Predicting Success in Entrepreneurial Finance Research

Emmanuel Yimfor
Jon A. Garfinkel

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Abstract

We study the relationship between buyout and venture capital (VC) funds' returns, and more typically available proxies - exits via M&A or IPO. We further explore the effects of filters on the selection of M&As and IPOs (to emphasize successes), on the relationship. We show that some of these filters can reduce the count of exits by as much as 80% without significantly improving the correlation between exits and fund returns. We also show that for venture capital funds, counting acquisitions that are at least twice the amount of funding raised results in the best correlation between exits via an acquisition and fund returns. Finally, when the sample comprises young startups - that are perhaps not yet ready for any form of exit - follow-on funding, employment, website ranking, and patent activity can be used as proxies for exits in place of IPOs or acquisitions.

JEL: G24, G30, G34, M14
Keywords: IPO, Acquisition, TVPI, Startups, Patents

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We study the relationship between buyout and venture capital (VC) funds' returns, and more typically available proxies - exits via M&A or IPO. We further explore the effects of filters on the selection of M&As and IPOs (to emphasize successes), on the relationship. We show that some of these filters can reduce the count of exits by as much as 80% without significantly improving the correlation between exits and fund returns. We also show that for venture capital funds, counting acquisitions that are at least twice the amount of funding raised results in the best correlation between exits via an acquisition and fund returns. Finally, when the sample comprises young startups - that are perhaps not yet ready for any form of exit - follow-on funding, employment, website ranking, and patent activity can be used as proxies for exits in place of IPOs or acquisitions.

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1. Introduction

Entrepreneurial finance researchers are frequently interested in how some variable affects the performance of private equity and venture capital groups or startups. The straight-forward approach would be to regress a measure of group performance such as fund returns on the variable of interest. However, private equity groups' fund returns are hard to come by. They are not available in the more commonly used academic databases, and the databases that *do report* private equity and VC fund returns are quite expensive. Thus researchers often proxy investment success with initial public offerings (IPOs) and acquisitions of startups - i.e. exits. (See, e.g., Howell (2017); Bernstein et al. (2016); Ewens and Townsend (2020); Nanda et al. (2020); Ewens and Farre-Mensa (2020).) This raises a natural question: are the proxies well-correlated with private equity and VC fund returns? We propose to answer this question.

There are reasonable concerns that cast doubt on the empirical validity of exits as proxies for returns in private capital. First, when researchers use exits in place of fund returns, they often impose a variety of filters. While some studies use only IPOs to measure success (e.g., Gompers et al. (2016); Farre-Mensa et al. (2020)), other researchers use IPOs and acquisitions (e.g., Hegde and Tumlinson (2014); Howell (2017)). Still others impose filters such as defining a successful IPO or acquisition as one that occurs only within a fixed number of years following a funding round (e.g., Gompers et al. (2008); Ewens and Farre-Mensa (2020)), or restricting acquisitions to be above a certain sale price or multiple of funding raised (e.g., Gompers et al. (2008); Bernstein et al. (2016); Ewens and Marx (2018)).[1] To the extent that the goal of researchers (imposing these filters) is to select the set of deals most highly correlated with cross-sectional variation in fund returns, research is needed to establish which filters - or combination of filters - do so. Filling this void in the literature is a primary goal of this paper.

[1] See Table A.10 for a fuller listing of different papers and the filters they employ.

Better understanding these filters has additional important implications for research. Because exits are often used as a dependent variable, utilizing these filters (for example when an exit via M&A does not clear a pricing threshold and is thus labeled zero) can introduce measurement bias in the estimated effect of independent variables. The bias would depend on the relationship between the filter and the independent variables, which is not commonly investigated by researchers. Thus, it is important to understand whether, and/or to what extent, these filters improve the correlation between exits and returns.

The traditional usage of exits to proxy success of funds that own the exiting company poses another concern. When the sample of startups comprises young firms, many of which are years away from an exit, the proportion of current exits might not mirror the proportion of future exits. Consequently, logistic regressions of exit outcomes on an independent variable can yield biased estimates (King and Zeng (2001)). For such samples, it may be important to use other proxies that have more cross-sectional variation and are related to eventual exits. Prior studies have used a variety of proxies (such as whether the startup raises a follow-on round of funding), but there has been little systematic study of the relationship between these proxies and eventual exits. Filling this gap in the literature is a third key goal of this study.

We speak to these issues and hope to contribute to the literatures on early stage financing and performance. Underlying our contribution is our main datasource, PitchBook, which includes information on fund returns. We study the general relationship between buyout and (separately) VC fund returns, and the more commonly-used investment success proxies of IPOs and M&As. We quantify the effect of restrictions on exit counts, and whether such filtering of exits improves correlation with returns. We also examine which characteristics of early-stage startups are correlated with eventual exits. Such characteristics may be used when there is little cross-sectional variation in future exits, such as when the sample mainly comprises young firms that are years away from an exit.

Our final sample comprises 927 buyout and 701 venture capital funds with vintage years between 1996 and 2010.[2] For these funds, we have data on two measures of fund returns: the total value to paid-in capital, TVPI, and internal rate of return, IRR. Note that most of these funds will have liquidated most of their investments by 2021, given the typical fund life of 10 years (Gompers et al., 2020). For each fund, we keep the last available observation for TVPI and IRR. Our analysis produces several important results.

First - and most importantly - there is a significant positive relationship between the typical exit proxies (IPO and/or M&A) and fund returns. When a fund shows more success via exit of portfolio companies, their returns are more positive. This lends credence to the use of exits to proxy performance in the large literature studying private equity investments.

Second, for buyout capital funds, we document that IPOs and acquisitions are essentially *equally* correlated with returns. Moreover, in this sample we show that no additional filters on these variables improve the correlation between exits and returns. This lack of improvement in correlation is surprising given the cost of imposing these filters. In some cases, researchers undercount the number of exits by as much as 80% when they impose these filters.

Third, for venture capital funds, we find that exits via IPOs and acquisitions are better predictors of fund returns than they are for buyout funds. We also show that exits via IPOs are a better predictor of cross-sectional variation in returns than exits via M&As. On the other hand, we show that filters can play a positive role in this setting; counting acquisitions that are at least twice the amount of funding that the startup raised pre-exit, results in the best correlation between exits via an acquisition and fund returns. We provide detailed steps on how to calculate the amount of funding

[2] Harris et al. (2014), who use data on fund returns data from Burgiss, study slightly fewer funds, spread over more vintage years looking-backward. Thus we provide both greater coverage and a more up-to-date sample.

raised for each startup to facilitate future research.

We emphasize that the above results are from the exploration of *fund* returns, which is what investors experience. The entrepreneur's return is likely highly correlated, especially when the company exits through an IPO, as all shares typically convert from preferred to common stock. This is also the case when the company exits for more capital than the amount of funding it raised, as preferred stockholders typically have a 1x non-participating liquidation preference, while founders and early-stage employees typically own a significant stake in the portfolio company prior to the exit. However, further research on the factors that determine, or even disrupt, the correlation between investor returns and entrepreneur returns would be welcome.

Finally, we explicitly recognize that not all firms are "near" exit and therefore would not appear in the above analysis. In fact we provide four early-stage proxies for likely exit. We show that raising a follow-on round of funding, obtaining a patent post-funding, growing employment, and increasing website traffic or ranking, all positively predict future exits via an IPO or an acquisition. These variables have more cross-sectional variation and can be useful when the sample mostly comprises young firms that are years away from an exit.

To summarize, we offer the following recommendations to researchers.[3] IPOs and M&As of portfolio companies are each viable exits (generally) to proxy for buyout fund and VC fund returns. Simple counts of these events outperform percentages of fund portfolio holdings that experience the exits, when explaining fund returns. Leadership of a deal-round by a buyout fund is a reliable indicator of returns from later exit, but filtering exits to M&As of a certain multiple is not. For VC funds, leadership of a prior deal-round helps with explanatory power of IPOs for fund returns, but only when returns are measured using TVPI. For M&A explanatory power of VC returns, filtering on those acquisitions of at least 2x also helps. Finally, we offer guidance

[3] See section 5.3 for more detailed descriptions.

on quality earlier indicators of success of portfolio companies when exit is still far away. Employment growth, patent grants, follow-on funding, and website visibility / popularity are all good proxies. We hope that researchers can use these findings to guide their choices.

The remainder of the paper is organized as follows. We discuss our data sources and characteristics in the next section. Section 3 then offers key statistics on our funds distribution, their returns, and portfolio company exits. Section 4 presents our empirical models for explaining returns with exits and for proxying exits with earlier indicators. This section also discusses motivations and tradeoffs for each model. In Section 5 we present our results, and the final section concludes.

2. Data

Data for our analyses come from one main source (PitchBook), and a couple of supplementary sources. The latter include the U.S. Patent and Trademark Office database (US PTO), LinkedIn (provided by Datahut), and Semrush. Data from PitchBook comprises fund investments, fund returns, and deal exits. We obtain early indicators of potential (for) exit via patent events (US PTO), employment growth (LinkedIn), and website traffic and rank (Semrush). The other early indicator for potential exit is follow-on financings, also from PitchBook.

2.1. PitchBook

2.1.1. Funds

Our data on funds come from PitchBook, which has one of the most comprehensive databases of private market investments available. Garfinkel et al. (2021) show that PitchBook's data are more comprehensive than those of VentureXpert and Crunchbase, two other databases frequently used in entrepreneurial finance research.

From PitchBook, we isolate venture capital and buyout funds as those classified as either "Venture General," "Venture Capital - Early Stage," "Venture Capital - Later

Stage," "Buyout," or "Growth/Expansion." We keep funds that have at least one non-missing observation of fund returns. We measure these returns as the ratio of total value to paid-in capital, TVPI, and (separately) as the internal rate of return, IRR.[4] We further restrict the sample to funds with vintage years between 1996 and 2010, as these funds likely would have liquidated most of their investments by 2021.[5] Lastly, we keep funds for which the year of group formation and fund size is not missing.[6] Our final sample comprises 927 buyout and 701 venture capital funds. The number of funds in our sample is slightly larger than that of Harris et al. (2014), who use data on fund returns from Burgiss. However, our sample period is shorter and more recent. Overall, the PitchBook data offers greater coverage (during the overlapping years with Harris et al. (2014), and Brown et al. (2015)), and an updated sample.

2.1.2. Portfolio companies

For funds with TVPI and IRR data, we identify all portfolio company investments. We keep deals that are not missing the offering date, deals denominated in U.S. dollars, and deals not missing offering size. For each portfolio company, we calculate the cumulative amount of funding raised.[7] This is the sum of funding raised until exit, when an exit date is available, or the sum of all funding raised as of Q2 2021 when no exit date is available.

We also use PitchBook to determine exit; whether the company had been acquired or had gone public as of Q2 of 2021.[8] Whenever the data are available, we track the acquisition value, whether the IPO market capitalization or acquisition value is not missing, the time between when the fund made the first investment to exit, and

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[4] Specific return calculations are described in section 3.2

[5] Given the typical fund life of 10 years (Gompers et al., 2020)

[6] Year of group formation is likely missing for nontraditional GP types such as corporate venture capital.

[7] We deflate the amount of funding raised in each year by the consumer price index (CPI), with a 2010 base of 100.

[8] We cross check these determinations with SDC data. PitchBook has somewhat better coverage, especially of IPOs. Details are in Table A.3 in the internet appendix.

whether the fund led at least one of the company's deals.[9]

We use these data to create a fund-level dataset that includes the following explanatory variables (for our analysis):

1. the number of portfolio company investments;
2. the number of investments that went public or the number that were acquired;
3. the number of investments that exited for which the fund led at least one funding round;
4. the number of exits within five years (or within seven years) of the initial investment date;
5. the number of exits not missing acquisition price, or not missing market capitalization at IPO;
6. and the number of acquisitions for which the acquisition price was greater than two, four, or six times the total amount of funding raised by the portfolio company.

2.2. Patent Data

For each portfolio company in PitchBook, we obtain its complete history of name changes (which PitchBook tracks). We merge these companies, based on name and the state where they are headquartered, to data on all assignees in the US PTO database as of 2020. We take the following steps to increase the accuracy of our matching. We standardize the company names in PitchBook and assignee names in the US PTO database by dropping common suffixes such as "llc," "inc," "corporation," "company," "the," "corp," "international," "technologies," "technology," "and," and, "business." We also convert all names to lowercase and remove all parentheses, punctuation, and

[9] We again normalize acquisition and market capitalization values over time using the CPI, with a 2010 base of 100.

extra spaces between names. Then, we match companies in the PitchBook data to the assignee data on first name and state where the company is headquartered. Within each matched set, we use the python package *fuzzywuzzy* to compare the standardized name in PitchBook to the standardized name in the US PTO assignee data. The scores on these standardized names can range from 100% for perfect matches to 0% if none of the strings match (which is impossible given that we first matched on first name and state where the company is located). For each company from PitchBook, we keep the closest match to the assignee data, conditional on a match score of at least 95%. Finally, we manually verify each match for accuracy.

2.3. Employee Count Data

We develop employee count numbers using the LinkedIn data provided by Datahut. Datahut scraped two datasets from LinkedIn in 2017; companies and individuals. The key items that we obtain from the companies dataset include the company name, the company website url, and the company's "LinkedIn profile url." From the individuals dataset, we are specifically interested in their work history. From that section of each individual's profile, we pull the name *and* the LinkedIn profile url of each company they reported working for, as well as the time-window over which they state they worked for that company.

We match our PitchBook sample to the LinkedIn companies dataset if there was an exact match on either company name, company website, or LinkedInprofile url.[10] Each company that matches, now has a LinkedInprofile url because all of the companies in the LinkedIn data have the url. We then count the number of individuals who said they worked for that company (with the corresponding LinkedInprofile url) in any particular year. The yearly sum of LinkedIn individuals who said they worked for the company in that year (based on their work histories), is the time-varying employment

[10] Some of our PB sample have an attached LinkedInprofile url from prior work done using these two datasets.

count for that firm.

2.4. *Website Traffic and Rank Data*

We obtain website traffic and associated (popularity) rank data, from Semrush. Data are available for just over 10% of our 7,075 firms, on a monthly basis, over the time period January 2012 through December 2020. Traffic data is organic traffic, which is based on searches and not from paid, social media, nor referral hits. Rank is determined in the cross-section each month. It is the position (based on traffic) of the focal company relative to all companies Semrush tracks.

3. Descriptive Statistics

3.1. *Number of Funds by Fund Type*

Table 1 shows the sample distribution of funds by vintage year. Column 2 shows the count of venture capital funds, and Column 3 shows the count of buyout funds.[11] We focus on funds formed between 1996 (the first year with meaningful numbers of funds in the data) and 2010, to keep funds that are the most likely to be fully liquidated by 2020. Our sample comprises 927 buyout and 701 VC funds. In comparison, over a longer time period, Harris et al. (2014) have 598 buyout and 775 VC funds. A year-by-year comparison of counts indicates better coverage by PitchBook in most years. Moreover, our sample ends more recently, providing an updated view of the private equity market. PitchBook collects fund return data by making Freedom of Information Act requests to limited partners, by conducting surveys of GPs, and by making voluntary reporting requests to GPs.

3.2. *Performance Measures: IRR and Investment Multiples*

We measure fund returns using IRR and investment multiples (TVPI). IRR captures an LP's annualized IRR based on fund contributions and distributions, net of

[11] Again, Buyout funds are funds whose fund type is "Buyout" or "Growth/Expansion," and venture capital funds are funds whose fund type is "Venture - General," "Venture Capital - Early Stage," or "Venture Capital - Later Stage."

fees and carried interest. When all the investments of the fund have not yet been realized, the IRR calculation includes the estimated value of unrealized investments as of the last reporting date. The ratio of total value to paid-in capital (TVPI) compares the sum of all fund contributions by investors to the sum of all fund distributions and the value of unrealized investments, net of fees and carried interest. For each fund with at least one non-missing value of returns, we keep the last available observation for TVPI and IRR.

Table 2 presents the average IRRs and TVPI multiples from the PitchBook data for buyout and VC funds. It shows the mean, median, and weighted-average (where the weights are fund size) for each vintage year as well as the overall average. For buyout funds, IRR has averaged about 12% per year and the investment multiple has averaged about 1.69. As in Harris et al. (2014), IRRs and investment multiples are lowest for funds that started investing before the financial crisis of 2007.

We see more variability in the performance of VC funds, as the dot-com bubble had a greater impact on these funds. Vintages right before and immediately following the dot-com bubble of 2000 have the largest negative IRRs. This finding is again consistent with Harris et al. (2014), who report very similar figures. The average IRR for VC funds over the sample period is 9.17% per year, and the average investment multiple is about 1.55.

3.3. Proxies for Investment Returns

A key goal of this paper is to identify the best proxies of investment success from more readily-available sources, as fund return data are not widely available (or are expensive to obtain). Second, we wish to clearly explain how to construct the proxies most correlated with returns, recognizing that the typical proxies can have subtle variation in the form of filters. To these ends, we construct several measures of investment success that have been used by other empirical studies in the literature. We then relate these measures - including variation in them due to filters - to fund returns to test which measures are most correlated with returns.

Table 3 lists these typical proxies for investment success that have been used in the literature. We calculate them using portfolio company data on exits. To relate these proxies to returns, we must fix the fund type, vintage year, group age (number of years since private equity group formation), and the total number of investments the fund has made.

 # IPOs (*# MAs*) is the total number of portfolio companies that went public (were acquired) following the investment, but before the quarter when we observe the fund's last IRR or TVPI.[12]

 # IPOs Lead (*# MAs Lead*) is the number of portfolio companies that went public (were acquired) and the fund led at least one of the company's funding rounds.

We know from Gorman and Sahlman (1989) that lead investors spend considerable time monitoring and advising the portfolio companies, and that they invest the largest amounts in a funding round. Given that ownership of the company is often proportional to the amount invested, these variables help test whether exits for deals-led explain more variation in fund returns relative to exits for deals the fund did not lead.

Parsing these broad measures into more filtered versions, we take into account the size of the exit and the time since investment. This helps us test how much the commonly used filters enhance (or not) the variables' ability to explain cross-sectional variation in returns.

Ln(# IPOs NM Size) and *Ln(# MAs NM Size)* are the log of the number of companies *with non-missing size (market cap or acquisition price)* in the fund's portfolio that went public or were acquired.

Ln(# IPOs LT 5) and *Ln(# MAs LT 5)* (*Ln(# IPOs LT 7)* and *Ln(# MAs LT*

[12] The results are similar if we count all exits without the restriction that an exit occurs before the last quarter for which we observe fund returns. We impose this restriction to ensure that information on exits is reflected in the returns we observe.

7)) is the log of the number of companies in the fund's portfolio that went public or were acquired within five years (seven years) of the initial investment.

#MAs 2X (*# MAs 4X*, *# MAs 6X*) is the number of portfolio companies that were acquired *and* for which the acquisition price is at least two times (four times, six times) the amount of funding the company raised.

On average, within the portfolio of buyout funds, one company went public and five were acquired. The corresponding figures for venture capital investments are three and four. As a sanity check, we see that each filter on IPOs or M&As reduces the average number of portfolio companies that exit in the funds portfolio. The most severe restriction on exits for both buyout and VC funds are acquisitions that were six times the total amount of invested capital.

4. Empirical Strategy

4.1. Predicting Returns

We begin our empirical analysis with simple documentation of relations between fund returns and portfolio company exits. We then examine to what extent various restrictions on how portfolio company exits are measured, improve their correlation with returns. While some studies use only IPOs to measure success (e.g., Gompers et al. (2016); Farre-Mensa et al. (2020)), some use IPOs and acquisitions (e.g., Hegde and Tumlinson (2014); Howell (2017)), and others impose filters such as defining a successful IPO or acquisition as one that occurs only within a fixed number of years following the funding round (e.g., Gompers et al. (2008); Ewens and Farre-Mensa (2020)) or restricting acquisitions to above a certain sale price or multiple of funding raised (e.g., Gompers et al. (2008); Bernstein et al. (2016); Ewens and Marx (2018)).

Researchers impose these filters in an attempt to select the set of deals most likely to have generated a meaningful return. However, there is no research on which filters, or combination of filters, result in the best correlation with returns. With no clear consensus on which filter is most correlated with returns, some researchers might be tempted to select the filter that validates the hypothesis they are trying to test. Put differently, choosing for example only those M&A exits that are 4x or higher as "success" indicators, could dismiss less profitable acquisition exits that influence the hypothesized relationship the researcher is testing.

Further, given that exits are typically used as a dependent variable, these filters can introduce measurement error. Again by example, if M&A exits of (say) less than 4x are treated as unsuccessful, they may be assigned a "zero" in regressions. To the extent that (for example) 3x M&A exits have a different relationship to the explanatory variable than 4x M&A exits, this biases the estimated relationship. Thus, it is important to understand whether, and/or to what extent, these filters improve the correlation between exits and returns.

In Table 3, we show how each restriction changes the number of companies that exit as a result of the filter. We then evaluate whether each filter improves the return-exit correlation by running the following regression:

$$\begin{aligned} Return_i = \ & \beta_1 \text{Exit Filter}_i + \beta_2 \text{Ln(Group Age)}_i + \beta_3 \text{Ln(\# Investments)}_i \\ & + \beta_4 \text{Ln(Fund Size)}_i + \beta_5 \text{I(Fund Type)}_i + \eta_t + \epsilon_i. \end{aligned} \tag{1}$$

In regression (1) the unit of observation is a fund. Given the differences in the types of investments made by VC vs. Buyout funds, we run separate regressions and present the results in separate tables for each strategy. The main dependent variables (*Return*) are *TVPI*, the ratio of total value to paid-in capital, and *IRR*, the internal rate of return. *Group Age* is the number of years since the group was formed, and *# Investments* is the number of investments the fund has made. When we estimate equation 1 for buyout funds, *I(Fund Type)* is an indicator that equals one for growth equity funds, with buyout as the omitted category. When we estimate equation 1 for venture capital funds, the regression comprises two indicators for funds whose fund type is *General VC* or *Early-Stage VC*, with *Late-Stage VC* as the omitted category;

η_t represents vintage year fixed-effects.

Exit Filter comprises the following:

1. IPOs for companies where the fund led at least one deal (*# IPOs Lead*);

2. IPOs not missing market capitalization at IPO (*# IPOs NM Size*);

3. Acquisitions of companies for which the fund led at least one deal (*# MAs Lead*);

4. Acquisitions not missing a sale price (*# MAs NM Size*);

5. Acquisitions not missing a sale price and data on the total amount of funding the company raised (*# MAs NM Size/Funding*);

6. Acquisitions with sale prices that are at least two, four, or six times the total amount of funding raised by the portfolio company (*# MAs 2X, # MAs 4X, and # MAs 6X*);

7. And IPOs and acquisitions within five or seven years of the first investment made by the fund (*# IPOs LT 5, # IPOs LT 7, # MAs LT 5, # MAs LT 7*).

We compute the relative importance of each filter by comparing the change in the adjusted R2 relative to imposing no filter. For example, in Table 4 the adjusted R2 of equation 1 is 0.055 when *Exit Filter* is a count of the number of portfolio companies that went public.[13] However, when the exit filter is the count of the number of portfolio companies for which the fund led at least one deal and that went public, the adjusted R2 jumps to 0.063. This implies a 14.5% increase in explanatory power by changing the filter from all IPO exits to IPO exits where the fund led at least one early-stage deal.

[13] We add one before taking the log count.

4.2. Predicting Exits

When researchers aim to explain why startups are successful, they typically use startup exits such as IPOs or acquisitions. However, when the sample of startups comprises young firms, many of which are unlikely to exit until many years following funding, use of these variables can introduce two issues. First, lack of exit may not imply lack of success for very early stage companies; just lack of readiness. At the opposite end, lack of readiness may be ignored in some circumstances. Exit variables might capture exit speed instead of success. For example Gompers (1996) shows that young venture capital firms take companies public earlier than older venture capital firms in order to establish a reputation and successfully raise capital for new funds. As a result, the age of the VC group is a potential omitted variable in regressions that use exits to predict success in samples of young firms. In both cases, the use of exits can create a measurement bias.

Given these concerns, some researchers instead use various proxies for success with more cross-sectional variation than future IPOs or acquisitions. However, we do not know whether, or to what extent, these proxies predict eventual exits. This section fills this gap in the literature.

We evaluate four categories of earlier-stage characteristics that typically serve as proxies for exit:

1. An indicator for companies that raised follow-on funding (*I(Raised Funding)*);
2. An indicator for companies that obtain a patent following funding (*I(Patent)*);
3. Measures of post-funding employment (*Employees*);
4. Measures of company website traffic (*Traffic*) and ranking (*Rank*);

For all of these proxies we construct time-varying measures to reflect the potential temporal importance of such indicators. For example, a company's follow-on funding two years after initial funding may carry different importance than if it raises subsequent funding four years after initial funding.[14]

We run the following regression:

$$Exit_i = \quad \beta_1 \text{Exit Proxy}_i + \beta_2 \text{Ln(Size First Deal)}_i + \beta_3 \text{Ln(Issuer Age)}_i + \lambda_j + \eta_t + \epsilon_i. \tag{2}$$

The unit of observation is a startup in the portfolio of the funds in our sample that raised an early-stage venture round.[15] To capture early-stage VC rounds, the sample only includes issuers whose first round of funding is either a Seed Round, Angel (individual), Convertible Debt, Accelerator/Incubator, or Early Stage VC. The main dependent variable (*Exit*) is an indicator that equals one if the issuer exits via an IPO or an acquisition (and the sale price is not missing (*I(IPO), I(MA NM Size)*). *Issuer Age* is the number of years from when the issuer was formed to the first funding round, and *Size First Deal* is the log of the offering amount of the issuer's first funding round. λ_j and η_t are industry and fundraising year fixed-effects, respectively. We calculate the predictive power of each exit proxy by comparing the adjusted R2 from equation 2 of each proxy.

5. Results

5.1. Predicting Returns

Tables 4 and 5 show results when estimating equation 1 for buyout and VC funds, respectively. The independent variables are the number of IPOs, the number of IPOs conditional on leading at least one funding round, the number of IPOs not missing market capitalization at IPO, the number of acquisitions, the number of acquisitions conditional on leading at least one funding round, and the number of acquisitions

[14] We thank the referee for highlighting this.
[15] And that is not missing data on deal size or founding year.

not missing sale price. For each table, Panel A shows the correlation between these variables and TVPI, and Panel B shows the correlation between these variables and IRR.[16] All of the regressions include the full set of controls shown in equation 1, as well as vintage year fixed effects, which are especially important in recognition of the effects of the financial crisis on private equity and VC funds' performance. The regressions also cluster standard errors by fund.

Both tables provide good preliminary news for researchers using IPOs and M&As as exit success indicators to proxy for fund returns. Despite the potential for mitigating factors (fund specialization, different investment timing or terms), the relationships are positive. In Table 4 (explaining buyout fund returns), the log-counts of IPOs and M&As carry significant coefficients with one exception (IPOs in the IRR regression). Comparing the two exit-based success proxies' influence on buyout fund returns, Columns (1) and (4) show that exits via IPOs or acquisitions are roughly equally correlated with fund returns measured with TVPI. On the other hand, the adjusted R2 increases by 15% for the correlation between the number of acquisitions and IRR compared to the correlation between the number of IPOs and IRR, potentially reflecting the weak explanatory power of log-IPO-count in the IRR regression.

Comparing the correlation results across the two *tables* also reveals better explanatory power of exits for VC fund returns. Despite both tables including the same control variables, the Panel A adjusted R2 jumps from around 5.5% in the buyout regressions when we use the simple count of IPOs or acquisitions, to more than 20% in the venture capital regressions. This represents a more than 250% increase. Further exploring the results in Columns (1) and (4) of Table 4, we see that IPOs are a better predictor of VC fund returns than acquisitions. The adjusted R2 is between 6% (Panel B) and 7% (Panel A) higher when the return proxy is the number of IPOs instead of the number of acquisitions.

[16] Coefficients on IRR reflect their Table 2 reporting (in percentages).

5.1.1. *Filtering on deals led and deals not missing an exit value*

Turning to the effect of filters on correlations between exits and fund returns, we find slight evidence of improvement in the buyout funds regressions. Again from Panel A of Table 4, the adjusted R2 rises by .005 and .004 when restricting the M&As to those with the fund leading at least one deal or to those not missing M&A deal size.[17] But according to Table 3, this comes at the "cost" of reducing the number of M&A exits for the average buyout fund by 50% and 40%, respectively. Roughly similar tradeoffs are seen when examining correlation improvements between IPO filters (on deals led or deals with non-missing market cap) and buyout fund returns. Overall, there is a small but discernible benefit in buyout fund return explanation when using "lead investor" (in at least one early deal) as a filter. But this filter also implies the greatest reduction in count of exits.

The results on filtering's correlation benefits from Table 5 are somewhat different. The lead filter on IPOs meaningfully improves the correlation between their count and fund returns measured with TVPI, by about 5.5%, but this result does not survive fund return measurement with IRR. It also comes at great cost in terms of observation loss - nearly 50% of IPOs. The filter requiring non-missing market cap on IPOs yields a more moderate 1% to 2% explanation improvement. The M&A lead filter (comparing results in Columns (4) and (5)) indicates little to no improvement in explanatory power over VC fund returns. However, there is evidence of moderate improvement in VC fund return explanation when filtering M&As on availability of sales price (3% to 4%). This latter filter shrinks the counted M&As by 43% (again see Table 3). If acquisitions are not missing sales prices across funds at random, this filter could generate measurement error that could lead to biased estimates, depending on the relationship between the measurement error and the primary independent variable that is the subject of a research paper. It is therefore important for researchers to

[17] In Panel B, correlations improve by .002 and .005 respectively with these filters.

discuss to what extent these filters are correlated with their independent variable of interest.

5.1.2. Filtering on deals' exit size

Tables 6 and 7 again show results from estimating equation 1 for buyout and VC funds respectively, but filtering M&As on size. In particular, the exit filters are the number of portfolio companies that were acquired and that are not missing data on deal size, that were acquired and are not missing data on deal size or funding raised by the company, and that were acquired for two, four, and six times the amount of funding the company raised. The number of companies that were acquired (or that were acquired and not missing deal size, depending on our comparison goal), is the baseline to evaluate whether restricting the acquisition count per fund to a multiple of funding raised improves the correlation between acquisitions and returns.

Table 6 shows that adding filters for the size of the exit does not improve the correlation between acquisitions and fund returns for buyout funds. For example, imposing the filter that the acquisition price is at least twice the amount of funding raised, reduces the average number of acquisitions by about 80% but does not improve the correlation between exits and returns for buyout funds. The decline in explanatory power appears to be driven by loss of observations without sufficient information to calculate the multiple. In column (3) where we simply count the number of M&As with non-missing price and non-missing pre-sale funding, the adjusted R2 is lowest (of the six regressions in the panel, regardless of panel). In fact, filtering on those deals with both sufficient information to calculate the multiple and also setting a threshold (2x or 4x or 6x) improves explanatory power, albeit slightly. Given the extreme effects on count of M&A transactions from any form of filtering - be it on data availability or multiples threshold - the lack of explanatory power improvement argues for using simple M&A counts when explaining buyout fund returns.

On the other hand, we see a different tradeoff calculation when explaining VC fund returns in Table 7. In particular, counting acquisitions that are at least twice the amount of funding raised increases the correlation between acquisitions and returns by between 12% (when the dependent variable is IRR) and 18.6% (when the dependent variable is TVPI). Adding further restrictions on the size of the acquisitions to beyond twice the amount of funding raised, further improves the correlation between M&As and returns for venture capital funds, though much more marginally. This increase in explanatory power must be weighed against the 44% drop in the number of M&As in a VC fund's portfolio that clear the 2x multiple threshold relative to simply having sufficient data to calculate a multiple.

5.1.3. Filtering on exit timing

Tables 8 and 9 show results when estimating equation 1 for buyout and VC funds, respectively, when the exit filters are the time since the fund last participated in a funding round before the exit date. Specifically, we compare the correlation between returns and the number of portfolio companies that were acquired or go public, to the correlation when we only count IPOs or M&As that occurred within five or seven years of the last funding round that the fund participated in.

The results show no improvement in the correlation between returns and exits when using a filter on time since investment. Note that because most exits occur five to seven years following the last investment, these filters have almost no impact on the IPO or M&A count. It is therefore unsurprising that these filters do not improve the correlation between exits and returns.

In conclusion, we find that while most of these filters on the exit count have a large effect on the average number of exits for each fund, the improvements in explanatory power of filtered events for returns are mostly moderate at best, especially for buyout funds. Only the filter on the ratio of the acquisition price to the amount of funding raised improves the correlation between exits and returns substantially, and only among VC funds. The other filters have an arguably small - or at least difficult to justify - effect on the return-exit correlation. These filters should either be avoided, or researchers imposing them must carefully consider the relationship between these filters and their primary independent variable, to ensure that the filters are not introducing measurement bias.

5.1.4. Potential Questions About Empirical Interpretation

Given Buyout and VC fund returns are significantly correlated with exits, we can side-step a couple of interpretative concerns. One is the recognition that funds often specialize, by stage or industry or location. If those specializations influence returns but not necessarily exit proclivities, we would expect this to hamper our attempts to link them. Our results indicate that such noise in our estimates is insufficient to render a significant relationship null. Also, we recognize that funds may invest in portfolio companies under different contract terms (Ewens et al. (2022)), which would obviously influence the shape of the relationship. However, again given our results of a positive relationship between exits and fund returns (despite these potentially confounding factors), researchers can be confident in using exits to proxy returns.

A second interpretation question arises because of the unchanging explanatory power across size of exit thresholds (2x, 4x, 6x M&A multiples). This may be due to stability across those thresholds in exit counts.[18] We explore whether exit counts are highly correlated across thresholds, and discover that they are. Our view is that similar explanatory power of the regression across exit multiple thresholds implies researchers need not be concerned about choosing an appropriate size threshold to qualify as a "successful" exit.

Third, the stronger explanatory power of exits for VC fund returns (when compared to buyout fund returns), may be explained by differences in return skewness. Figures 2Panel A and 2Panel B illustrate that VC fund returns are more skewed. Given count variables for our regressors, the lower skewness in buyout fund returns

[18] We thank the referee for suggesting this and the associated test.

may explain some of the relative weakness in explanatory power of exit counts.[19]

Fourth, one may naturally contemplate whether simple counts of exits are more or less appropriate to explain fund returns. Instead, ratios of exits to total fund investments may be more informative. We explore this by re-running our equation (1) regression with exit ratios and offer the results in our internet appendix. Tables A.6 and A.7 both indicate weaker explanatory power from the fraction measures of exits than when we use level counts. One view of this lower explanatory power is that it would presume "home run" exits are half as important to fund returns when the fund has twice as many investments. We prefer the more flexible approach of having the data dictate the shape of the relationship.

Finally, some papers combine M&A with IPOs to create a single exit dummy. To ascertain whether this improves explanatory power for fund returns, we collapse the two types of exits in regressions resembling (1), and present results in the internet appendix. Tables A.4 and A.5 indicate there is insufficient benefit to combining them once we recognize two things. First, the correlations improve slightly for buyout funds but decline for VC funds. Second, the relationships between IPOs as exit with returns and M&As as exit with returns are sufficiently different (in our view) to warrant separation of analyses.

5.2. Predicting Exits

The relevance of exits (IPOs and M&As) for fund returns raises an important issue: what to do about younger portfolio companies that are simply not ready for exit and likely won't be ready for years? This is a consideration particularly among funds that either enter the portfolio company's funding life cycle late or sell before the company exits. If the fund enters late, they likely seek leading indicators for successful eventual exit. If the fund plans to sell before exit, the sale price (to perhaps another fund) would likely also depend on leading indicators. Finally, researchers seeking to

[19] We also thank the referee for suggesting this possibility.

understand exit determinants need reliable early indicators. Overall, discerning highly correlated leading indicators with exits is a potentially valuable tool for both funds and researchers studying early stage companies.

The next few sections examine which early indicator variables best predict exits following the startups' first funding round. A characteristic best predicts exits if it is positively or negatively correlated with the probability that a company exits via an IPO or an acquisition and has the highest adjusted R2 relative to other predictive characteristics.

For consistency, our study sample comprises startups in the portfolio of funds in Table 1. We further restrict the sample to companies that are not missing founding year, amount of funding raised, and companies raising an early-stage VC round. These are the startups for which proxies for exits are most often used as these companies have a limited operating history. As seen in Table 10, the roughly 7,000 portfolio companies were formed about two-and-a-half years before their first funding round; 14% of all companies eventually exited via an IPO; and 24% of companies exited via an acquisition with data on the sale price.

We correlate exits with the size of the follow-on funding round, as well as the timing of follow-on fundings and patent outcomes, time-varying website traffic and rankings, and time-varying employment. Table 10 provides simple descriptive stats on key early indicators. It shows that one in two issuers raises a follow-on round within two years (*I(Raise Funding 2Y)*), 40% of all issuers raise a follow-on round that is twice as large as their first round, 26% of issuers are granted a patent, and 57% of all issuers have employment counts built using the LinkedIn (Datahut) data. The median amount of funding raised for the first deal is about $4 million, and one in two issuers is in the information technology sector.

5.2.1. Predicting exits using employee counts over time

If a company isn't hiring or has few employees, particularly growth-stage companies like the ones studied here, the chances of eventual profitable (fund-investor) exit seem dim. However, measuring employment for a large cross-section of such companies over time is challenging. Data are not readily and cheaply available. We use the LinkedIn (provided by Datahut) data and the technique described in section 2.3 to overcome this hurdle. We can then offer guidance to both researchers interested in employment-based determinants of early stage company exits, as well as potential fund investors.

Table 11 explains company exits (IPO or M&A) with data on employee counts derived from LinkedIn. The main inference is that more employees augurs greater chance of exit via IPO or M&A. While unsurprising, this is still useful information. Moreover, there are subtle differences in the effect of employment over time on the two types of exits. IPOs are better explained by employment over time. The explanatory power of later employment counts is also monotonically increasing. M&As are different across both dimensions. Explanatory power of companies' employee counts is weaker. It is also declining as the time of employee count since first funding, extends. While we do not wish to overstate, these differences suggest different signal values of employment for investors planning to exit via M&A vs. IPO.

5.2.2. Predicting exits using follow-on funding size/timing

Follow-on funding is an oft-studied indicator of early-stage company performance. (See e.g. Kerr et al. (2014)). We offer two perspectives on the general relation in this section. First, we confirm follow-on funding's performance on exits specifically. Second, we offer a time-varying perspective on the relative importance of quicker vs. slower second funding rounds.

Table 12 examines the relationship between exits and whether a company raises a follow-on round of funding as well as its size. Panel A documents the correlation between follow-ons and IPOs, while Panel B examines the same correlations for M&As. From Column (1), we see that the size of the first deal and the indicator for raising a follow-on round are positively related to exits. Comparing exit via an IPO or an acquisition, we further see that these variables are better predictors of IPOs than of acquisitions (higher adjusted R2 in Panel A). However, the results also indicate that restrictions on the size of the follow-on round do not meaningfully improve the correlation between raising a follow-on round and exits. This suggests that researchers are better off not imposing filters on the size of the follow-on round when they explore exits and perhaps other variables likely to influence exits.

Table 13 similarly examines the relationship between exits and whether a company raises a follow-on round, but with further exploration of the influence of the timing of follow-on. Explaining IPO exits, there is moderate influence of follow-on timing. If a company has another funding round within two years of the first, adjusted R2 rises by about 3%. However, longer waits between first and second funding rounds slightly diminish the explanation of IPO exit likelihood. Notably, the effects of filters on explanatory power for M&A exits are negligible across the time windows. Overall, the preponderance of the evidence suggests exits are more likely when there is a follow-on round, but there is little gain to filtering on either size or timing of the second round.[20]

5.2.3. Predicting exits using post-funding patents

Prior work by Kerr et al. (2014) and Farre-Mensa et al. (2020) suggests that patent awards are positively correlated with early-stage company success. We study their impact on both IPO and M&A exits of early stage companies, with the added focus of patent award timing on exits. Table 14 examines these relationships. Panel A documents the correlation between patent activity and IPOs, and Panel B documents the same correlation for M&As. The results confirm prior work indicating patents precede

[20] With the possible exception of quick follow-ons signaling greater likelihood of IPO exit.

exits. However, we also see that there is no incremental benefit to the explanatory power of the regression through filtering on the timing of the patent post-funding. In all other regressions of the Table, the adjusted R2 is either equal to or lower than we see in column (1).

5.2.4. Predicting exits with website "popularity" metrics

Prior work (again, see Kerr et al. (2014)) considers website rank as an indicator of startup success, correlated with other outcomes. We use this relationship to directly test how two indicators of website popularity correlate with exits. Our tests also recognize time-variation in this relationship. Because the data on website traffic and rank (from Semrush) is spottier (see section 3.2), we report our regression results in the internet appendix.

Tables A.8 and A.9 document the relationship between exits and indicators for company website popularity. The results indicate that better rankings (a lower number, since the best-ranked website receives a one) and also higher traffic values, associate with more likely exit. When exit is via IPO, later rankings and traffic are more highly correlated with it. When exit is via M&A, earlier rankings carry the day.

5.3. Summary of Results and Recommendations for Researchers

We have presented two broad sets of results. We link buyout and VC fund returns with exits of their portfolio companies (via IPO and/or M&A). Both types of exit reliably correlate (positively) with fund returns. We further explored the effect of typical exit filters on the shapes of these relationships. Our most common result from filtering effects analysis was that the limitation placed on "successful" exits did not improve the explanatory power of exits for buyout fund returns, but there was some improvement for VC fund returns when acquisitions values were at least twice the amount of funding raised.

Our second broad set of results concerned company exits and early indicators of them. This was motivated by the joint recognition that exits can be used as proxies for fund returns (when the latter are difficult / expensive to obtain), and that some companies are sufficiently young that exit is not near but reliable early indicators would be useful. We studied four types of early signals and found that all four show positive relations between early indicator health and exit via IPO or M&A. The early indicators are employee count, patent grant, follow-on funding round, and website popularity.

Research into (broadly-defined) private equity fund performance can use both sets of results to inform their data selection and definitions as well as methods. We offer a few specific suggestions.

1. If fund returns are unavailable or expensive, exits of portfolio companies via either IPO or M&A are suitable proxies.

2. When using successful exits to proxy fund performance, the *count* of them is a better predictor of fund returns than the *fraction* of the fund's portfolio companies that successfully exited.

3. When studying specifically buyout funds, filtering on exits where the fund led at least one deal round, is the single reliable filter for increasing explanatory power of the exit.

4. By contrast for buyout funds, restricting on M&A multiples does not improve explanatory power. Notably this is (also) in contrast to the case for VC funds - see below.

5. When studying specifically VC funds, filtering on exits where the fund was a lead on an earlier round improves explanatory power. So too does filtering on specifically M&As of at least 2x the cumulative amount of funding pre-exit.

6. If exits are unlikely because the portfolio company is too young (years from readiness for exit), the following variables are suitable early indicators for even-

tual exit: employee count; patent grant; follow-on funding event; website rank or traffic.

Summary of Recommendations for Researchers

Panel A summarizes the relationship between fund return proxies, *Exit Filters*, (and various filters on these proxies) and fund returns. ✓ implies that the proxy is positively correlated with returns; + implies that the filter improves the proxy's correlation with returns; − implies it decreases correlation with returns; and 0 implies no effect of filter on the proxy's correlation with returns relative to no-filter benchmark. Panel B summarizes the relationship between early indicators of success and the exit proxies of IPO or M&A. *Count IPO Vs. Fraction* (*Count M&A Vs. Fraction*) compares the correlation between the Ln(Count of IPOs) (M&As) and fund returns, to the correlation between the fraction of investments (*Fraction*) that IPO. *Timing filters* explores variation in the timing of IPOs or M&As 5 or 7 years following the initial investment. *Other filters Early Proxies* explores variation in when the early proxies in the first four rows of Panel B are measured.

Panel A: Exit Filter	**Buyout Returns**	**Venture Returns**
No filter IPOs	✓	✓
No filter M&As	✓	✓
Count IPO Vs. Fraction	Count > Fraction	Count > Fraction
Count M&A Vs. Fraction	Count > Fraction	Count > Fraction
Lead Investor	+	+
M&A > 2X	0	+
M&A > 4X, 6X	0	0
Timing filters M&A or IPO	0	0
Panel B: Early Proxies	**I(IPO)**	**I(M&A)**
No filter I(Patent)	✓	✓
No filter Ln(Employment)	✓	✓
No filter I(Raise Funding)	✓	✓
No filter (Website Traffic)	✓	✓
Other filters Early Proxies	0	0

6. Concluding Remarks

Entrepreneurial finance researchers frequently use exits via an IPO or an acquisition as a proxy for returns in early-stage financing. They also often impose filters on the types of exits that count as an IPO or an acquisition and justify these restrictions as being likely to improve the correlation between exits and returns.

However, most studies never quantify the magnitude of the restriction's effect on exit counts nor empirically justify the restrictions. Further, given that exits are typically used as a dependent variable, these filters can create measurement bias if they are assigned a zero value when in fact it was positive. As such, it is important to understand the magnitude of these restrictions and whether, or to what extent, these filters improve the correlation between exits and returns.

We take advantage of data on fund returns from PitchBook, which most researchers do not have access to, to inform multiple queries. We quantify the restrictions on exit counts, and then we test whether imposing filters on exits improves the correlation between exits and returns. We also examine which characteristics of early-stage startups are correlated with eventual exits, which can be used when the sample comprises young firms and therefore contains little cross-sectional variation in future exits.

We summarized our results in section 5.3 above, but we repeat a few key findings here. Among buyout funds, we find that exits via IPOs or acquisitions are roughly equally correlated with returns. Further, none of the size-based filters on these variables greatly improve the correlation between exits and returns (though some small improvements are seen). This is despite the fact that in some cases the filters can lead researchers to undercount the number of exits by as much as 80%.

For venture capital funds, we find that exits via IPOs and acquisitions are better predictors of fund returns than they are for buyout funds, and that exits via IPOs are a better predictor of cross-sectional variation in returns. We also find that filtering acquisitions that are at least twice the amount of funding raised, results in the best correlation between exits via an acquisition and venture fund returns.

Finally, we show that early indicators of portfolio company success presage the typical exits. These early indicators include: raising a follow-on round of funding, gaining a patent grant, increasing employee count, and increasing website popularity. We hope that researchers use these findings as a guide to choose how to count exits when looking at startup outcomes, and/or how to proxy for issuer outcomes in settings with very young startups that are years away from an exit.

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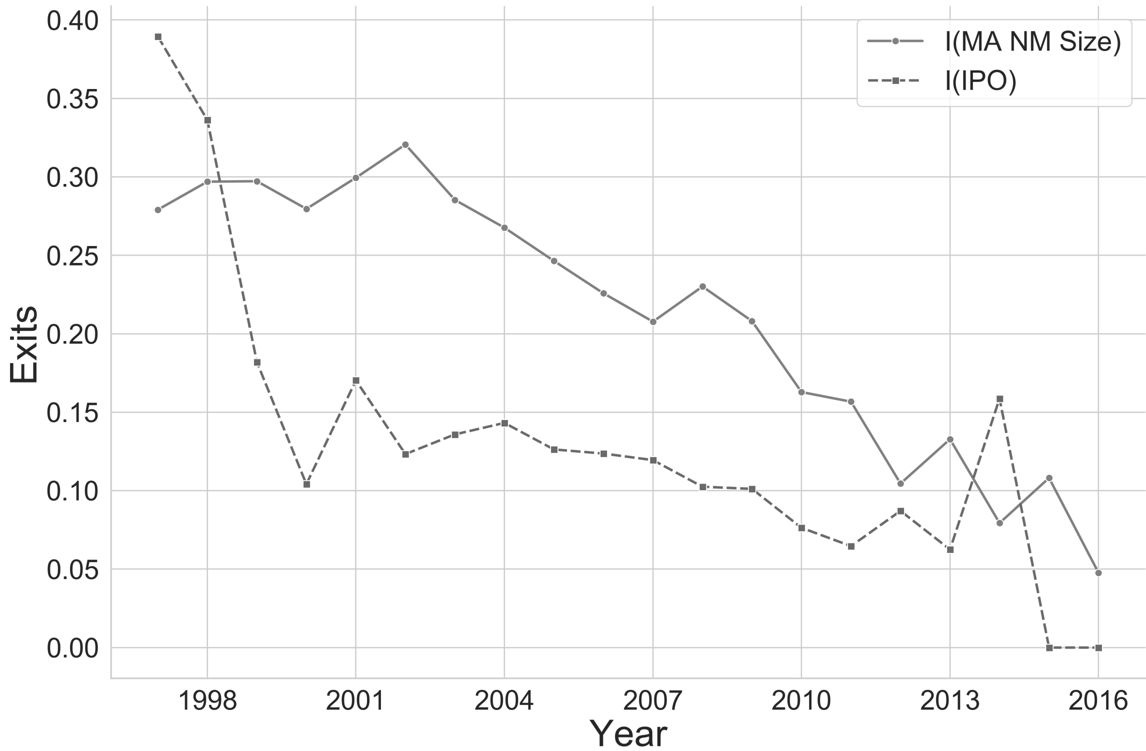
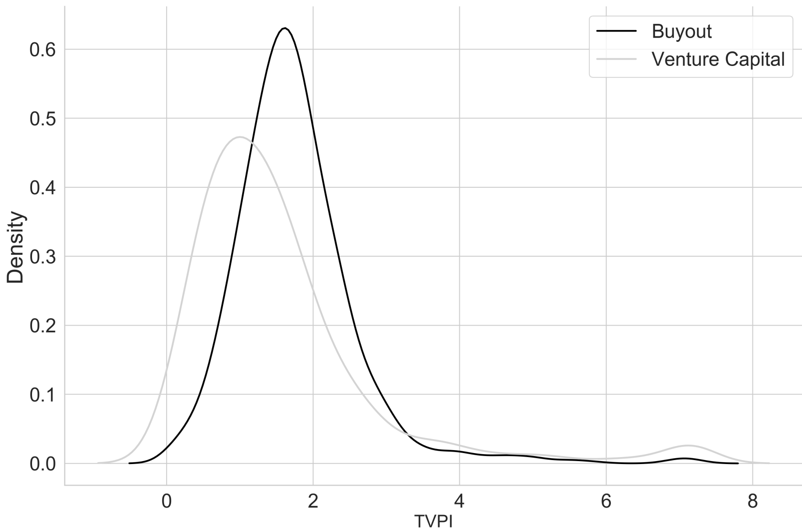
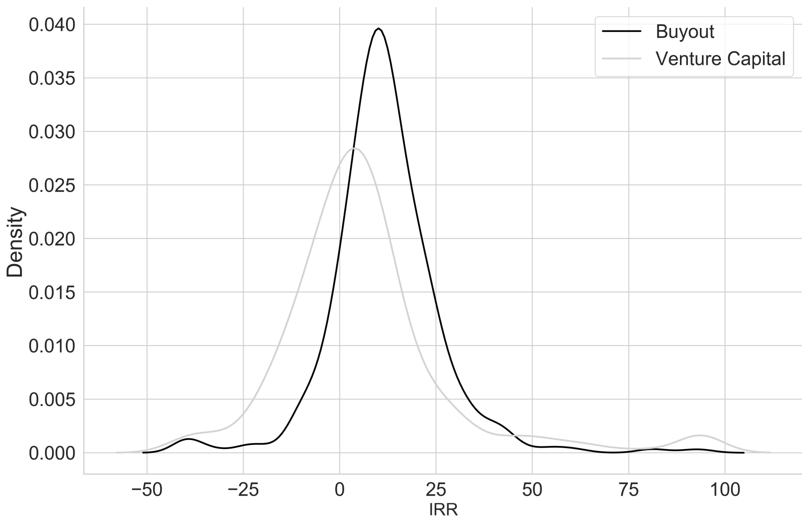


Figure 1: Exits Over Time
This figure shows the percentage of the exits by exit type for the companies in Table 10. These companies are in the portfolio of funds analyzed in Table 1. *I(IPO)* is an indicator that equals one if the portfolio company goes public by Q2 2021 and zero otherwise. *I(MA NM Size)* is an indicator that equals one if the portfolio company is acquired and the acquisition price is not missing.



Panel A: Histogram TVPI



Panel B: Histogram IRR

Figure 2: Distribution of Returns

This figure plots the distribution of returns by venture capital and buyout funds.

Table 1: Number of Funds by Vintage and Fund Type

This table shows the number of funds in our PitchBook sample by fund type and vintage. Only U.S.-based funds with a vintage between 1996 and 2010, with either investment multiple or IRR data, fund size, and year of group formation are included in the count for a given year. *Buyout Funds* is an indicator for funds whose fund type is "Buyout" or "Growth/Expansion." *Venture Capital Funds* is an indicator for funds whose fund type is "Venture - General," "Venture Capital - Early Stage," or "Venture Capital - Later Stage."

Vintage	Venture Capital Funds	Buyout Funds
1996	21	35
1997	39	36
1998	39	50
1999	64	61
2000	89	71
2001	61	40
2002	33	48
2003	30	39
2004	39	59
2005	48	81
2006	62	110
2007	53	112
2008	57	88
2009	34	46
2010	32	51
Total	701	927

Table 2: Buyout and VC Funds' Internal Rates of Return and Investment Multiples

This table shows average internal rates of return (IRR) and investment multiples by vintage year on the individual funds using PitchBook data. Investment multiples are the ratio of total value to paid-in capital (TVPI). Total value is the sum of the cash returned to investors and the remaining net asset value as estimated by the fund manager. Weighted averages use the capital committed for each fund as a proportion of the total commitments for each vintage year. Only U.S.-based funds with a vintage between 1996 and 2010, with either investment multiple or IRR data, fund size, and year of group formation are included.

	Buyout Funds (N = 927)						**Venture Capital Funds (N = 701)**					
	Internal Rate of Return			Investment Multiple			Internal Rate of Return			Investment Multiple		
Vintage Year	Mean	Median	Weighted Average	Mean	Median	Weighted Average	Mean	Median	Weighted Average	Mean	Median	Weighted Average
1996	8.92	6.73	11.62	1.53	1.30	1.60	47.71	48.80	37.24	3.46	2.97	2.96
1997	8.64	8.40	8.40	1.54	1.46	1.51	34.88	26.00	42.76	2.55	1.71	2.94
1998	6.58	7.81	5.77	1.47	1.46	1.38	12.25	8.10	12.73	1.44	1.46	1.53
1999	9.16	9.79	7.60	1.71	1.55	1.51	-5.04	-4.21	-4.71	0.88	0.78	0.89
2000	14.75	13.00	16.37	1.80	1.78	1.81	-0.88	-0.30	-1.26	1.15	0.94	1.02
2001	21.39	16.59	22.97	1.99	1.86	2.04	1.14	2.01	4.09	1.17	1.16	1.29
2002	16.80	16.50	22.30	2.00	1.96	2.07	-2.63	0.42	-1.98	1.01	1.04	1.04
2003	13.39	11.02	18.84	1.66	1.62	1.81	-0.59	3.13	3.94	1.20	1.22	1.45
2004	12.17	11.20	11.60	1.88	1.72	1.74	-0.34	0.30	-0.06	1.32	1.03	1.27
2005	7.60	7.80	8.94	1.63	1.51	1.59	4.46	3.81	5.75	1.52	1.29	1.57
2006	8.55	8.66	7.74	1.62	1.60	1.58	1.28	3.99	4.71	1.39	1.31	1.53
2007	11.68	10.86	10.63	1.87	1.76	1.71	8.61	9.70	7.04	2.00	1.71	1.82
2008	12.61	12.43	12.35	1.74	1.68	1.72	8.73	10.94	8.49	2.03	1.79	1.82
2009	16.46	15.65	17.86	2.01	1.82	2.07	10.72	10.56	13.03	1.77	1.68	2.13
2010	14.12	13.17	14.74	1.83	1.70	2.01	16.29	12.39	18.18	2.04	1.68	2.19
Average	12.27	11.08	9.87	1.69	1.60	1.34	9.17	9.04	6.53	1.55	1.45	1.16

Table 3: Buyout and VC Fund-Quarter Characteristics

This table reports quarterly characteristics of private equity funds in PitchBook. *IRR* is the internal rate of return. *TVPI* is the ratio of total value to paid-in capital. Total value is the sum of the cash returned to investors and the remaining net asset value as estimated by the fund manager. *# Cumulative Investments* is the total number of cumulative investments a fund has made as of the quarter in which fund return is calculated. *# IPOs* (*# MAs*) is the total number of portfolio companies that went public (been acquired) following the investment, but before the quarter when we observe the fund's last IRR or TVPI. *# IPOs Lead* is the number of portfolio companies, of the deals the fund led, that went public. *Ln(# IPOs NM Size)* and *Ln(# MAs NM Size)* are the log number of companies in the fund's portfolio that were acquired or went public and the acquisition price or market capitalization at IPO is not missing. *Ln(# IPOs LT 5)* and *Ln(# MAs LT 5)* (*Ln(# IPOs LT 7)* and *Ln(# MAs LT 7)*) are the log number of companies in the fund's portfolio that went public or were acquired within five years (seven years) of the initial investment. *#MAs 2X* (*# MAs 4X*, *# MAs 6X*) is the number of portfolio companies that were acquired *and* the acquisition price is at least two times (four times, six times) the amount of funding the company raised. I(Growth Equity), I(General VC), and I(Early-stage VC) are indicators that equals one for funds whose fund type is "Growth/Expansion," "Venture - General," and "Venture Capital - Early stage," respectively. Only U.S.-based funds with a vintage between 1997 and 2010 with data on fund size and year of group formation are included.

	Buyout Funds) (N = 927)			**Venture Capital Funds (N = 701)**		
	Mean	Std	Median	Mean	Std	Median
Fund Size ($ Millions)	1076.27	2101.63	418.2	305.36	367.98	195
IRR	11.77	14.39	10.81	6.45	22.12	3.84
TVPI	1.75	0.83	1.66	1.55	1.32	1.23
Vintage Year	2003.84	4.02	2005	2002.99	4.03	2003
Group Age (Yrs)	28.71	14.8	26	27.85	17.78	24
# Investments	23.42	24.37	17	23.62	21.46	18
# IPOs	1.35	2.11	1	3.43	4.38	2
# IPOs Lead	0.69	1.39	0	1.76	3.01	1
# IPOs NM Size	1.23	1.99	1	3.14	4.08	2
# IPOs LT 5	1.34	2.1	1	3.28	4.15	2
# IPOs LT 7	1.35	2.12	1	3.39	4.33	2
# MAs	5	5.04	4	12.1	11.74	9
# MAs Lead	2.6	3.29	2	5.98	7.55	4
# MAs NM Size	2.94	3.26	2	6.83	6.89	5
# MAs NM Size/Funding	1.76	2.37	1	6.51	6.73	4
# MAs 2X	0.96	1.46	0	3.66	4.01	3
# MAs 4X	0.62	1.08	0	2.58	2.95	2
# MAs 6X	0.44	0.87	0	1.87	2.28	1
# MAs LT 5	4.95	4.96	4	11.62	11.29	9
# MAs LT 7	5	5.05	4	12.01	11.67	9
I(Growth Equity)	0.13	0.34	0			
I(General VC)				0.82	0.38	1
I(Early-stage VC)				0.14	0.35	0

Table 4: Association Between Buyout Fund Returns and Exits

This table reports results for regressions of fund-level TVPI (Panel A) and IRR (Panel B) on portfolio company exits. *Ln(# IPOs)* and *Ln(# MAs)* are the log number of companies in the fund's portfolio that went public or were acquired as of Q2 2021. *Ln(# IPOs NM Size)* and *Ln(# MAs NM Size)* are the log number of companies in the fund's portfolio that were acquired or went public and the acquisition price or market capitalization at IPO is not missing. *Ln(# IPOs Lead)* and *Ln(# MAs Lead)* are the log number of companies in the fund's portfolio that were acquired or went public where the fund led at least one of the company's deals. Controls include *Ln(Fund Size)*, the log of assets under management, *Ln(Group Age)*, the log number of years since the group was formed, *Ln(# Investments)*, the log number of investments the fund made, and *I(Fund Type)* is an indicator that equals one for growth equity funds, with buyout as the omitted category. $^{***}p < 0.01$ denotes significance at the 1% level, $^{**}p < 0.05$ denotes significance at the 5% level, and $^{*}p < 0.10$ denotes significance at the 10% level. We cluster standard errors by fund.

Dependent Variable:			**Panel A: TVPI**			
Ln(# IPOs)	0.120^{**} (0.048)					
Ln(# IPOs Lead)		0.219^{***} (0.051)				
Ln(# IPOs NM Size)			0.147^{***} (0.050)			
Ln(# MAs)				0.104^{*} (0.058)		
Ln(# MAs Lead)					0.137^{***} (0.047)	
Ln(# MAs NM Size)						0.145^{***} (0.049)
Adjusted R^2	0.055	0.063	0.057	0.053	0.058	0.057
Dependent Variable:			**Panel B: IRR**			
Ln(# IPOs)	1.079 (0.799)					
Ln(# IPOs Lead)		2.576^{***} (0.936)				
Ln(# IPOs NM Size)			1.498^{*} (0.816)			
Ln(# MAs)				2.876^{***} (1.049)		
Ln(# MAs Lead)					2.667^{***} (0.848)	
Ln(# MAs NM Size)						3.385^{***} (0.929)
Adjusted R^2	0.060	0.065	0.062	0.069	0.071	0.074
# Funds	927	927	927	927	927	927
Has Controls?	X	X	X	X	X	X
Vintage Year FE?	X	X	X	X	X	X

Table 5: Association Between VC Fund Returns and Exits

This table reports results of regressions of fund-level TVPI (Panel A) and IRR (Panel B) on portfolio company exits. *Ln(# IPOs)* and *Ln(# MAs)* are the log number of companies in the fund's portfolio that went public or were acquired as of Q2 2021. *Ln(# IPOs NM Size)* and *Ln(# MAs NM Size)* are the log number of companies in the fund's portfolio that were acquired or went public and the acquisition price or market capitalization at IPO is not missing. *Ln(# IPOs Lead)* and *Ln(# MAs Lead)* are the log number of companies in the fund's portfolio that were acquired or went public where the fund lead at least one of the company's deals. Controls include *Ln(Fund Size)*, the log of assets under management, *Ln(Group Age)*, the log number of years since the group was formed, *Ln(# Investments)*, the log number of investments the fund made, and *I(General VC)* and *I(Early-stage VC)*, indicators that equal one for funds whose fund type is "Venture - General" and "Venture Capital - Early Stage," respectively. $^{***}p < 0.01$ denotes significance at the 1% level, $^{**}p < 0.05$ denotes significance at the 5% level, and $^{*}p < 0.10$ denotes significance at the 10% level. We cluster standard errors by fund.

Dependent Variable:			**Panel A: TVPI**			
Ln(# IPOs)	0.335*** (0.066)					
Ln(# IPOs Lead)		0.431*** (0.079)				
Ln(# IPOs NM Size)			0.372*** (0.067)			
Ln(# MAs)				0.274*** (0.090)		
Ln(# MAs Lead)					0.218*** (0.068)	
Ln(# MAs NM Size)						0.349*** (0.080)
Adjusted R^2	0.219	0.231	0.224	0.204	0.205	0.213
Dependent Variable:			**Panel B: IRR**			
Ln(# IPOs)	5.365*** (1.042)					
Ln(# IPOs Lead)		5.103*** (1.214)				
Ln(# IPOs NM Size)			5.999*** (1.057)			
Ln(# MAs)				3.185** (1.570)		
Ln(# MAs Lead)					0.585 (1.248)	
Ln(# MAs NM Size)						5.431*** (1.351)
Adjusted R^2	0.307	0.303	0.311	0.290	0.286	0.300
# Funds	701	701	701	701	701	701
Has Controls?	X	X	X	X	X	X
Vintage Year FE?	X	X	X	X	X	X

Table 6: Association Between Buyout Fund Returns, and M&A Filters

This table reports the results of regressions of fund-level TVPI (Panel A) and IRR (Panel B) on the size of portfolio company exits. *Ln(# MAs)* is the log number of companies in the fund's portfolio that were acquired as of Q2 2021. *Ln(# MAs NM Size)* is the log number of companies in the fund's portfolio that were acquired and the acquisition price is not missing. *Ln(# MAs NM Size/Funding)* is the log number of companies in the fund's portfolio that were acquired and the acquisition price and data on the amount of funding the portfolio company raised is not missing. *Ln(# MAs 2X)* (*Ln(# MAs 4X)*, *Ln(# MAs 6X)*) is the log number of acquisitions where the acquisition price is at least two times (four and six times) the cumulative amount of funding the portfolio company raised. Controls include *Ln(Fund Size)*, the log of assets under management, *Ln(Group Age)*, the log number of years since the group was formed, *Ln(# Investments)*, the log number of investments the fund made, and *I(Fund Type)* is an indicator that equals one for growth equity funds, with buyout as the omitted category. $^{***}p < 0.01$ denotes significance at the 1% level, $^{**}p < 0.05$ denotes significance at the 5% level, and $^{*}p < 0.10$ denotes significance at the 10% level. We cluster standard errors by fund.

Dependent Variable:			**Panel A: TVPI**			
Ln(# MAs)	0.104*					
	(0.058)					
Ln(# MAs NM Size)		0.145***				
		(0.049)				
Ln(# MAs NM Size/Funding)			0.065			
			(0.046)			
Ln(# MAs 2X)				0.110**		
				(0.049)		
Ln(# MAs 4X)					0.104*	
					(0.056)	
Ln(# MAs 6X)						0.135**
						(0.064)
Adjusted R^2	0.053	0.057	0.051	0.053	0.052	0.053
Dependent Variable:			**Panel B: IRR**			
Ln(# MAs)	2.876***					
	(1.049)					
Ln(# MAs NM Size)		3.385***				
		(0.929)				
Ln(# MAs NM Size/Funding)			1.108			
			(0.884)			
Ln(# MAs 2X)				1.774*		
				(0.934)		
Ln(# MAs 4X)					1.818*	
					(1.019)	
Ln(# MAs 6X)						2.346**
						(1.146)
Adjusted R^2	0.069	0.074	0.060	0.062	0.062	0.063
# Funds	927	927	927	927	927	927
Has Controls?	X	X	X	X	X	X
Vintage Year FE?	X	X	X	X	X	X

Table 7: Association Between VC Fund Returns, and M&A Filters

This table reports the results of regressions of fund-level TVPI (Panel A) and IRR (Panel B) on the size of portfolio company exits. *Ln(# MAs)* is the log number of companies in the fund's portfolio that were acquired as of Q2 2021. *Ln(# MAs NM Size)* is the log number of companies in the fund's portfolio that were acquired and the acquisition price is not missing. *Ln(# MAs NM Size/Funding)* is the log number of companies in the fund's portfolio that were acquired and the acquisition price and data on the amount of funding the portfolio company raised is not missing. *Ln(# MAs 2X)* (*Ln(# MAs 4X)*, *Ln(# MAs 6X)*) is the log number of acquisitions where the acquisition price is at least two times (four and six times) the cumulative amount of funding the portfolio company raised. Controls include *Ln(Fund Size)*, the log of assets under management, *Ln(Group Age)*, the log number of years since the group was formed, *Ln(# Investments)*, the log number of investments the fund made, and *I(General VC)* and *I(Early-stage VC)*, indicators that equals one for funds whose fund type is "Venture - General" and "Venture Capital - Early Stage," respectively. $^{***}p < 0.01$ denotes significance at the 1% level, $^{**}p < 0.05$ denotes significance at the 5% level, and $^{*}p < 0.10$ denotes significance at the 10% level. We cluster standard errors by fund.

Dependent Variable:			Panel A: TVPI			
Ln(# MAs)	0.274***					
	(0.090)					
Ln(# MAs NM Size)		0.349***				
		(0.080)				
Ln(# MAs NM Size/Funding)			0.334***			
			(0.077)			
Ln(# MAs 2X)				0.550***		
				(0.077)		
Ln(# MAs 4X)					0.524***	
					(0.088)	
Ln(# MAs 6X)						0.589***
						(0.089)
Adjusted R^2	0.204	0.213	0.213	0.242	0.237	0.245
Dependent Variable:			Panel B: IRR			
Ln(# MAs)	3.185**					
	(1.570)					
Ln(# MAs NM Size)		5.431***				
		(1.351)				
Ln(# MAs NM Size/Funding)			5.062***			
			(1.294)			
Ln(# MAs 2X)				8.691***		
				(1.260)		
Ln(# MAs 4X)					8.323***	
					(1.363)	
Ln(# MAs 6X)						9.579***
						(1.399)
Adjusted R^2	0.290	0.300	0.299	0.326	0.322	0.331
# Funds	701	701	701	701	701	701
Has Controls?	X	X	X	X	X	X
Vintage Year FE?	X	X	X	X	X	X

Table 8: Association Between Buyout Fund Returns and Exit Time Filters

This table reports the results of regressions of fund-level TVPI (Panel A) and IRR (Panel B) on the timing of portfolio company exits. *Ln(# IPOs)* and *Ln(# MAs)* is the log number of companies in the fund's portfolio that went public or were acquired as of Q2 2021. *Ln(# IPOs LT 5)* and *Ln(# MAs LT 5)* (*Ln(# IPOs LT 7)* and *Ln(# MAs LT 7)*) is the log number of companies in the fund's portfolio that went public or were acquired within five years (seven years) of the initial investment. Controls include *Ln(Fund Size)*, the log of assets under management, *Ln(Group Age)*, the log number of years since the group was formed, *Ln(# Investments)*, the log number of investments the fund made, and *I(Fund Type)* is an indicator that equals one for growth equity funds, with buyout as the omitted category. $^{***}p < 0.01$ denotes significance at the 1% level, $^{**}p < 0.05$ denotes significance at the 5% level, and $^{*}p < 0.10$ denotes significance at the 10% level. We cluster standard errors by fund.

Dependent Variable:			**Panel A: TVPI**			
Ln(# IPOs)	0.120^{**}					
	(0.048)					
Ln(# IPOs LT 5)		0.124^{***}				
		(0.048)				
Ln(# IPOs LT 7)			0.125^{***}			
			(0.047)			
Ln(# MAs)				0.104^{*}		
				(0.058)		
Ln(# MAs LT 5)					0.111^{*}	
					(0.058)	
Ln(# MAs LT 7)						0.105^{*}
						(0.057)
Adjusted R^2	0.055	0.055	0.055	0.053	0.054	0.053
Dependent Variable:			**Panel B: IRR**			
Ln(# IPOs)	1.079					
	(0.799)					
Ln(# IPOs LT 5)		1.227				
		(0.807)				
Ln(# IPOs LT 7)			1.242			
			(0.808)			
Ln(# MAs)				2.876^{***}		
				(1.049)		
Ln(# MAs LT 5)					2.979^{***}	
					(1.050)	
Ln(# MAs LT 7)						2.882^{***}
						(1.044)
Adjusted R^2	0.060	0.061	0.061	0.069	0.070	0.069
# Funds	927	927	927	927	927	927
Has Controls?	X	X	X	X	X	X
Vintage Year FE?	X	X	X	X	X	X

Table 9: Association Between VC Fund Returns and Exit Time Filters

This table reports the results of regressions of fund-level TVPI (Panel A) and IRR (Panel B) on the timing of portfolio company exits. *Ln(# IPOs)* and *Ln(# MAs)* is the log number of companies in the fund's portfolio that went public or were acquired as of Q2 2021. *Ln(# IPOs LT 5)* and *Ln(# MAs LT 5)* (*Ln(# IPOs LT 7)* and *Ln(# MAs LT 7)*) is the log number of companies in the fund's portfolio that went public or were acquired within five years (seven years) of the initial investment. Controls include *Ln(Fund Size)*, the log of assets under management, *Ln(Group Age)*, the log number of years since the group was formed, *Ln(# Investments)*, the log number of investments the fund made, and *I(General VC)* and *I(Early-stage VC)*, indicators that equals one for funds whose fund type is "Venture - General" and "Venture Capital - Early Stage," respectively. $^{***}p < 0.01$ denotes significance at the 1% level, $^{**}p < 0.05$ denotes significance at the 5% level, and $^{*}p < 0.10$ denotes significance at the 10% level. We cluster standard errors by fund.

Dependent Variable:			**Panel A: TVPI**			
Ln(# IPOs)	0.335***					
	(0.066)					
Ln(# IPOs LT 5)		0.349***				
		(0.066)				
Ln(# IPOs LT 7)			0.344***			
			(0.066)			
Ln(# MAs)				0.274***		
				(0.090)		
Ln(# MAs LT 5)					0.303***	
					(0.088)	
Ln(# MAs LT 7)						0.287***
						(0.091)
Adjusted R^2	0.219	0.222	0.221	0.204	0.206	0.205
Dependent Variable:			**Panel B: IRR**			
Ln(# IPOs)	5.365***					
	(1.042)					
Ln(# IPOs LT 5)		5.788***				
		(1.044)				
Ln(# IPOs LT 7)			5.629***			
			(1.044)			
Ln(# MAs)				3.185**		
				(1.570)		
Ln(# MAs LT 5)					3.923**	
					(1.556)	
Ln(# MAs LT 7)						3.502**
						(1.581)
Adjusted R^2	0.307	0.310	0.309	0.290	0.291	0.290
# Funds	701	701	701	701	701	701
Has Controls?	X	X	X	X	X	X
Vintage Year FE?	X	X	X	X	X	X

Table 10: Issuer Characteristics

This table reports summary statistics for the issuers in the portfolio of the funds in Table 1. The unit of observation is an issuer. To capture early-stage VC rounds, the sample only includes issuers whose first round of funding is either Seed Round, Angel (individual), Convertible Debt, Accelerator/Incubator, or Early Stage VC. *I(IPO)* and *I(MA NM Size)* are indicators for whether a company goes public or is acquired (as of Q2 2021) and the acquisition price is not missing. *I(Raise Funding)* is an indicator that equals one for issuers that raised a follow-on round of funding as of Q2 2021. *I(Raise Funding 2X)* is an indicator that equals one for issuers that raised a follow-on round of funding that was more than twice as large as their initial first funding round. *I(Raise Funding 2Y)* (*I(Raise Funding 4Y)*, *I(Raise Funding 6Y)*) is an indicator that equals one for issuers that raised a follow-on round of funding less than two years (four years, six years) following their first round. *I(Raise Funding 4X)* and *I(Raise Funding 6X)* are indicators for issuers that raised follow-on rounds that were at least four and six times larger than the initial round, respectively. *I(Has Employee LinkedIn)* is an indicator for whether the company has any employees on LinkedIn according to Datahut. (*# Employees 2Y)*), (*# Employees 4Y*), and (*# Employees 6Y*) are the number of employees two, four, and six years following the first round of funding. *I(Has Patent)* is an indicator that equals one for issuers that were ever assigned a patent by the USTPO. *I(Has Rank)* (*I(Has Traffic)*) is an indicator for whether the company's website is ranked (traffic is tracked) by Semrush. *Issuer Age* is the number of years between when the issuer was founded and when it raised its first funding round. *I(Business Products & Services)*, *I(Computer Products & Services)*, *I(Energy)*, *I(Financial Services)*, *I(Healthcare)*, and *Information Technology* are indicators for the primary industry sector of the company according to PitchBook.

	N	Mean	Std	25%	50%	75%	Max
I(IPO)	7,075	0.14	0.35	0.00	0.00	0.00	1.00
I(M&A)	7,075	0.24	0.42	0.00	0.00	0.00	1.00
I(Raise Funding)	7,075	0.83	0.38	1.00	1.00	1.00	1.00
I(Raise Funding 2Y)	7,075	0.51	0.50	0.00	1.00	1.00	1.00
I(Raise Funding 4Y)	7,075	0.77	0.42	1.00	1.00	1.00	1.00
I(Raise Funding 2X)	7,075	0.44	0.50	0.00	0.00	1.00	1.00
I(Raise Funding 4X)	7,075	0.23	0.42	0.00	0.00	0.00	1.00
I(Raise Funding 6X)	7,075	0.14	0.35	0.00	0.00	0.00	1.00
I(Has Employee LinkedIn)	7,075	0.57	0.49	0.00	1.00	1.00	1.00
# Employees 2Y	4,063	22.99	41.62	6.00	13.00	26.00	1338.00
# Employees 4Y	4,063	45.26	90.31	11.00	24.00	47.00	2139.00
# Employees 6Y	4,063	65.69	151.06	10.00	28.00	62.00	2846.00
I(Has Patent)	7,075	0.26	0.44	0.00	0.00	1.00	1.00
I(Patent 2Y)	7,075	0.05	0.21	0.00	0.00	0.00	1.00
I(Patent 4Y)	7,075	0.11	0.31	0.00	0.00	0.00	1.00
I(Patent 6Y)	7,075	0.17	0.38	0.00	0.00	0.00	1.00
I(Has Traffic)	7,075	0.12	0.33	0.00	0.00	0.00	1.00
Ln(Traffic 2Y)	854	3.57	3.31	0.00	3.13	6.17	13.15
Ln(Traffic 4Y)	854	5.08	3.62	1.65	5.45	7.76	14.77
Ln(Traffic 6Y)	854	5.68	3.93	2.22	6.30	8.63	15.43
I(Has Rank)	7,075	0.10	0.30	0.00	0.00	0.00	1.00
Ln(Rank 2Y)	682	13.48	1.84	12.24	13.72	14.83	17.84
Ln(Rank 4Y)	682	12.92	2.15	11.62	12.95	14.43	17.28
Ln(Rank 6Y)	682	13.14	2.59	11.51	13.00	14.80	17.79
Size first deal ($ Millions)	7,075	8.30	19.65	1.50	4.15	9.00	550.00
Issuer Age	7,075	2.65	2.02	1.00	2.00	3.00	19.00
I(Business Products and Services)	7,075	0.13	0.34	0.00	0.00	0.00	1.00
I(Consumer Products and Services)	7,075	0.11	0.31	0.00	0.00	0.00	1.00
I(Energy)	7,075	0.02	0.15	0.00	0.00	0.00	1.00
I(Financial Services)	7,075	0.02	0.13	0.00	0.00	0.00	1.00
I(Healthcare)	7,075	0.21	0.41	0.00	0.00	0.00	1.00
I(Information Technology)	7,075	0.50	0.50	0.00	1.00	1.00	1.00
I(Materials and Resources)	7,075	0.01	0.08	0.00	0.00	0.00	1.00

Table 11: Association Between Exits and Employee Growth (DataHut)

This table report regressions of indicators for whether a company goes public, *I(IPO)*, or is acquired and the acquisition price is not missing *I(MA NM Size)* on whether the company has any employees on LinkedIn according to Datahut (*I(Has Employee LinkedIn)*) and the log number of employees in the two (*Ln(Employees 2Y)*), four (*Ln(Employees 4Y)*), and six years (*Ln(Employees 6Y)*) following the first round of funding, according to LinkedIn data from Datahut. The unit of observation is an issuer. The sample is restricted to issuers in the portfolios of the funds in Table 1. To capture early-stage VC rounds, the sample only includes issuers whose first round of funding is either Seed Round, Angel (individual), Convertible Debt, Accelerator/Incubator, or Early Stage VC. *Industry FE* are the indicators listed in Table 10. *Fundraising Year FE* are year dummies for the year the issuer raised its first round. *Ln(Size first deal)* is the log amount of funding an issuer raised in its first funding round, and *Ln(Issuer Age)* is log of the issuer's age at the first funding round. $^{***}p < 0.01$ denotes significance at the 1% level, $^{**}p < 0.05$ denotes significance at the 5% level, and $^{*}p < 0.10$ denotes significance at the 10% level. We cluster standard errors by issuer.

Dependent Variable:	**Panel A: I(IPO)**			
I(Has Employee LinkedIn)	0.059***			
	(0.008)			
Ln(Employees 2Y)		0.071***		
		(0.006)		
Ln(Employees 4Y)			0.073***	
			(0.005)	
Ln(Employees 6Y)				0.066***
				(0.004)
Ln(Size first deal)	0.014***	0.001	0.003	0.008*
	(0.003)	(0.004)	(0.004)	(0.004)
Ln(Issuer Age)	-0.009	0.024**	0.006	-0.024***
	(0.007)	(0.010)	(0.009)	(0.009)
Adjusted R^2	0.132	0.185	0.206	0.223
Dependent Variable:	**Panel B: I(MA NM Size)**			
I(Has Employee LinkedIn)	0.003			
	(0.010)			
Ln(Employees 2Y)		0.025***		
		(0.007)		
Ln(Employees 4Y)			0.017***	
			(0.006)	
Ln(Employees 6Y)				0.010**
				(0.004)
Ln(Size first deal)	0.020***	0.011**	0.013***	0.015***
	(0.003)	(0.005)	(0.005)	(0.005)
Ln(Issuer Age)	-0.013	-0.005	-0.015	-0.022*
	(0.008)	(0.013)	(0.012)	(0.012)
Adjusted R^2	0.025	0.022	0.021	0.020
# Issuers	7073	4061	4061	4061
Fundraising Year and Industry FE?	X	X	X	X

Table 12: Association Between Exits and Fundraising Size

This table report regressions of indicators for whether a company goes public, *I(IPO)*, or is acquired and the acquisition price is not missing *I(MA NM Size)* on how the size of an issuer's follow-on round of funding after their initial round. *I(Raise Funding)* is an indicator that equals one for issuers that raised a follow-on round of funding as of Q2 2021. *I(Raise Funding 2X)* is an indicator that equals one for issuers that raised a follow-on round of funding that was more than twice as large as their initial first funding round. *I(Raise Funding 4X)*, and *I(Raise Funding 6X)* are indicators for issuers that raised follow-on rounds that were at least four and six times larger than the initial round. The sample is restricted to issuers in the portfolios of the funds in Table 1. To capture early-stage VC rounds, the sample only includes issuers whose first round of funding is either Seed Round, Angel (individual), Convertible Debt, Accelerator/Incubator, or Early Stage VC. *Industry FE* are the indicators listed in Table 10. *Fundraising Year FE* are year dummies for the year the issuer raised its first round. *Ln(Size first deal)* is the log amount of funding an issuer raised in its first funding round, and *Ln(Issuer Age)* is log of the issuer's age at the first funding round. $^{***}p < 0.01$ denotes significance at the 1% level, $^{**}p < 0.05$ denotes significance at the 5% level, and $^{*}p < 0.10$ denotes significance at the 10% level. We cluster standard errors by issuer.

Dependent Variable:	**Panel A: I(IPO)**			
I(Raise Funding)	0.047***			
	(0.009)			
I(Raise Funding 2X)		0.046***		
		(0.009)		
I(Raise Funding 4X)			0.060***	
			(0.011)	
I(Raise Funding 6X)				0.096***
				(0.014)
Ln(Size first deal)	0.016***	0.021***	0.023***	0.026***
	(0.003)	(0.004)	(0.004)	(0.004)
Ln(Issuer Age)	-0.011*	-0.010	-0.012*	-0.012*
	(0.007)	(0.007)	(0.006)	(0.006)
Adjusted R^2	0.127	0.128	0.129	0.132
Dependent Variable:	**Panel B: I(MA NM Size)**			
(Raise Funding)	0.027**			
	(0.013)			
I(Raise Funding 2X)		0.023**		
		(0.011)		
I(Raise Funding 4X)			0.013	
			(0.013)	
I(Raise Funding 6X)				0.016
				(0.016)
Ln(Size first deal)	0.021***	0.023***	0.022***	0.022***
	(0.003)	(0.004)	(0.004)	(0.004)
Ln(Issuer Age)	-0.011	-0.011	-0.013	-0.013
	(0.008)	(0.008)	(0.008)	(0.008)
Adjusted R^2	0.025	0.025	0.025	0.025
# Issuers	7074	7074	7074	7074
Fundraising Year and Industry FE?	X	X	X	X

Table 13: Association Between Exits and Fundraising Timing

This table report regressions of indicators for whether a company goes public, *I(IPO)*, or is acquired and the acquisition price is not missing *I(MA NM Size)* on how quickly an issuer raised a follow-on round of funding after their initial round. *I(Raise Funding)* is an indicator that equals one for issuers that raised a follow-on round of funding as of Q2 2021. *I(Raise Funding 2Y)* is an indicator that equals one for issuers that raised a follow-on round of funding less than two years following their first round. *I(Raise Funding 3Y)*, and *I(Raise Funding 4Y)* are indicators for issuers that raised a follow on round less than three and four years following the first round. The sample is restricted to issuers in the portfolios of the funds in Table 1. To capture early-stage VC rounds, the sample only includes issuers whose first round of funding is either Seed Round, Angel (individual), Convertible Debt, Accelerator/Incubator, or Early Stage VC. *Industry FE* are the indicators listed in Table 10. *Fundraising Year FE* are year dummies for the year the issuer raised its first round. *Ln(Size first deal)* is the log amount of funding an issuer raised in its first funding round, and *Ln(Issuer Age)* is log of the issuer's age at the first funding round. $^{***}p < 0.01$ denotes significance at the 1% level, $^{**}p < 0.05$ denotes significance at the 5% level, and $^{*}p < 0.10$ denotes significance at the 10% level. We cluster standard errors by issuer.

Dependent Variable:	**Panel A: I(IPO)**			
I(Raise Funding)	0.047***			
	(0.009)			
I(Raise Funding 2Y)		0.055***		
		(0.008)		
I(Raise Funding 3Y)			0.057***	
			(0.008)	
I(Raise Funding 4Y)				0.048***
				(0.009)
Ln(Size first deal)	0.016***	0.017***	0.017***	0.016***
	(0.003)	(0.003)	(0.003)	(0.003)
Ln(Issuer Age)	-0.011*	-0.012*	-0.010	-0.011
	(0.007)	(0.006)	(0.006)	(0.007)
Adjusted R^2	0.127	0.131	0.130	0.128
Dependent Variable:	**Panel B: I(MA NM Size)**			
I(Raise Funding)	0.027**			
	(0.013)			
I(Raise Funding 2Y)		0.026***		
		(0.010)		
I(Raise Funding 3Y)			0.019*	
			(0.011)	
I(Raise Funding 4Y)				0.032***
				(0.012)
Ln(Size first deal)	0.021***	0.021***	0.020***	0.021***
	(0.003)	(0.003)	(0.003)	(0.003)
Ln(Issuer Age)	-0.011	-0.012	-0.012	-0.011
	(0.008)	(0.008)	(0.008)	(0.008)
Adjusted R^2	0.025	0.026	0.025	0.026
# Issuers	7074	7074	7074	7074
Fundraising Year and Industry FE?	X	X	X	X

Table 14: Association Between Exits and Patents

This table report regressions of indicators for whether a company goes public, *I(IPO)*, or is acquired and the acquisition price is not missing *I(MA NM Size)* on whether the issuer applied for a patent following the first funding round. *I(Has Patent)* is an indicator that equals one for issuers that were ever assigned a patent by the USTPO, as of Q2 2020. *I(Patent 2Y)*, *I(Patent 4Y)*, *I(Patent 6Y)*, are indicators that equals one when the startup obtained a patent within two, four, and six years following the first round of funding. The unit of observation is a startup. The sample is restricted to startups in the portfolios of the funds in Table 1. To capture early-stage VC rounds, the sample only includes issuers whose first round of funding is either Seed Round, Angel (individual), Convertible Debt, Accelerator/Incubator, or Early Stage VC. *Industry FE* are the indicators listed in Table 10. *Fundraising Year FE* are year dummies for the year the issuer raised its first round. *Ln(Size first deal)* is the log amount of funding an issuer raised in its first funding round, and *Ln(Issuer Age)* is log of the issuer's age at the first funding round. $^{***}p < 0.01$ denotes significance at the 1% level, $^{**}p < 0.05$ denotes significance at the 5% level, and $^{*}p < 0.10$ denotes significance at the 10% level. We cluster standard errors by issuer.

Dependent Variable:	**Panel A: I(IPO)**			
I(Has Patent)	0.093***			
	(0.010)			
I(Patent 2Y)		-0.004		
		(0.019)		
I(Patent 4Y)			0.017	
			(0.014)	
I(Patent 6Y)				0.042***
				(0.011)
Ln(Size first deal)	0.013***	0.014***	0.014***	0.013***
	(0.003)	(0.003)	(0.003)	(0.003)
Ln(Issuer Age)	-0.004	-0.014**	-0.013**	-0.010
	(0.006)	(0.007)	(0.007)	(0.007)
Adjusted R^2	0.136	0.125	0.125	0.127
Dependent Variable:	**Panel B: I(MA NM Size)**			
I(Has Patent)	0.049***			
	(0.013)			
I(Patent 2Y)		0.048*		
		(0.025)		
I(Patent 4Y)			0.045**	
			(0.018)	
I(Patent 6Y)				0.057***
				(0.015)
Ln(Size first deal)	0.019***	0.019***	0.019***	0.019***
	(0.003)	(0.003)	(0.003)	(0.003)
Ln(Issuer Age)	-0.008	-0.011	-0.010	-0.008
	(0.008)	(0.008)	(0.008)	(0.008)
Adjusted R^2	0.027	0.025	0.026	0.027
# Issuers	7074	7074	7074	7074
Fundraising Year and Industry FE?	X	X	X	X

Predicting Success in Entrepreneurial Finance Research

Internet Appendix

Table A.1: Correlation Amongst Success Proxies Buyout

This table presents univariate correlations amongst several proxies for success. ***, **, and * indicate that the correlation is statistical significance at 1%, 5%, and 10% level, respectively.

	Ln(# IPOs)	Ln(# IPOs Lead)	Ln(# IPOs NM Size)	Ln(# MAs)	Ln(# MAs Lead)	Ln(# MAs NM Size)	Ln(# MAs 2X)	Ln(# MAs 4X)	Ln(# MAs 6X)	Ln(# IPOs LT 5)	Ln(# IPOs LT 7)	Ln(# MAs LT 5)	Ln(# MAs LT 7)
Ln(# IPOs)													
Ln(# IPOs Lead)	0.79***												
Ln(# IPOs NM Size)	0.98***	0.78***											
Ln(# MAs)	0.55***	0.48***	0.54***										
Ln(# MAs Lead)	0.4***	0.54***	0.39***	0.78***									
Ln(# MAs NM Size)	0.58***	0.51***	0.57***	0.9***	0.7***								
Ln(# MAs 2X)	0.54***	0.47***	0.53***	0.64***	0.51***	0.73***							
Ln(# MAs 4X)	0.51***	0.46***	0.51***	0.57***	0.46***	0.65***	0.88***						
Ln(# MAs 6X)	0.48***	0.42***	0.48***	0.53***	0.43***	0.6***	0.79***	0.89***					
Ln(# IPOs LT 5)	1.0***	0.79***	0.97***	0.54***	0.39***	0.58***	0.53***	0.51***	0.47***				
Ln(# IPOs LT 7)	1.0***	0.79***	0.98***	0.55***	0.4***	0.58***	0.54***	0.52***	0.48***	1.0***			
Ln(# MAs LT 5)	0.55***	0.48***	0.54***	1.0***	0.77***	0.9***	0.64***	0.57***	0.53***	0.55***	0.55***		
Ln(# MAs LT 7)	0.55***	0.48***	0.54***	1.0***	0.77***	0.9***	0.64***	0.58***	0.53***	0.54***	0.55***	1.0***	

Table A.2: Correlation Amongst Success Proxies Venture

This table presents univariate correlations amongst several proxies for success. ***, **, and * indicate that the correlation is statistical significance at 1%, 5%, and 10% level, respectively.

	Ln(# IPOs)	Ln(# IPOs Lead)	Ln(# IPOs NM Size)	Ln(# MAs)	Ln(# MAs Lead)	Ln(# MAs NM Size)	Ln(# MAs 2X)	Ln(# MAs 4X)	Ln(# MAs 6X)	Ln(# IPOs LT 5)	Ln(# IPOs LT 7)	Ln(# MAs LT 5)	Ln(# MAs LT 7)
Ln(# IPOs)													
Ln(# IPOs Lead)	0.82***												
Ln(# IPOs NM Size)	0.99***	0.81***											
Ln(# MAs)	0.67***	0.6***	0.67***										
Ln(# MAs Lead)	0.59***	0.69***	0.58***	0.85***									
Ln(# MAs NM Size)	0.73***	0.64***	0.73***	0.93***	0.8***								
Ln(# MAs 2X)	0.73***	0.64***	0.72***	0.84***	0.74***	0.92***							
Ln(# MAs 4X)	0.73***	0.66***	0.74***	0.78***	0.71***	0.86***	0.94***						
Ln(# MAs 6X)	0.69***	0.62***	0.7***	0.72***	0.66***	0.79***	0.87***	0.93***					
Ln(# IPOs LT 5)	0.99***	0.79***	0.98***	0.66***	0.57***	0.72***	0.71***	0.72***	0.68***				
Ln(# IPOs LT 7)	1.0***	0.81***	0.98***	0.67***	0.58***	0.73***	0.72***	0.73***	0.69***	0.99***			
Ln(# MAs LT 5)	0.67***	0.59***	0.66***	1.0***	0.84***	0.92***	0.84***	0.78***	0.72***	0.66***	0.67***		
Ln(# MAs LT 7)	0.67***	0.6***	0.66***	1.0***	0.85***	0.93***	0.84***	0.78***	0.72***	0.66***	0.67***	1.0***	

Table A.3: PitchBooks Vs. SDC Coverage of Exits

This table presents statistics on exits in PitchBook and exits in our matched PitchBook-SDC sample. *IPO SDC* (*M&A SDC*) are indicators that equals one for startups that went public (were acquired) as of Q3 2022, and we could match to issuers in the Securities Data Corporation (SDC) database, which tracks initial public offerings and acquisitions. *IPO PitchBook* (*M&A PitchBook*) were indicators for startups that went public or were acquired by Q2 2021 according to PitchBook.

Panel A: IPOs			
	IPO PitchBook	No IPO PitchBook	Total
IPO SDC	219	2	221
No IPO SDC	792	6,062	6,854
Total	1,011	6,064	7,075
Panel B: Acquisitions			
	M&A PitchBook	No M&A PitchBook	Total
M&A SDC	601	242	843
No M&A SDC	1,070	5,162	6,232
Total	1,671	5,404	7,075

Table A.4: Association Between Buyout Fund Returns and Combined Exits

This table reports the results of regressions of fund-level TVPI (Panel A) and IRR (Panel B) on the timing of portfolio company exits. *Ln(# Exits)* and *Ln(# Exits)* is the log number of companies in the fund's portfolio that went public or were acquired as of Q2 2021. *Ln(# Exits LT 5)* and *Ln(# Exits LT 7)* is the log number of companies in the fund's portfolio that went public or were acquired within five years and seven years of the initial investment. Controls include *Ln(Fund Size)*, the log of assets under management, *Ln(Group Age)*, the log number of years since the group was formed, *Ln(# Investments)*, the log number of investments the fund made, and *I(General VC)* and *I(Early-stage VC)*, indicators that equals one for funds whose fund type is "Venture - General" and "Venture Capital - Early Stage," respectively. $^{***}p < 0.01$ denotes significance at the 1% level, $^{**}p < 0.05$ denotes significance at the 5% level, and $^{*}p < 0.10$ denotes significance at the 10% level. We cluster standard errors by fund.

Dependent Variable:			**Panel A: TVPI**		
Ln(# Exits)	0.134** (0.057)				
Ln(# Exits Lead)		0.163*** (0.044)			
Ln(# Exits NM Size)			0.166*** (0.049)		
Ln(# Exits LT 5)				0.142** (0.057)	
Ln(# Exits LT 7)					0.136** (0.057)
Adjusted R^2	0.056	0.064	0.061	0.057	0.056
Dependent Variable:			**Panel B: IRR**		
Ln(# Exits)	2.943*** (1.040)				
Ln(# Exits Lead)		2.873*** (0.798)			
Ln(# Exits NM Size)			3.238*** (0.900)		
Ln(# Exits LT 5)				3.102*** (1.040)	
Ln(# Exits LT 7)					3.004*** (1.038)
Adjusted R^2	0.070	0.074	0.074	0.071	0.071
# Funds	927	927	927	927	927
Has Controls?	X	X	X	X	X
Vintage Year FE?	X	X	X	X	X

Table A.5: Association Between VC Fund Returns and Combined Exits

This table reports the results of regressions of fund-level TVPI (Panel A) and IRR (Panel B) on the timing of portfolio company exits. *Ln(# Exits)* and *Ln(# Exits)* is the log number of companies in the fund's portfolio that went public or were acquired as of Q2 2021. *Ln(# Exits LT 5)* and *Ln(# Exits LT 7)* is the log number of companies in the fund's portfolio that went public or were acquired within five years and seven years of the initial investment. Controls include *Ln(Fund Size)*, the log of assets under management, *Ln(Group Age)*, the log number of years since the group was formed, *Ln(# Investments)*, the log number of investments the fund made, and *I(General VC)* and *I(Early-stage VC)*, indicators that equals one for funds whose fund type is "Venture - General" and "Venture Capital - Early Stage," respectively. $^{***}p < 0.01$ denotes significance at the 1% level, $^{**}p < 0.05$ denotes significance at the 5% level, and $^{*}p < 0.10$ denotes significance at the 10% level. We cluster standard errors by fund.

Dependent Variable:			**Panel A: TVPI**		
Ln(# Exits)	0.364*** (0.085)				
Ln(# Exits Lead)		0.290*** (0.066)			
Ln(# Exits NM Size)			0.400*** (0.072)		
Ln(# Exits LT 5)				0.397*** (0.085)	
Ln(# Exits LT 7)					0.378*** (0.086)
Adjusted R^2	0.212	0.215	0.222	0.214	0.213
Dependent Variable:			**Panel B: IRR**		
Ln(# Exits)	5.296*** (1.504)				
Ln(# Exits Lead)		2.052* (1.238)			
Ln(# Exits NM Size)			6.684*** (1.245)		
Ln(# Exits LT 5)				6.111*** (1.523)	
Ln(# Exits LT 7)					5.655*** (1.526)
Adjusted R^2	0.297	0.289	0.311	0.301	0.299
# Funds	701	701	701	701	701
Has Controls?	X	X	X	X	X
Vintage Year FE?	X	X	X	X	X

Table A.6: Association Between Buyout Returns and Exits (Normalizing Exit Counts)

This table reports results for regressions of fund-level TVPI (Panel A) and IRR (Panel B) on portfolio company exits. *P(# IPOs)* and *P(# MAs)* are the proportion of companies in the fund's portfolio that went public or were acquired as of Q2 2021. *P(# IPOs NM Size)* and *P(# MAs NM Size)* are the proportion of companies in the fund's portfolio that were acquired or went public and the acquisition price or market capitalization at IPO is not missing. *P(# IPOs Lead)* and *P(# MAs Lead)* are the proportion of companies in the fund's portfolio that were acquired or went public where the fund led at least one of the company's deals. Controls include *Ln(Fund Size)*, the log of assets under management, *Ln(Group Age)*, the log number of years since the group was formed, *Ln(# Investments)*, the log number of investments the fund made, and *I(General VC)* and *I(Early-stage VC)*, indicators that equal one for funds whose fund type is "Venture - General" and "Venture Capital - Early Stage," respectively. $^{***}p < 0.01$ denotes significance at the 1% level, $^{**}p < 0.05$ denotes significance at the 5% level, and $^{*}p < 0.10$ denotes significance at the 10% level. We cluster standard errors by fund.

Dependent Variable:			**Panel A: TVPI**			
P(IPOs)	0.277* (0.166)					
P(IPOs Lead)		0.605** (0.291)				
P(IPOs NM Size)			0.357** (0.177)			
P(MAs)				0.279* (0.165)		
P(MAs Lead)					0.705* (0.378)	
P(MAs NM Size)						0.292* (0.158)
Adjusted R^2	0.051	0.052	0.052	0.054	0.061	0.052
Dependent Variable:			**Panel B: IRR**			
P(IPOs)	0.978 (2.695)					
P(IPOs Lead)		7.017 (5.476)				
P(IPOs NM Size)			2.465 (2.807)			
P(MAs)				6.890** (2.753)		
P(MAs Lead)					13.550** (5.934)	
P(MAs NM Size)						8.036*** (2.854)
Adjusted R^2	0.059	0.060	0.059	0.068	0.073	0.067
# Funds	927	927	927	927	927	927
Has Controls?	X	X	X	X	X	X
Vintage Year FE?	X	X	X	X	X	X

Table A.7: Association Between Venture Returns and Exits (Normalizing Exit Counts)

This table reports results of regressions of fund-level TVPI (Panel A) and IRR (Panel B) on portfolio company exits. *Ln(# IPOs)* and *Ln(# MAs)* are the log number of companies in the fund's portfolio that went public or were acquired as of Q2 2021. *Ln(# IPOs NM Size)* and *Ln(# MAs NM Size)* are the log number of companies in the fund's portfolio that were acquired or went public and the acquisition price or market capitalization at IPO is not missing. *Ln(# IPOs Lead)* and *Ln(# MAs Lead)* are the log number of companies in the fund's portfolio that were acquired or went public where the fund lead at least one of the company's deals. Controls include *Ln(Fund Size)*, the log of assets under management, *Ln(Group Age)*, the log number of years since the group was formed, and *I(General VC)* and *I(Early-stage VC)*, indicators that equal one for funds whose fund type is "Venture - General" and "Venture Capital - Early Stage," respectively. $^{***}p < 0.01$ denotes significance at the 1% level, $^{**}p < 0.05$ denotes significance at the 5% level, and $^{*}p < 0.10$ denotes significance at the 10% level. We cluster standard errors by fund.

Dependent Variable:			**Panel A: TVPI**			
P(IPOs)	0.997***					
	(0.280)					
P(IPOs Lead)		1.933***				
		(0.541)				
P(IPOs NM Size)			1.113***			
			(0.299)			
P(MAs)				0.525***		
				(0.198)		
P(MAs Lead)					0.494	
					(0.317)	
P(MAs NM Size)						0.681***
						(0.227)
Adjusted R^2	0.211	0.214	0.213	0.203	0.200	0.205
Dependent Variable:			**Panel B: IRR**			
P(IPOs)	18.496***					
	(5.205)					
P(IPOs Lead)		25.601***				
		(9.498)				
P(IPOs NM Size)			21.097***			
			(5.653)			
P(MAs)				7.931**		
				(3.567)		
P(MAs Lead)					-0.102	
					(4.933)	
P(MAs NM Size)						13.456***
						(4.182)
Adjusted R^2	0.303	0.297	0.307	0.291	0.286	0.298
# Funds	701	701	701	701	701	701
Has Controls?	X	X	X	X	X	X
Vintage Year FE?	X	X	X	X	X	X

Table A.8: Association Between Exits and Website Rank

This table report regressions of indicators for whether a company goes public, *I(IPO)*, or is acquired and the acquisition price is not missing *I(MA NM Size)* on whether the company's website is ranked by Semrush (*I(Has Rank)*) and the log rank of the companies website amongst all the companies Semrush tracks in the two (*Ln(Rank 2Y)*), four (*Ln(Rank 4Y)*), and six years (*Ln(Rank 6Y)*) following the first round of funding, according to Semrush. The unit of observation is an issuer. The sample is restricted to issuers in the portfolios of the funds in Table 1. To capture early-stage VC rounds, the sample only includes issuers whose first round of funding is either Seed Round, Angel (individual), Convertible Debt, Accelerator/Incubator, or Early Stage VC. *Industry FE* are the indicators listed in Table 10. *Fundraising Year FE* are year dummies for the year the issuer raised its first round. *Ln(Size first deal)* is the log amount of funding an issuer raised in its first funding round, and *Ln(Issuer Age)* is log of the issuer's age at the first funding round. $^{***}p < 0.01$ denotes significance at the 1% level, $^{**}p < 0.05$ denotes significance at the 5% level, and $^{*}p < 0.10$ denotes significance at the 10% level. We cluster standard errors by issuer.

Dependent Variable:	**Panel A: I(IPO)**			
I(Has Rank)	0.036**			
	(0.015)			
Ln(Rank 2Y)		-0.014**		
		(0.007)		
Ln(Rank 4Y)			-0.018***	
			(0.005)	
Ln(Rank 6Y)				-0.021***
				(0.004)
Ln(Size first deal)	0.014***	0.023***	0.022***	0.021***
	(0.003)	(0.008)	(0.008)	(0.007)
Ln(Issuer Age)	-0.011*	-0.027	-0.037	-0.042
	(0.007)	(0.027)	(0.026)	(0.026)
Adjusted R^2	0.125	0.144	0.155	0.172
Dependent Variable:	**Panel B: I(MA NM Size)**			
I(Has Rank)	0.022			
	(0.021)			
Ln(Rank 2Y)		-0.020**		
		(0.008)		
Ln(Rank 4Y)			-0.007	
			(0.006)	
Ln(Rank 6Y)				-0.004
				(0.005)
Ln(Size first deal)	0.020***	0.018***	0.018***	0.018***
	(0.003)	(0.007)	(0.007)	(0.007)
Ln(Issuer Age)	-0.011	-0.013	-0.027	-0.028
	(0.008)	(0.032)	(0.032)	(0.032)
Adjusted R^2	0.025	0.010	0.002	0.001
# Firms	7073	679	679	679
Observations	7073	679	679	679
Fundraising Year and Industry FE?	X	X	X	X

Table A.9: Association Between Exits and and Website Traffic

This table report regressions of indicators for whether a company goes public, *I(IPO)*, or is acquired and the acquisition price is not missing *I(MA NM Size)* on whether the company's website traffic is tracked by Semrush (*I(Has Traffic)*) and the log number of unique visitors to the company's website in the two (*Ln(Traffic 2Y)*), four (*Ln(Traffic 4Y)*), and six years (*Ln(Traffic 6Y)*) following the first round of funding, according to Semrush. The unit of observation is an issuer. The sample is restricted to issuers in the portfolios of the funds in Table 1. To capture early-stage VC rounds, the sample only includes issuers whose first round of funding is either Seed Round, Angel (individual), Convertible Debt, Accelerator/Incubator, or Early Stage VC. *Industry FE* are the indicators listed in Table 10. *Fundraising Year FE* are year dummies for the year the issuer raised its first round. *Ln(Size first deal)* is the log amount of funding an issuer raised in its first funding round, and *Ln(Issuer Age)* is log of the issuer's age at the first funding round. $^{***}p < 0.01$ denotes significance at the 1% level, $^{**}p < 0.05$ denotes significance at the 5% level, and $^{*}p < 0.10$ denotes significance at the 10% level. We cluster standard errors by issuer.

Dependent Variable:	**Panel A: I(IPO)**			
I(Has Traffic)	0.031*			
	(0.017)			
Ln(Traffic 2Y)		0.006*		
		(0.003)		
Ln(Traffic 4Y)			0.010***	
			(0.003)	
Ln(Traffic 6Y)				0.012***
				(0.002)
Ln(Size first deal)	0.014***	0.025***	0.024***	0.023***
	(0.003)	(0.007)	(0.007)	(0.007)
Ln(Issuer Age)	-0.011*	-0.040*	-0.040*	-0.046**
	(0.007)	(0.023)	(0.023)	(0.023)
Adjusted R^2	0.125	0.129	0.142	0.153
Dependent Variable:	**Panel B: I(MA NM Size)**			
I(Has Traffic)	0.003			
	(0.024)			
Ln(Traffic 2Y)		0.010***		
		(0.004)		
Ln(Traffic 4Y)			0.007**	
			(0.003)	
Ln(Traffic 6Y)				0.005*
				(0.003)
Ln(Size first deal)	0.020***	0.017***	0.017***	0.017***
	(0.003)	(0.006)	(0.006)	(0.006)
Ln(Issuer Age)	-0.013	-0.013	-0.022	-0.027
	(0.009)	(0.028)	(0.027)	(0.027)
Adjusted R^2	0.025	0.016	0.012	0.010
# Firms	7073	851	851	851
Observations	7073	851	851	851
Fundraising Year and Industry FE?	X	X	X	X

Table A.10: Exit Outcomes Survey

Table surveying what exit outcomes and filters people are using in the literature.

Paper	Outcome	Filter
Sørensen (2007)	I(IPO)	Company exited via an IPO
Nanda et al. (2020)	I(IPO)	Company exited via an IPO
Ewens and Marx (2018)	I(IPO or M&A)	Acquisition that exceeds 125% of total capital raised
Bernstein et al. (2016)	I(IPO or M&A)	Acquisition that exceeds $25 million in 2000 dollars
Gompers et al. (2008)	I(IPO or M&A)	IPO or Acquisition within seven years of first funding round
Hochberg et al. (2007)	I(IPO or M&A or Follow-on)	Company survived from round N to round N+1 or if it exited via an IPO or M&A transaction
Ewens and Farre-Mensa (2020)	I(IPO or M&A)	Acquisition value is greater than total capital raised by the firm
Cumming (2008)	I(M&A)	Using IRRs of the investment to avoid misclassification of write-offs as acquisitions
Gompers et al. (2016)	I(IPO or M&A)	Acquisitions with a transaction value exceeding the total amount invested or exceeding a threshold of $25 million (or alternatively, $50 million or $100 million)
Aggarwal and Hsu (2014)	I(IPO or M&A)	No Filter
Conti and Graham (2020)	I(IPO or M&A)	No Filter
Howell (2017)	I(IPO or M&A)	No Filter
Puri and Zarutskie (2012)	I(IPO or M&A)	No Filter