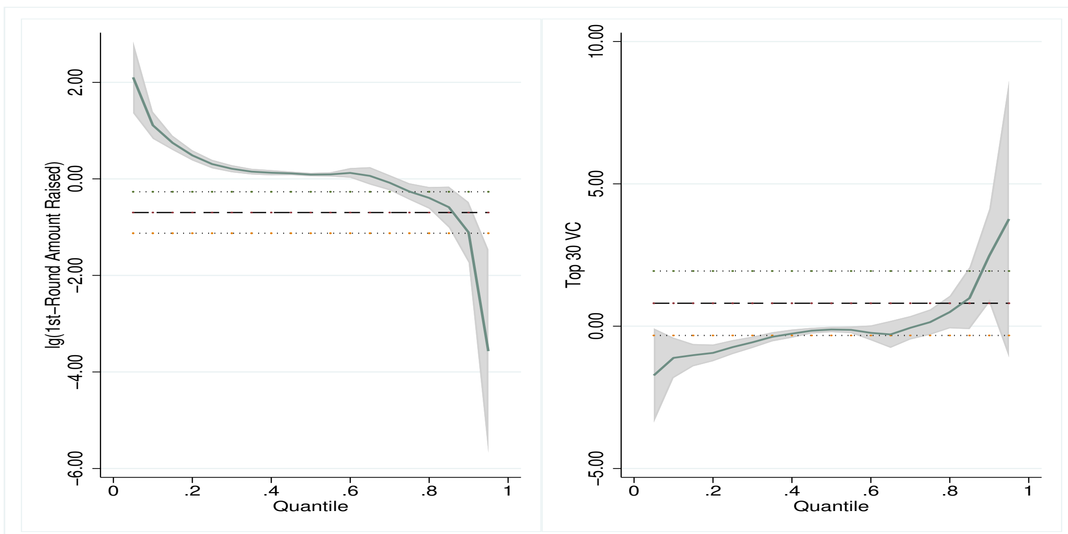
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$ according to Bootstrap p-value

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.



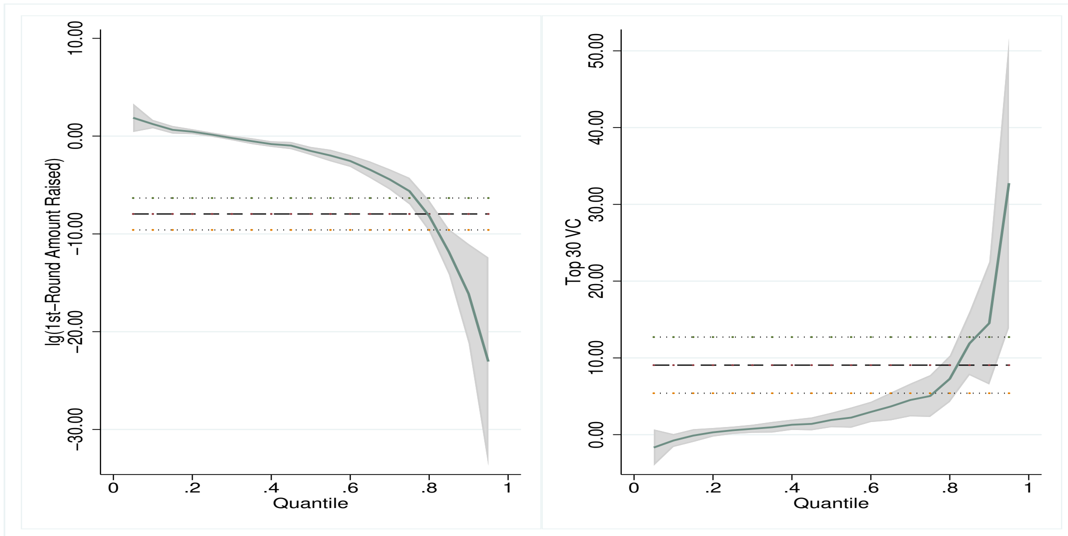
(a) Before the Structural Break



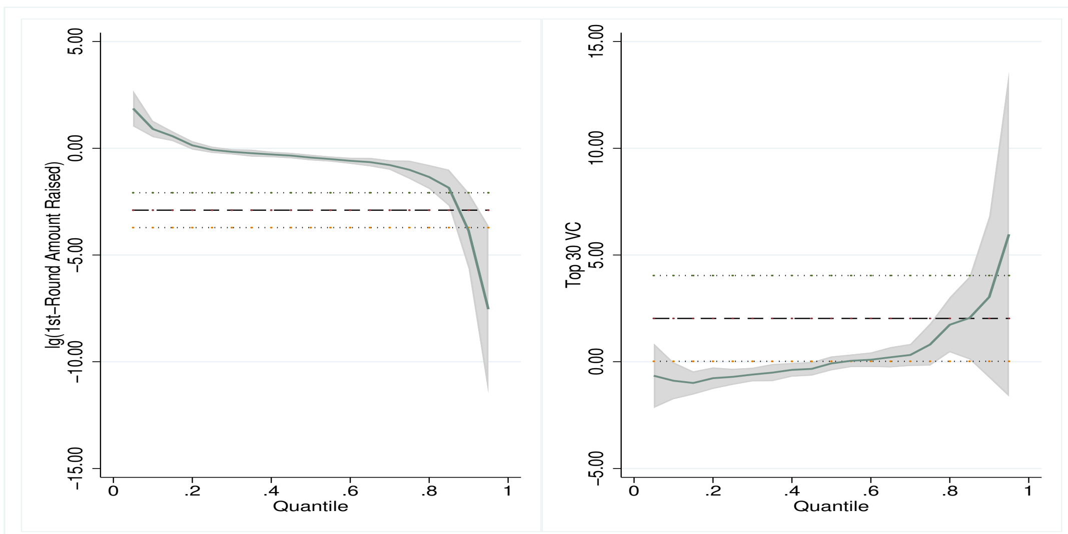
(b) After the Structural Break

Figure 16: 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 17: 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.

Table 16: 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 17: 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 18: 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.

Table 19: 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.

Table 20: 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.

A Appendix

A.1 Data Sources and Data Cleaning

Table 21 lists the venture IPOs that occurred according to other data sources while we do not find in the VentureXpert database .

Table 21: 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	

A.2 Imputation of 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.

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

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, we impute the missing values using linear regression models given below.

$$Valuation_i = \alpha + \beta_1 \overline{Valuation}_i + \beta_2 lastPMVtoExit_i + \beta_3 \overline{Valuation}_i \times lastPMVtoExit_i + \beta_4 \log FinalAmountRaised_i + \beta_5 FinalRoundtoExit_i + \beta_6 NASDAQReturn_i + \epsilon_i \quad (3)$$

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. $FinalRoundtoExit_i$ is the number of days from venture i's last funding round to the its exit. $NASDAQReturn_i$ is the cumulative NASDAQ stock return from venture i's last funding round to its exit.

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