Human Capital in Venture Capital: Evidence From 100,000 Venture Capitalists*

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Abstract

We study the role of individual human capital in venture capital using a new dataset covering nearly 100,000 professionals affiliated with U.S. venture capital firms from 1996 to 2025. Investment success is extremely concentrated: fewer than 40% of venture capitalists credited with any investments are ever credited with a successful investment, and only 6% achieve six or more successes over their careers. Differences in education, prior work experience, and demographics predict career progression and investment outcomes at the deal and individual levels, consistent with persistent investor-specific skills. Individual characteristics currently have a weaker relationship with fund-level returns. Quasi-experimental variation from marginal inclusions on the Forbes Midas List show that achieving superstar status increases subsequent investment success, driven by new investments in highly-valued startups, in contrast to superstar effects in other settings. The results show that human capital accounts for persistent variation in venture capital outcomes and that status amplifies performance by improving access to high-quality companies.

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The U.S. venture capital industry has had an outsized impact on U.S. innovation, firm creation, and the broader economy in the last fifty years. Venture capital-backed companies account for 41% of total US market capitalization and 62% of US public companies' R&D spending (Gornall and Strebulaev 2021). Seven out of top ten largest companies by market capitalization as of December 2025 were primarily backed by venture capital (VC) funds earlier in their lifecycle. Moreover, Gornall and Strebulaev (2021) show that the U.S. VC industry has been causally responsible for the rise of many of these successful companies. Other developed nations that historically have lacked a VC industry have not witnessed the creation of large new non-trivial companies in the last 50 years.

The individual venture capitalists (VCs) that deploy venture capital are known for spotting and backing innovative companies and founders early on. Michael Moritz, of the VC firm Sequoia, is widely credited for making early investments in Google and PayPal. Peter Thiel, of another VC firm Founder's Fund, has made early investments in Meta (FaceBook) and Palantir. Marc Andreessen, of yet another VC firm a16z, is well known for highly successful venture investments in Airbnb and Lyft. The ability of these VCs to make successful investments seems to persist, skewing returns largely towards a small sample of the more successful VCs. At the fund level, VC funds at the top quartile of returns tend to stay in the top quartile of returns, outperforming those in the lowest quartile by upwards of 30 percentage points per year (Harris, Jenkinson, Kaplan, and Stucke 2023).

In short, the VC industry exhibits substantial skewness, persistence, and economic impact. Yet, it is also a highly human capital-intensive business, requiring substantial effort on the part of individual VCs to identify startups in which to invest and ultimately help contribute to the success of these investments (Gompers, Gornall, Kaplan, and Strebulaev 2020). Existing evidence strongly suggests that the identity of individual VCs – the difference between Peter Thiel and Marc Andreessen – matters. For example, the identity of the VC sitting on the board of a startup accounts for 12% of cross-sectional variation in whether the startup subsequently goes public (Ewens and Rhodes-Kropf 2015). Indeed, we find that a relatively small number of VC investment professionals have made most of the successful VC investments. However, surprisingly little is known about these individual VCs. Are there persistent differences in the backgrounds of successful VCs? What individual characteristics of VCs, if any, can explain investment outcomes, career paths, and

returns?

In this paper, we aim to answer these questions. Studying the impact of human capital on outcomes is important given the rising importance of the innovation economy in the US and around the world. However, such a research agenda has historically been hampered by incomplete, potentially biased, and opaque data. Therefore, we assemble the largest and most comprehensive dataset of individual U.S. VCs to date, by using a novel method, tracking their entire careers, deals, outcomes, as well as collecting data on their individual characteristics and relevant biographical details. Using these new data, we study the extent to which investment success is concentrated among few VCs, characteristics of the VCs' demography, educational and work experiences that predict their subsequent investment returns, as well as the effects of "superstar" status in this economically important industry.

We start by presenting a new dataset of VCs based on historical and archived websites of the professionals listed on the websites of U.S. VC firms. The key distinction of our data, relative to pre-existing datasets, is its focus on individual VCs and their career backgrounds, not just those affiliated with the boards of startup companies. Our data spans 1996 through 2025 and covers information about venture capitalists, each year, as of that year. We assemble this dataset using Large Language Models (LLMs) prompted to collect the biographical information about each professional listed on archived websites alongside large scale manual collections of each website to validate the extracted information. The resulting 85,000 VC affiliated professionals we collect, 31,000 of whom are investment professionals, combine to have raised and deployed 96% of capital for institutional U.S. venture capital funds over our sample period.

The key economic advantage of this new dataset is that it allows us to study how past investment success, educational experiences, work experiences, and demographics jointly contribute to explaining variation in VC success. While a substantial literature has documented an important role for past success in predicting future VC success (e.g., Kaplan and Schoar (2005) and Nanda, Samila, and Sorenson (2020)), much less work has focused on identifying the persistent dimensions on which successful VCs differ from unsuccessful VCs.

It further allows us to document, in detail, the compositional makeup of human capital in the U.S. VC industry. 69% of VCs are white. 24% are female. 16.6% have an undergraduate degree from an Ivy league school. 2.7% have an MBA from Stanford GSB. 22% worked at a

startup. 7.2% were C-suite executives or founders of a successful startup. 7.7% came to VC after working in private equity. Previous work has also shown that many senior level VCs have degrees from highly ranked schools or experience working at a startup (e.g., Gompers and Mukharlyamov (2025)). Our dataset also uniquely covers junior level employees at VC firms, not just the most senior professionals. This allows us to document whether these backgrounds indeed predict career progression in the industry. Is it the case that the VC industry only hires professionals from these backgrounds? Or, instead, are professionals with particular backgrounds consistently and differentially likely to become more successful VCs?

One striking relationship we find is that individuals entering at a junior associate level are extremely unlikely, 80% less likely that is, to eventually become VC partners, compared to those that join at a more senior middle level position. Female professionals are also 2.9% less likely be promoted to partner, though this promotion penalty has become much less severe in more recent years. Professionals with MBA degrees and advanced terminal degrees are also more likely to see career progressions, though the pedigree of the degree granting institution carries little correlation with promotion. Professionals with work experience at a startup (irrespective of success or seniority at the startup) or a technology focused firm similarly are more likely to become senior deal-makers in the VC industry. These results show that the VC professionals with particular backgrounds, namely, specialized skills, knowledge, or experience, are more likely to succeed in the promotion process. This is consistent with general findings in the labor economics literature that professionals who join an industry later are more likely to be a better match for the industry (e.g, Topel and Ward (1992)).

When we turn to performance, we find that many of the same features of VCs' backgrounds that contribute to their career success also help to account for differences in the highly skewed distribution of VC investment success. We gather investment attributions from a full suite of commercial datasets (PitchBook and VentureSource) as well as investments that we parse from archived website biographies that are often missing from other datasets, improving coverage by about 20% for the average VC in our sample.[1]

In our data, investments made by VCs with one prior successful deal are 2% more likely

[1]Our additions further help to improve the representativeness of our sample of deals, especially for investments from outside of the technology and software industries that did not involve a board seat, are from earlier years, are made earlier in a venture capitalist's career, or are made by VCs with degrees from prestigious U.S. schools.

to have a successful outcome. Investments made by VCs with five prior successful deals are about 7% more likely to succeed (a 40% increase relative to the sample mean). Taking into account that affiliated VCs are typically minority stakeholders with limited corporate governance rights, only one of several board members (if they are a board member at all), and do not engage in day-to-day of company operations, these results strongly suggest the presence of VC-specific skills that they can use across the span of their investments and across time, though our analysis does not allow us to disentangle selection and post-investment investment value additive contribution. Further, investments associated with female VCs are 1% less likely to succeed, while investments attributed to VCs with an MBA are 2% less likely to succeed. The pedigree of the MBA program plays a role, as investments attributed to VCs with a Stanford GSB MBA, for instance, are more likely to succeed.

However, perhaps the most striking differences in investment success explained by the backgrounds of VCs appear when we examine whether the VCs that have had more investment success over their lifetimes differ systematically from those that did not. We again find a negative result for female VCs, who have, on average, been credited with 36% fewer successful investments over their VC careers compared to the average VC that joined the industry in the same cohort. Successful VCs, instead, tend to have come from an Ivy league or Ivy+ school, have degrees from a top MBA program, hold advanced terminal degrees, have founded or held a C-suite position in a successful startup, or transitioned from a technology firm or investment banking firm. Given the high selectivity of the hiring policies for companies in each of these industries, the results are consistent with a mechanism where the specialized human capital (acquired, i.e., from technology experience or banking experience) are relevant for specialized VC investments.

A further result delivered by these analyses is a quantification of the extreme concentration of success in the VC industry at the individual VC level. While variation in VCs' experiences and demographics provide useful explanatory power for whether VCs fall into the group of highly successful VCs or not, few ultimately do. We find that only 38% of VCs that have been credited with at least one investment have been credited with at least one successful investment over their careers. 15% have made three or more successful investments. And the number further collapses to 6% when calculating the fraction of VCs that have made six or more successful investments over their lifetimes.

These patterns imply that compensation and status, much like returns, follow a highly skewed distribution in the U.S. VC industry, akin to that described by Rosen (1981): a small number of "superstar" venture capitalists, with particular backgrounds, enjoy the bulk of the rewards of venture capital investing. Michael Moritz, Marc Andreessen, and Peter Thiel appear to be the exception rather than the rule. This is not unlike, for instance, the distribution of compensation and success among CEOs of U.S. companies. The key finding in studies of superstar CEOs, however, is that achieving superstar status appears to have negative effects on the performance of their firms (e.g., Malmendier and Tate (2009)).

We use the full extent of our newly assembled data to design an empirical test enabling us to estimate the effects of achieving superstar status for U.S. VCs. The primary empirical concern is that the label of "superstar" is not randomly assigned. An ideal experiment that more closely approximates the random assignment needed for estimating this effect compares VCs that barely achieve such status with those that just missed it. Estimating such an experiment would allow us to identify a credible counterfactual for the VCs that achieve such superstar status.

One important institutional feature of the VC industry allows us to approximate such an experiment is the the annual "Midas List" rankings of the top-100 VCs reported by Forbes. The list started in 2001 and has been updated annually every year since then except for 2010. The annual lists report 100 VCs each year, deemed to have the "Midas touch" by its publisher. The limited size of the list, at 100, gives a natural cutoff from which we can estimate our experiment. Our goal is to empirically solve for the methodology used to construct the Midas list each year, as of the year, and construct various counterfactuals around this cutoff to estimate the effect of superstar status. Our replication is reasonably successful, correctly predicting which U.S. VCs are on the list about 60% of the time.

With estimates of the Midas List near makes, near misses, surprise makes, and surprise misses, we then examine the effects of superstar status on individual VCs' investment success. We estimate stacked difference-in-differences regressions (employing the methodology outlined by Baker, Larcker, and Wang (2022)) to compare those marginally awarded such status to those not. The identifying assumption is that outcomes of marginally included VCs and marginally excluded VCs would evolve in parallel, but for their inclusion on the list. Visual inspections support this assumption.

What we find runs counter to the results in the CEO literature. VCs that are marginally included on the list are about 4 to 8% more likely to have invested in companies with successful investment outcomes in the few years following their marginal exclusion. These results represent about a 10% increase in investment success relative to the sample mean, or, an increase of about 0.2 new successful investments. Increased success is driven primarily by new investments in companies that go public or report high post money valuations, not by companies that have high exit multiples.

Inclusion on the Midas list is unlikely to confer additional investment skills for the VC. These results, instead, are most consistent with a mechanism where the increased media coverage allows the VC to obtain better access to higher quality startups and helps to further attract resources and other investors into the startups in which they invest in the few years following their recognition on the list. Our results favor the access mechanism more than the resource-attraction mechanism given that pre-existing startup investments (which may also benefit from any new resources) do not see an increase in successful outcomes for the VC. This result underscores prior results of persistency in return outcomes at the individual VC level, providing evidence of a new channel through which the ability to make successful investments is accessed (e.g., Ewens and Rhodes-Kropf (2015) and Nanda et al. (2020)).

The paper proceeds as follows. Section 1 describes dataset construction and discusses descriptive statistics. Section 2 presents our results on human capital and investment success in the VC industry at the deal, person, and fund levels. Section 4 presents our analysis on superstar VCs using the evidence from the Midas List. Section 5 concludes.

1 Data Sources and Descriptive Statistics

Institutional VC investing involves three main economic layers: VC firms, the VC funds sponsored by these firms, and the investments in portfolio companies held in funds sponsored by these firms. The funds are typically closed-end, limited life, limited partnerships, lasting ten or more years. VC firms raise VC funds and manage capital on behalf of large institutional investors, such as pension funds, endowments, and sovereign wealth funds, as well as high net worth individuals. Fund managers are predominantly compensated with management fees and carried interest.

This study focuses on the extent and mechanisms of the relationship between human capital of the VC investment professionals that are responsible for investing and managing capital raised by VC funds and their ultimate investment success. Doing so requires identifying the relevant investment professionals, collecting data on their individual characteristics, their career experiences, the portfolio companies they have been involved with, as well as data on VC outcomes at all the three layers. We do so by developing and utilizing a novel method to assemble the largest dataset to date of U.S. VC firms and people affiliated with them, which we discuss in this section. Internet Appendix Section IA.1 provides further details on data collection, sample construction, and descriptive statistics.

1.1 Venture Capitalists

The main sample includes the investment professionals employed by institutional U.S. VC firms from 1996 to 2025. We consider institutional U.S. VC firms to be all firms that are (1) headquartered in the United States; (2a) have raised at least $10 million for a closed or liquidated VC fund in 1995 or later according to PitchBook or VentureSource or (2b) have invested in a VC-backed company that has achieved a $1 billion post-money valuation or a comparable randomly sampled VC-backed company; and (3) primarily sponsor venture capital funds (i.e., excluding firms that mostly sponsor buyout funds, fund of funds, or hedge funds, for instance). We exclude corporate venture capital firms and their employees, which typically invest from the balance sheets of parent companies rather than manage stand-alone venture funds (Strebulaev and Wang 2021). We identify 4,402 firms that meet these criteria.

We collect data on VC professionals affiliated with each of these firms using archived webpages hosted on the internet archive and accessed via the Wayback machine. 1996 is the first year that archived website data are available for firms in our sample. The archived website data on VC professionals, which are novel to this study, provide historical snapshots of a firm's professionals over time, displaying the team of professionals who work for a given VC firm each year as of that year. Figure 1 displays examples of archived webpages for New Enterprise Associates (a large VC firm) in 2005 and 2025.

We collect the website data by prompting a Large Language Model (LLM) to iterate through

each firm's archived website, locate the team and personal pages of each professional displayed on the website, and then return the biographical information about each person contained in the underlying HTML. Section IA.1.1 further discusses the dataset construction. To control for any potential hallucinations that are often associated with LLM implementation, we further employ a large-scale manual collection of the historical webpages, wherein one or more data assistants manually copy and paste all available person, title, and biographical data for the VC firm as of that year. We find similar coverage across the separately applied LLM and manual tracks, implying the two are interchangeable, although the LLM track is substantially more efficient. In related work, Jackson (2025) also uses LLMs and hand-collections to parse the historical webpages of U.S. buyout firms.

The final sample includes historical webpage data for 3,374 of the 4,402 U.S. VC firms (77% of firms). The 23% of firms that are not retained in the final sample are excluded because we could not identify a historical URL, the historical URL was not accessible, or the firms do not list professionals on their website or have website formats that do not allow for automatic parsing of the HTML. Consistent with the Wayback machine web crawling algorithms prioritizing more heavily trafficked websites, the excluded firms are more likely to be defunct and tend to have raised fewer funds and invested in fewer unicorns compared to the included firms. Still, the resulting sample represents the overwhelming fraction of the U.S. VC industry, accounting for 96% of capital raised by the 4,402 institutional U.S. VC funds and having sponsored 95% of all U.S. VC funds in the 1996-2025 period (based on PitchBook data).

Our sample of all the professionals affiliated with US-headquartered VC firms consists of 84,796 unique people. Within each year that a professional is observed, we use reported titles to flag whether the person is a full-time investment professional – those working on sourcing, due diligence, negotiating, and managing investments – or non-investment professionals that do not work at the firm full time or primarily work in firm operations (e.g., professionals involved in internal functions such as compliance and human resources), portfolio operations professionals (often venture partners and advisors), and retired investment professionals (such as emeritus partners). Section IA.1.2 reports that non-investment professionals are more common among larger more successful firms, especially in more recent years.

Our sample of investment professionals includes 30,568 individuals. As one comparison

providing a useful measure of our coverage, PitchBook reports that the U.S. VC firms in our sample were represented by 12,959 individuals on 83,695 investments in 45,840 companies. These counts are markedly lower than the number of VCs, deals, and companies reported in our sample, even though this PitchBook sample additionally includes non-investment professionals.

Using the title stems, we further classify professionals by the seniority every year they are observed, reflecting the three-layer hierarchy observed in practice: junior-level (analysts, associates), middle-level (vice presidents and principals), and senior-level (partners) professionals. We adjust our classification to take into account firm-specific rules. For example, a16z, a well-known VC firm, currently presents almost all of its full-time investment professionals as partners, reserving a title "general partner" for senior investment professionals.

1.2 Venture Capital Investments

An important part of our analysis includes identifying the VC-backed companies that VCs in our sample are credited with investing in. To match VCs with portfolio companies, we use a multi-pronged analysis. First, many historical archived webpages include biographies of VCs or the list of company names or logos that constitute their then portfolio. Importantly, this information is often reported contemporaneously, before the outcome of these investments is known. Second, we source affiliations reported in PitchBook and VentureSource, two well-known commercial datasets used widely in the VC literature (e.g., Ewens and Rhodes-Kropf (2015), Gompers and Mukharlyamov (2025), and Chen and Ewens (2025)). The PitchBook-reported affiliations include lead partner positions and board seats. The VentureSource affiliations include board seats. Third, Forbes has published an annual ranking of top VCs starting in 2001, known as the "VC Midas List." To arrive at rankings, Forbes solicits information on attribution from VCs and their firms directly. The description of VCs in the Midas list contains their notable investments that we use to complement our other sources.

Our main sample includes investments in 64,391 unique VC-backed companies that have at least one VC investment professional in our sample that has an affiliation with that company. In total, 16,660 U.S. VC investment professionals, or 54.5% of the VC investment professionals in our sample, have at least one such affiliation. This is not surprising as many VCs never become

senior investment professionals that are affiliated with most deals.[2] These 16,600 VCs representing 3,261 institutional U.S. VC firms comprise our final main sample. Relative to the sample of VCs in Gompers and Mukharlyamov (2025), who also study human capital in the U.S. VC industry and source primarily from professionals who have had a board seat on a startup in the VentureSource dataset, our sample is larger, including 19,000 more VC investment professionals, and 5,000 more VCs with investment affiliations. Calder-Wang, Gompers, Huang, and Levinson (2023a) report a sample of 14,490 venture capital investors based on deals gathered by VentureSource. For another comparison, the sample used by Ewens and Rhodes-Kropf (2015) to examine persistence in VC returns from 1987 to 2012 includes about 5,000 VC partners with at least two board seats.

1.2.1 Coverage Improvements

Our data collection process adds approximately 21,000 person×company affiliations that are otherwise not available in commercial datasets, equal to a coverage improvement of about 20%. This addition includes nearly 9,000 board seats that are not in either PitchBook or VentureSource, which similarly represents about a 15% increase in the number of board positions that we could otherwise observe.

Table IA1 helps to summarize. 53% of the person-company involvements we recover are unique to PitchBook or VentureSource and 16% are unique to the archived webpages.[3] The remaining 31.1% of involvements are present in both types of sources. An example of a company involvement we extract from websites but not from PitchBook or VentureSource is Mary Meeker's investment in Airbnb while she worked at Kleiner Perkins in 2015. Commercial data identify that Kleiner Perkins invested in Airbnb's 2015 Series E,[4] five years before Airbnb went public and four years after it first became a unicorn. Neither PitchBook nor VentureSource, however, capture which partner(s) at Kleiner Perkins were responsible for the investment. Meeker's Airbnb investment is mentioned in her 2017 biography on the Kleiner Perkins archived website, predating Airbnb's 2020 IPO, as follows:

[2]These are usually junior professionals or investment professionals that worked in the industry for only a few years; 72.5% of all senior investment professionals that worked in the VC industry for five or more years have at least one portfolio company affiliation.

[3]A small fraction, 0.2%, are unique to the collections from the archived Midas lists.

[4]See, e.g., here: WSJ Article Airbnb 2015 Series E

. . . Mary serves on the boards of Square, Lending Club and DocuSign and has been involved in KP's investments in Ring, Airbnb, Pinterest, Stance, Instacart, . . .

Table IA2 compares the characteristics of investment attributions recovered from PitchBook and VentureSource to those recovered from parsing archived website biographies. Doing so helps to quantify potential bias in commercially available data. Section 1.3 discusses the construction of several relevant variables. PitchBook and VentureSource data tend to be comprised of less successful affiliations compared to affiliations from website data (10.7% versus 20.1%). The commercial data are comprised more so of early-stage investments, investments in 2011 or later, investments in New York startups and software ventures. In addition, the commercial data more heavily represent investments by White VCs, male VCs, VCs without Ivy-league degrees or MBAs, VCs that were previously CXO/Founders or successful startups, VCs from the technology industry, VCs that joined the industry as partners, and VCs that have made six or more investments prior to the focal investment. As a result, the website data help to improve the representativeness of our sample of deals especially when it comes to successful outcomes that did not involve a board seat, are from earlier years (especially 2001-2009), are made earlier in a venture capitalist's career, are made by VCs with less press coverage or MBAs or degrees from prstigious schools or are made outside of the technology and software industries.

1.3 Descriptive statistics

Table 1 describes the characteristics of all VC investment professionals as well as those that are affiliated with at least one deal in our sample. For reference, the first column of the Table 1 describes all investment professionals in our sample. However, from now on, when we use "VCs" in relation to our data, we mean the final sample of the 16,600 investment professionals that are affiliated with at least one deal in our sample.

We retrieve biographical data from historical archived websites, complemented by data from Revelio, PitchBook, VentureSource, and LinkedIn. If information is available from multiple datasets, we reconcile and prioritize data obtained from historical websites. Demographic variables of race and gender are estimated based on names and biographical text, discussed further in Section IA.1. We identify educational background for 86.5% and pre-VC work experience for 77.1% of the final sample. We report means for the entire sample, as well as for subsamples that contain VCs

that are affiliated with 0, 1–2, 3–5, or 6 or more successful investments. We define an investment to have been successful, following Ewens and Rhodes-Kropf (2015), if the startup subsequently went public or was acquired at a valuation of at least twice the total capital raised. We additionally consider an investment to have been successful if it subsequently achieved a unicorn valuation (defined as post-money valuation of at least $1 billion). While the IPO measure is standard in the literature, it is well known that the overall IPO rates have declined over time, particularly in the United States (e.g., Gao, Ritter, and Zhu (2013) and Doidge, Karolyi, and Stulz (2017)), meaning other measures are necessary to capture successful investments more fully. Post-money valuations of $1 billion and above and exits at higher multiples are generally more likely to indicate successful investments.[5] Furthermore, taking into account unicorns allows us to include successful deals that are still private, thus reducing the bias against more recent investments.

Panel A shows that, demographically, 75% of VCs are white and 16.5% of VCs are female. For the subsample of VCs that are affiliated with at least six successful deals, only 5.6% are females. Panel B focuses on pre-VC education experience and shows that 17.2% of VCs attended Ivy League schools as undergraduates, while 10.1% attended Ivy+ school, with Ivy+ including other highly ranked private schools.[6] Overall, 40.1% attended top-30 undergraduate schools as defined by the US News 2025 ranking. Stanford is the most common undergraduate school (4.3%), followed by Harvard (4.2%) and University of Pennsylvania (3.2%). Panel B also shows the distribution of undergraduate majors, with business (including economics, finance, and accounting) at 36.4%, STEM at 39.6%, social sciences at 10.4%, and humanities and arts at 9.4%. Even though business and STEM majors are roughly equally represented in the full sample, among VCs with at least six successful deals, the fraction with a business major declines to 25.2% while the fraction with a STEM major increases to 51.7%.

More than a third of VCs, 38.1%, and almost half of those with at least six successful deals, 49.5%, have an MBA degree. More than half of all MBAs are from top-10 MBA schools according to the US News 2025 ranking. The most common MBA is from Harvard Business

[5]Our results are robust to using more stringent cutoffs for acquisition multiples of five-times and 10-times the amount invested.

[6]Ivy League schools include Brown University, Columbia University, Cornell University, Dartmouth College, Harvard University, University of Pennsylvania, Princeton University, and Yale University. Ivy+ schools include Stanford University, MIT, California Institute of Technology, Duke University, Johns Hopkins University, Northwestern University, and University of Chicago.

School (5.9% of all VCs and 17.5% of those with MBAs), followed by Stanford GSB (3.9% and 12.6%, respectively) and Wharton (3.0% and 9.2%). Among the VCs with at least six successful deals, the number of Harvard and Stanford MBAs increases substantially, to 13.5% and 11.2%, respectively. Every seventh (14.5%) VC has an advanced degree, such as Ph.D. or MD. Table IA3 lists the 20 most frequently attended undergraduate and MBA schools.

Panel C shows pre-VC work experience, where we include only full-time work. Every third VC joined the VC industry after working in a VC-backed startup, with every fourth working at a successful VC-backed startup, where we use the same definition of success, with 60% of these (or 14.7% of all VCs) were either a founder or a C-suite executive of such startups. Interestingly, 75% of all VCs with startup experience, and 87% of all VCs with startup experience with at least six successful investments, were employees of successful startups.

Another third (35%) worked in a technology focused firm that is not (or was no longer at the time of employment) a startup, such as Apple or Google. Almost a fourth have an investment banking background and about a fifth worked in management consulting. Fewer VCs have buy-out (7.5%), hedge fund (2.4%), law firm (3.4%), or government (8.4%) backgrounds. Note that a third of VCs worked in "other" institutions that are often more general operating companies defying these classifications, such as Proctor & Gamble, Boeing, or Nike. The most common prior employer is McKinsey (3.7%), followed by Goldman Sachs (3.0%), and Morgan Stanley (2.7%). Table IA4 lists the 20 most frequent previous employers.

Panel D presents some stylized facts on the VC industry experience of those in our sample. 55% of the sample, where we can observe the seniority level at the time of entry into the VC industry, joined at the senior level. The majority of VCs (69.5%) have worked in the VC industry for 10 or fewer years, 23.1% for 10-20 years, and the remaining 7.5% for two decades or more. Not surprisingly, those with two decades or more of VC experience are disproportionately represented in the subsample of those with at least six successful deals (47.7%). A very small fraction of our sample, 2.5%, were named to the Midas list in at least one year.[7] A quarter of VCs with at least six successful deals have been recognized on the Midas list at least once. Overall, more than 60%

[7] A smaller fraction of those without successful affiliations (0.3%) have been recognized on the Midas list at least once. For these professionals, we are often able to correctly attribute them to the notable investments the Forbes Midas list reports (if any), but we are not able to establish the year of their initial investment, which we require throughout all affiliations we study.

of VCs are affiliated with at least three deals: 38.9% with at least six investments, and 21.7% with between three and five.

As implied by other rows, the final row of Table 1 highlights the skewness in investment success across VCs most directly. The average investment professional has 0.6 successful investments. The average VC with at least one affiliated company has 1.3, and the average VC with six or more successful investments has 10.5 successful investments.

Comparing our sample to that of Gompers and Mukharlyamov (2025), we report similar rates of graduation from highly ranked U.S. schools and statistics on race and gender. The most common prior employer, McKinsey, is also the same in our sample. The fraction of VCs that founded a startup before they worked in the VC industry is similar in our sample and theirs (10%), however, we also focus on VCs with C-suite experience at a startup as well, bringing our statistic up to 16%. Lerner and Nanda (2020) report statistics for 417 U.S. based partners at the largest U.S. VC firms as of their writing, 265 of which they find to have at least one board seat, slightly below our percentage coverage of company affiliations. They report higher rates of males, top-schools, and Harvard or Stanford MBAs compared to our full sample statistics. Calder-Wang and Gompers (2021) report slightly lower rates of females and non-white VCs and higher success and IPO rates among a sample of U.S. VCs up to mid-2016.

Another interesting comparison point is with Jackson (2025) who reports a similar set of statistics for U.S. buyout investment professionals. The conclusion is that buyout and VC investment professionals have non-trivially different backgrounds. Those entering the buyout industry tend to have similarly attended highly ranked schools (although University of Pennsylvania is more popular than Stanford among buyout professionals and vice versa). However, VCs tend to have had far more varied work experiences, with nearly 70% of buyout professionals having investment banking experience, compared to only 23% among VCs. For instance, 18% of buyout professionals worked at the three most common prior employers, while this fraction is only 9.6% among VCs. However, the fractions of buyout and VC professionals with management consulting backgrounds are similar, near 20% among both groups, indicating that management consulting backgrounds likely offer general human capital. Startup experience is instead more central to VC careers, whereas banking experience is likely more relevant for buyout careers.

Table 2 summarizes characteristics of the 64,391 companies invested in by the U.S. VCs

in our sample. We report the composition for all companies in the left-most column. Additional columns report the composition among companies that have generated a successful outcome for their investors versus those that have not. Panel A reports the founding years, sourced from PitchBook. The majority of companies in our sample, 53.1%, were founded after 2010 and before 2020. Companies that have not generated a successful exit are mostly founded in 2020 or later, reflecting the fact that several years often need to elapse for a company to achieve a unicorn valuation, IPO exit, or be acquired. Panels B, C, and D report the proportion of companies assigned to the five most common industries, countries, and states/provinces, respectively. These variables are also sourced from PitchBook and are well covered.[8] 42.6% of companies are software companies. By location, our sample predominantly includes companies located in the United States (75% for the full sample, 82% for the sample of successful companies) with California being the most popular state, accounting for 28.7% of companies compared to only 9% for New York, which is the second most popular state. Table IA5 additionally summarizes the composition of companies in our sample over time. Software and non-U.S. investments have become more prevalent, while successful outcomes tend to be concentrated among earlier investments. Subsequent specifications account for these dynamics by including time-series fixed effects, comparing investments made within the same year.

Table 3 summarizes the sample of person-company deals in total and by each outcome achieved. 65% of the deals in our sample are made within the first five years of a company's founding. An additional 14.1% are made 6-10 years after a company's founding. The remaining 20% are later stage investments (6%) or those where the founding year of the company is missing (14%). Panel C shows statistics on VCs' successful investments prior to making a deal. While 2.5% of VCs are ever in the Midas list, they made 5.5% of all deals. VCs with at least five successful deals made almost a fifth of all the deals. Note that VCs with many successful deals are also observed to have invested in many deals that are not successful.

[8]The industry variable is `primaryindustrygroup`, which has 41 unique entries in our sample. The country variable is `hqcountry`, which has 127 unique entries. The variable denoting the state or province of the company is `hqstateprovince`, which has 583 unique entries.

2 Human Capital and Career Success

Previous work has shown that many senior level VCs have degrees from highly ranked schools or experience working at a startup (e.g., Gompers and Mukharlyamov (2025)). Our findings are no exception. However, a key advantage of the data we have collected is that we can observe junior level employees at VC firms, not just the most senior professionals. This allows us to document whether these backgrounds indeed predict career progression in the industry. Is it the case that the VC industry only hires professionals from these backgrounds? Or, instead, are professionals with particular backgrounds consistently and differentially likely to become more successful VCs?

We focus our analysis on the 12,627 investment professionals in our sample that entered the U.S. VC industry at a junior or middle-level position (e.g., associates or vice presidents). We consider three main measures of career progressions: an indicator for whether the professional was promoted to the senior level at a U.S. VC firm, an indicator for whether the professional is credited with at least one investment, and a third indicator for whether the professional is credited with at least five investments.[9]

All specifications include fixed effects for the year an investment professional first entered the industry. Doing so accounts for the fact that it can take several years for a VC to be promoted, while absorbing the explanatory power of cohort effects (e.g., Oyer (2008)). Further, for all specifications, we report separate results focusing only on professionals that entered the industry in 2010 or earlier, allowing professionals 15 years to realize a career outcome. Table 4 presents the results of our regression analysis.

One of the most powerful predictors of career progression is the initial seniority at which professionals entered the industry; junior professionals are 70 to 80 percentage points less likely to become senior VCs compared to professionals that entered at a middle level. Their odds of being credited with at least one investment are 26 percentage points lower as well, as middle-level VCs can be senior enough to sit on portfolio company boards or source and lead investments themselves. This is consistent with general findings in the labor economics literature that turnover and mobility are higher earlier in careers and that professionals who join an industry later are more likely to be

[9]The differing measures typically correlate as well with higher compensation. Senior level partners are more likely to have an ownership position in the VC partnership or management company compared to those in less senior positions, and deal-makers are more likely to earn (higher) carried interest from their investments compared to non deal-makers.

a better match for the industry (e.g, Topel and Ward (1992)).

Demographics are also useful predictors of career progression within the U.S. VC industry. White investment professionals are about one percent more likely to be promoted; however, the difference in eventual deal-making between White and non-White investment professionals fails to consistently attain statistical significance. Female investment professionals are up to six percentage points less likely to be promoted, and 14 percentage points less likely to be identified as active deal-makers. Female career progression rates are lower in the first part of our sample compared to the later part of our sample, consistent with findings by Calder-Wang, Gompers, and Sweeney (2023b), which documents increasing female hiring in VC following the 2015 Pao versus Kleiner Perkins gender discrimination trial.

Some characteristics of investment professionals' education predict career progressions also. Variation in undergraduate majors plays a small role. VCs who obtained an undergraduate degree from an Ivy league school are not more likely to be promoted, but are about five percentage points more likely to be identified as an active deal-maker. Evidence of career progressions is more pronounced for VCs who obtained an undergraduate degree from an Ivy+ school, displaying about a two percent increase in promotion odds and five to either percentage point increase in deal-making. Those with an MBA or an advanced degree are also much more likely to experience career progressions. The institution granting the MBA, however, has little marginal predictive power, with VCs who have Top-10, Harvard, or Stanford MBAs not exhibiting incrementally higher rates of career progression.

Those with different pre-VC work experiences also demonstrate markedly different career progressions. VCs with work experience at a startup, technology company, or management consultancy are much more likely to progress in seniority or be identified as active dealmakers. Interestingly, career progressions depend little on the success of the startup. Middle and junior-level VCs who worked at failed startups, successful startups, or as rank and file employees or instead as founders/C-suite professionals are all more likely to be promoted.

Table IA6 examines career progressions among VCs that entered the industry at the junior level. The results are overall similar to those reported in Table 4, except for the relationship between the institution granting an MBA and career progression. VCs that entered the industry as a junior and subsequently obtained MBAs from Harvard or Stanford are more likely to be sub-

sequently observed as a partner. This result is consistent with a mechanism where highly ranked MBA programs are important for the career progressions of junior investment professionals.

3 Human Capital and Investment Success

It is well-documented that investment success is concentrated among a relatively small number of VCs and that such success is persistent at the fund and even the individual VC level (e.g., Kaplan and Schoar (2005), Ewens and Rhodes-Kropf (2015), Nanda et al. (2020), and Harris et al. (2023)). In this section, we explore whether any features of VC's backgrounds or experiences contribute meaningfully to such investment success. We study the relationship between individual VC characteristics and outcomes at three different levels: the outcome of investments in individual portfolio companies, cumulative success of a VC investment professional, and the return outcome of a VC fund.

3.1 Deal Level

In this subsection, we examine whether characteristics of VCs predict return outcomes of individual VC investments. Our findings extend previous research on the relationship between investor characteristics and investment outcomes. In a sample ending in 2003, Gompers, Mukharlyamov, Weisburst, and Xuan (2022) report that female VCs tend to have a lower probability of achieving an IPO outcome on a given investment, while VCs with entrepreneurial experience or a degree from a top undergraduate school tend to have a higher likelihood of doing so. They report little predictive power for other characteristics. Chevalier and Ellison (1999) find that mutual fund managers with undergraduate degrees from schools with higher composite SAT scores perform better. Gompers, Kovner, and Lerner (2009) find that VC firms with more specialized partners, as classified by the characteristics of their prior investments, tend to perform better.

Table 5 shows the results of the regression analysis, in which the dependent variable is a dummy taking the value of one for a positive investment outcome. Positive outcomes include IPOs, achieving a unicorn status, a sale for the value at least twice the total capital raised. We define an outcome to have been "successful" if at least one of these three scenarios materializes. In all regressions, we include fixed effects for: the year the investment was first made (and thus

the affiliation between the individual VC and the portfolio company established), the state of the company's headquarters, the industry of the company, the age of the company, and our primary data source used to identify the affiliation.[10] We further present these results visually in Figure 2.

While, as expected, predicting investment outcomes of VC-backed companies involves a lot of noise, many of VCs' characteristics play an economically important role in explaining outcomes. For one, our analysis confirms return persistence at the individual VC level. Relative to the omitted category of investments affiliated with VCs that do not have any successful prior investments, a deal is 1.7% more likely to result in a successful outcome if the VC affiliated with the deal has previously, through a different fund, invested in at least one company that has had a successful outcome. The probability of a successful outcome monotonically increases with the number of prior successful investments a VC has had. If the company is affiliated with a VC who has previously made five or more successful investments, it is 6.8% more likely that the company will subsequently have a successful outcome (1.7% + 1.5% + 3.6%), relative to the omitted category of investments affiliated with VCs that do not have any successful prior investments. Such an increase is economically substantial, equal to 49% of the sample mean.

Taking into account that affiliated VCs are typically minority stakeholders with limited corporate governance rights, only one of several board members (if they are a board member at all), and do not engage in day-to-day of company operations, these results strongly suggest presence of VC-specific skills that they can use across the span of their investments and across time. This supports findings by Gompers et al. (2020) on VCs self-reporting on their value add. It also supports findings by Bernstein, Giroud, and Townsend (2016), even though our analysis does not allow us to disentangle selection and post-investment investment value additive contribution. The experience of a VC also correlates with the odds of a successful outcome: deals led by VCs within the first ten years of their VC careers are 2.6% more likely to result in a successful outcome compared to the omitted category of deals led by VCs that have worked in the industry for at least 10 years. This result can favor a survivorship mechanism, whereby VCs with earlier success are more likely to have longer and more successful careers (e.g., Nanda et al. (2020)) or also a mechanism where the skills of younger VCs led them to be more successful investors.

[10] Our results are robust to instead considering the subsample in which only the deals where VCs are on the board are included.

We find that demographic characteristics also correlate with individual deal outcomes, though the overall effect economically is relatively small. Companies affiliated with female VCs have a 1% lower chance of a successful investment outcome, similar to the most stringent specification reported by Gompers et al. (2022). Investments credited to white VCs are also marginally less likely to achieve a successful outcome relative to those credited to the omitted category of non-white VCs – those with an ethnicity categorized as Asian & Pacific Islander (18.5% of the sample), Hispanic (3.3%), or Black (3.1%).

Some characteristics of VCs' education exhibit meaningful correlations with the likelihood of investment success. Investments by VCs with an undergraduate degree from an Ivy league school are 1.7% more likely to achieve a successful outcome. Interestingly, deals led by professionals with an MBA degree have a 2.1% lower likelihood of a successful outcome. Of the two most frequent MBA schools, Harvard Business School has no marginal impact, while an MBA from Stanford GSB has a significantly positive impact. Most other educational variables, including the undergraduate major or whether the VC has an advanced degree, are not significant.

Being a founder or a C-suite executive of a VC-backed startup before joining the VC industry matters for outcomes. Investment by VCs that had such positions with successful startups have a higher chance of a positive outcome, while investments by VCs with non-successful startup experience are less likely to have a successful outcome. Rank and file employee startup experience does not matter. These findings corroborate typical informal assessments in the VC industry that "operators of VC-backed startups" are more successful as investors, with the subtlety that success of previous ventures matters. One potential mechanism is that successful founder-turned VCs are better able to identify which startups are more likely to become successful and more likely to win competitive deals. Another mechanism that could be at work is that successful founders are better able to help other management teams with advice, necessary resources, and through their network connections. Gompers and Mukharlyamov (2025) find evidence of both mechanisms but favors the former. Of other industry experience, deals led by investment bankers that entered the VC industry are 1.7% more likely to be successful.

Table IA8 examines whether correlations between VC's human capital and deal-level success vary based on whether the VC is more involved with the company (proxied by having held a board seat) or whether the VC was an earlier investor in the company (having made an initial in-

vestment within three years of the company's founding). Within each of the subsamples, whether an investment achieves a successful outcome is similarly positively correlated with prior success, and characteristics of VCs' education and prior work experiences. Differences emerge primarily for race and gender; the negative correlation between deal success and whether the VC is female or white is driven mostly by VCs that invested early in the company (rather than later) or sat on the board of the company (rather than those that did not).

3.1.1 Missing Data

An important observation is that, despite our use of a variety of data sources, education and work experience data are not available for every investment professional in our data. If investment success is correlated with data availability, then our estimated coefficients may be biased.

Table IA9 presents results examining this concern, assuming that all professionals without available data take the value of either one in the first specification (missing values become one) or instead a value of zero (missing values become zero) in another specification to help bound the potential bias. These specifications assume the most extreme forms of possible selection. For instance, in the first case, if the **1**(Stanford MBA) variable is missing it takes a value of one and in the second case, if the **1**(Stanford MBA) variable is missing it takes a value of zero. Applying these imputations, however, has a limited impact on our results relative to the baseline findings. Continuing the example, the estimated coefficient between investment success and whether the investing VC has an MBA from Stanford GSB at the deal-level is 0.038 in the baseline specification, 0.04 after assuming missing values take a value of zero, and 0.041 if instead assuming missing values have a value of one. More generally, the results presented in Table IA9 are similar to our main results even after assuming extreme selection in either direction, suggesting the missing data are unlikely to change our conclusions.

3.2 Investment Professional Level

In this subsection, we examine whether characteristics of VCs observed before they enter the industry can predict whether individual VCs perform well over their observed career span. Prior literature, often focused on mutual fund managers, generally suggests that superior investment

performance is related to specialized knowledge and information acquired from multiple channels including past investing experiences, education, fields of training, and differential industry experiences (e.g., Coval and Moskowitz (2001), Kacperczyk, Sialm, and Zheng (2005), Cohen, Frazzini, and Malloy (2008), Kacperczyk, Van Nieuwerburgh, and Veldkamp (2014), Kempf, Manconi, and Spalt (2017), and Cici, Gehde-Trapp, Göricke, and Kempf (2018)). One measure of lifetime VC success is the number of successful deals VC have been affiliated with. To this end, we aggregate each investment professional's lifetime deals and examine whether the VCs that have had more investment success differ systematically from those that did not. We employ the same three specific measures and one aggregate measure of successful outcomes, but now we add all the investments with successful outcomes so that each VC investment professional with at least one investment deal affiliation is represented by the total number of positive outcomes over their observed lifetime.

Table 6 presents the results, using a fixed effects Poisson regression specification, since our outcome variables are counts, following the specifications suggested by Cohn, Liu, and Wardlaw (2022). The specification further includes fixed effects for the year investment professionals entered the VC industry such that we compare VCs within their initial cohorts. Figure 3 displays our results visually. The regression sample includes VCs that are affiliated with at least one deal and for whom we know all the individual characteristics and can thus estimate the regression coefficients. The overall conclusion is that the VCs that have made relatively more successful investments substantially differ from those that have not, both statistically and economically. A substantial fraction of variation in the lifetime success by VCs is captured by conditioning on known characteristics by the time VCs entered the VC industry.

Across all specifications, female VCs have made substantially fewer successful investments over their VC careers. The estimated regression coefficient of -0.44 implies that female VCs, on average, have about 0.94 successful deals over their lifetime, which is a 36% reduction ($= \exp(-0.44) - 1$) relative to the regression sample mean of 1.48. The 95% confidence interval for this count covers 0.70 to 1.27. This finding is consistent with our previous deal-level results showing that deals with female VCs are less likely to be successful. These results can be driven by a mechanism where female VCs have differential access to eventually successful startups, due perhaps, to networking frictions. Another possibility is that women's male colleagues in the same VC firm can get attribution for some of their deals. VCs with more lifetime success also tend

not to have been white (relative to the omitted category containing mostly Asian VCs), although the differences in lifetime success across VCs with differing races are not nearly as pronounced as the differences in lifetime success across Male and Female VCs. Our current data does not allow presently to test a specific mechanism behind these differences, but it is certainly an important avenue for future research, given the sharp distinctions in outcomes when conditioning on race and gender documented here, more generally, and in other related work (e.g., Bertrand and Mullainathan (2004), Ewens and Townsend (2020), and Howell and Ramana (2024)).

The educational backgrounds of VCs with more lifetime success also vary substantially from those of VCs with less lifetime success. Estimated coefficients show that VCs who majored in business or social sciences are respectively credited with 19% and 17% fewer successful investments over their VC careers, relative to the mean. VCs with an undergraduate degree from an Ivy league school are credited with 44% more successful investments. Those with an Ivy+ degree are credited with 34% more. VCs with advanced terminal degrees display a positive, but economically smaller, increase cumulative investing success of 14%. The relationship between investment success and MBA degree varies strikingly by institution. VCs with MBAs have, on average, completed 21% fewer deals relative to the mean. By contrast, VCs with a top-10 MBA, a Harvard MBA, or a Stanford MBA, have incrementally completed 21%, 29%, and 35% more successful investments, respectively. These results are consistent with a selection mechanism, wherein the highly ranked MBA programs are more likely to attract skilled future VCs, or also a training and networking mechanism, whereby the resources, networking, and coursework at highly ranked MBA institutions better equips VCs with access to deal flow, hiring and placement opportunities, or also skills to evaluate startups. While both channels are plausibly important, evidence from Garfinkel, Mayer, Strebulaev, and Yimfor (2025) provides support for an important role of the latter.

Similar to the results presented at the deal-level, VCs that have had more investment success also differ systematically in their pre-VC work experiences from those with less investment success. The estimated coefficients show that the most meaningful distinction comes from experience as a C-suite executive or founder of a successful startup. VCs with this experience have completed 39% more successful investments (almost 0.59 more) compared to those without this experience. Some of these differences appear driven by the success of the startup itself, as even VCs with rank-and-file experience at a successful startup have completed about 0.21 more success-

ful investments, on average, compared to the sample mean. Conversely, pre-VC work experience in a startup that had not been successful either does not have an impact or is weakly negative on the VCs' eventual success. VCs that became VCs after stints at technology and pharmaceutical firms or as investment bankers (but not as management consultants), are also more likely to have had more successful investments throughout their careers. Given the high selectivity of the hiring policies for companies in each of these industries, the results are consistent with a mechanism where the specialized human capital (acquired, i.e., from technology experience or banking experience) are more relevant for specialized VC investments compared to the relatively more general human capital acquired from experience as a management consultant.

3.3 Fund Level

Previous work has shown that various characteristics of VC funds, related to their size, vintage, and strategy correlate with the final returns of the fund (e.g., Kaplan and Schoar (2005)). Previous subsections show that characteristics of VCs predict investment outcomes at the deal-level and especially for the differing lifetime investment success measures of VCs. The goal of this section is to examine whether characteristics of VCs affiliated with a given fund correlate with the returns of the fund.

We restrict our sample to closed, liquidated, or fully invested primary U.S. venture capital funds managing at least $10mm and with a vintage year prior to 2020 sponsored by a U.S. VC firm in our sample. We source these 3,256 "institutional" funds and their performance from PitchBook as well as Preqin.[11] The VC team said to be responsible for deploying each fund in our sample includes all VCs identified as having deployed capital for that particular fund based on data available from PitchBook, which connects individual deals to funds. The average fund has a team of five VCs that have made 12 investments for the fund, about 5 of which are credited to the most active professional on average. For each fund, we characterize differences in teams based on whether any professional on the team has a particular characteristic. For instance, in a team of five VCs, if any one of the five VCs has an MBA degree, then the "MBA" value for that fund takes a value of one. The MBA indicator takes a value of zero only if none of the team members have an

[11] The next version will also incorporate and reconcile the Stepstone data on fund returns as well. The results in this subsection, therefore, are very preliminary.

MBA degree. We then examine whether better performing funds tend to have a team member with characteristics that systematically differ from the characteristics of the team members associated with worse performing funds.

Figure 4 displays the results with corresponding regressions presented in Table 7. All specifications include fixed effects for the vintage of the fund, the investment approach of the fund (e.g., early stage versus later stage), and the status of the fund (e.g., fully invested versus liquidated). Specifications also include controls for the natural logarithm of capital committed to the fund, the percent of capital called, and the number of VCs and companies affiliated with the fund. Return outcomes are estimated by counting the number of companies with a successful exit associated with the fund.

Similar to prior results at the deal and the fund level, affiliations with successful companies tend to have been made funds where the team members possess particular characteristics. Funds where the team includes a white VC (94% of funds) tend to have invested in about 1.59 ($= e^{0.466}$) more companies with a successful outcome compared to the 6% of funds that do not include any white team members – a quantity equal to about 35% of the regression sample mean. The 38% of funds where at least one team member is Asian also tend to have invested in more companies with outcomes that are subsequently successful. The number of successful outcomes associated with the 33% of funds invested by teams with at least one female VC see, on average, the same number of successful outcomes compared with VC funds where no team members are female.

Turning to education, the 60% of funds where at least one team member studied a business subject during their undergraduate years tend to have invested in about 1.24 ($= e^{0.218}$) more companies with a successful outcome compared to the 40% of funds where no VCs have a business degree. The pedigree of the undergraduate school also matters too, where the presence of at least one VC with an Ivy-league or Ivy-plus degree correlates with similar increases in the count of successful outcomes. The 75% of funds where at least one VC has an MBA perform similarly to the 25% where no VCs have an MBA. But, the 60% of funds where a VC has a Top-10 MBA and especially the 23% of funds where at least one VC has a Stanford MBA or 42% of funds where a VC has an advanced degree make more investments in subsequently successful companies.

Also similar to outcomes at the deal and person level, funds comprised of VCs associated with successful startups (45% of funds) or with pharmaceuticals experience (21%) tend to have

made more investments in successful companies. The presence of former bankers, consultants, of technologists does not distinguish funds with many successes from those with fewer successes.

However, in the results presented in the last two columns of Table 7, and in contrast to the prior results at the deal, person, and the fund level, we fail to find evidence that teams distinguished by their possession of particular human capital, correlate with the returns of the fund when measured using net IRR or TVPI. Even the striking differences in gender, work experiences, or educational backgrounds do not persist at the fund level for these different measures of return outcomes.

One interpretation of this result is that the composition of the full team may offer significant variation such that the role of any one professional is insufficient for explaining fund returns. This, however, does not seem to be the case as similar results attain if we instead use various aggregations of all investment professionals affiliated with the fund. Another interpretation is that the presence of particular characteristics correlates with the tendency for VCs to extract a larger share of profits, leading to a positive correlation with gross of fee return measures but not net of fee return measures. Yet another interpretation is that the quantity of successful companies a fund invested in may not translate directly to net of fee fund return outcomes given the skewed distribution of return outcomes and potentially small or otherwise inconsequential investments in each company. However, a necessary caveat, and an important limiting factor in this analysis is the availability of performance data in our combined Preqin and PitchBook datasets. We thus aim to subsequently improve our estimation of the relationship between VCs' human capital and fund return outcomes in subsequent iterations.

4 Superstar Venture Capitalists: Evidence from the Midas List

The evidence presented in Section 3 shows that a relatively small proportion of VCs that have had repeated investment success differ substantially from those VCs that have not had repeated investment success. Having different work experiences, educational experiences, and demographic compositions matters for outcomes at deal and person levels. These results imply that compensation and status follow a highly skewed distribution in the U.S. VC industry, akin to that described by Rosen (1981): a small number of "superstar" venture capitalists, with particular backgrounds,

enjoy the bulk of the rewards of venture capital investing. This is not unlike, for instance, the distribution of compensation and success among CEOs of U.S. companies. The key finding in studies of superstar CEOs, however, is that achieving superstar status appears to have negative effects on the performance of their firms (e.g., Malmendier and Tate (2009)). In this section, we use the full extent of our newly assembled data to design an empirical test enabling us to estimate the effects of achieving "superstar" status for U.S. VCs.

An ideal experiment for estimating this effect awards some VCs with superstar status and compares the VCs that barely achieve such status with those that just missed it. Doing so would allow us to identify a credible counterfactual for the VCs that achieve such superstar status. A key assumption we make in this ideal experiment is that superstar status is a binary variable: there is a threshold for which all VCs above this threshold receive the status while all VCs below this threshold do not receive such status.

One important institutional feature of the VC industry allows us to approximate such an experiment is the the annual "Midas List" rankings of the top-100 VCs reported by Forbes. The list started in 2001 and has been updated annually every year since then except for 2010. We hand collect the constituents of each annual list, the counts of which are reported each year in Table IA10 alongside the release date of the list for that year. The annual lists report 100 people each year, giving us a natural cutoff from which we can estimate our experiment. Our goal is to replicate the Midas list each year, as of the year, and construct two sets of counterfactuals to estimate the effect of superstar status. The first compares VCs who made the Midas List but we did not anticipate them to ("Surprise Makes") to VCs who we predict to have made the list based on their investment histories but did not ("Surprise Misses"). The second compares VCs that just made the list (i.e., ranked 95 through 100 or 90 through 100) with those that just missed the cutoff for such status (i.e., those we estimate to have been ranked 101 through 105 or 101 through 110).[12]

Table IA11 reports the composition of professionals reported on the list, with 2,175 unique listings of 559 people. Of the 559 people that have been on the Midas list, 399 are classified as U.S. venture capital (or growth equity) investors. We focus on these professionals; the excluded professionals are not based in the U.S. (84 people), or have held a variety of different positions

[12]Note that in recent years Forbes also publishes a "Midas Brink List," which includes VCs that Forbes expects to be on the Midas list in the future. This is not, however, a list of people ranked 101 or higher by their methodology as it is mostly assembled via a committee of VCs selected to identify potential up and coming VCs.

given the slightly less standardized definition of a venture capitalist in earlier years of the rankings (i.e., bankers, angel investors, PE fund managers, lawyers, hedge fund managers, recruiters, executives, professors, government employees, entrepreneurs, or consultants).

4.1 Replicating the Midas List Rankings

An important part of our experiment is replicating the methodology that Forbes (in conjuction with an investment manager TrueBridge in recent years) uses.[13] To arrive at rankings, Forbes solicits information on attribution from VCs and their firms directly. Table IA12 reports quotations about the reported methodology. The methodology is fairly standard over time, generally involving identifying which VCs are credited with investing in the largest and most successful startups to have gone public, been acquired, or been highly valued over a rolling five year window. Forbes further awards points if the VC is more heavily involved in the investment, identified by board positions or other information it receives from submissions.

The key inputs we cannot observe are: (1) precisely which companies Forbes chose to count for a professional's involvement, (2) the precise way in which Forbes weighted the valuations of these companies, and (3) the precise way in which Forbes weighted the differing levels of involvement. However, what we can observe are the companies each professional in our sample invested in, their reported involvements with these companies (i.e., as board members, lead investors, or other investors), and the financial outcomes of these investments (i.e., whether the company went public, was acquired, or received a sufficiently high post money valuation; for almost all successful outcomes we also observe the relevant valuation). Using these data, we observe each professional's investments, each year as of that year, and attempt to score and aggregate investments in a way that replicates the Midas list released in the subsequent year.[14]

Our replication gives each company one point per dollar of valuation to split among all the VCs invested in the company as of the year. For instance, in our replication, SpaceX was valued at $127 billion as of 2022, so it has 127 billion points to divide among nine U.S. VCs credited

[13] Our attempts to collaborate with the producers of the Forbes Midas list have not been successful to date.

[14] In an early version of our paper, we attempted to empirically solve for the weighting scheme that Forbes used each year, systematically iterating over a large number of potential companies, outcomes, and involvement weightings, for each professional and adopting the methodology that best replicates Midas each year. The results estimating the effect of Midas list inclusion are similar.

in our data with being important investors in SpaceX as of 2022. Within the company, we split points among the VCs such that VCs that invested earlier, took a board seat, or led a round receive a larger share of the points compared to VCs that did not. Based on Forbes and Truebridge reports about the methodology behind the Midas list, we also adjust the sample to only consider companies that went public or were acquired at a valuation of at least $200 million or instead are privately held with a valuation of at least $400 million. Following public reports, we also place a premium on liquid exits over unrealized returns, such that $2 of value from a post-money private valuation award the same number of points to a VC as $1 of value from an IPO or acquisition. IPO valuations are the first-day market capitalizations, sourced primarily from Jay Ritter's IPO dataset.

Our replication then ranks each VC based on the sum of points awarded to them from all companies they are credited with investing in. Doing so produces a ranking of VCs that comes close to replicating the official lists released by Forbes. Pooled across years, 58% of all entries on the Midas List are in our top-100 ranked VCs for the corresponding year. 74% are in our highest scoring 150 VCs and 91% are in our highest scoring 200. Figure 5 further summarizes our replication success by actual ranking. Panel A shows that those predicted to be in the top-5 by our rankings are included in the actual Midas List 58% of the time. Those that are lower on our rankings are much less likely to appear on the actual Midas list. VCs ranked 51-100 on our list appear on the Midas list only 32% of the time. And those ranked 501+ or higher on our list appear on the Midas List only 0.1% of the time. Panel B shows that if a professional is ranked 1-10 on the actual Midas list, there is a 75% chance they are in our estimated top-100 ranking and nearly a 100% chance they are in our top-500 for that year. We have less success for individuals ranked lower on the actual Midas list. Of those ranked 91-100, we include them on our top-100 about 40% of the time, and our top-500 nearly 85% of the time.

Taken together, these results indicate that our replication procedure accounts for the majority of the list that Forbes creates.

4.2 The Effect of Inclusion on the Midas List

4.2.1 Counterfactual #1: Surprise Makes Versus Surprise Misses.

Table 8 presents the results estimating the effect of inclusion on the Midas list using our first counterfactual. These specifications include annual observations for each professional that we predicted to be on the Midas list but did not make it ("Surprise Misses") to those that we did not predict to be on the list but did ("Surprise Makes"). We estimate the Midas List effect using a stacked differences-in-differences model of the form:

$$Y_{i,t} = \beta\left(Post_{i,g,t} \times Treat_{i,g}\right) + \gamma_{i,g} + \delta_{g,t} + \varepsilon_{i,g,t}, \tag{1}$$

where i indexes the VC, t indexes the year, and g indexes the stacked cohort. We form cohorts for each Midas List iteration, defining surprise misses and surprise makes based on each iteration of the actual list. Each surprise-make and surprise-miss is then included in the regression sample for the three years around their reference list. For instance, the 2008 cohort ($g = 2008$) includes all surprise makes and surprise misses for the 2008 list, each observed from 2005 through 2011. $\text{Post}_{i,g,t}$ is an indicator that takes a value of one once the list for the specific cohort is published. $\text{Treat}_{i,g}$ takes a value of one for the surprise makes in the cohort. Figure IA1 reports the surprise makes for each list iteration, averaging about 40% across the sample. All specifications include controls for whether the person was recognized on the Midas list in any of the two prior years. Following Baker et al. (2022), we include fixed effects for each VC-by-stack ($\gamma_{i,g}$) and each stack-by-year ($\delta_{g,t}$).

The main outcome variables we focus on in these regressions are indicators for whether professional i made any particular type of successful investment in year t (the extensive margin), alongside additional tests for the number of each type of successful investment they made in year t. The results presented in Table 8 show positive effects of Midas list inclusion. Compared to professionals that were predicted to be on the list, but were not, the surprise makes are more likely to be subsequently credited with successful investments.

Panel A reports that VCs are 4.5% more likely to have a successful investment following a surprise make, an increase which is statistically and economically significant, equaling 17% of the regression sample mean. The increase in successful investments following a surprise make

comes primarily from an uptick in investments that are highly valued, which shows a 6% increase in unicorns and a 4% increase in decacorns, respectively 20% and 16.5% of the regression sample means. By contrast, the incidence of investments that are exited at higher multiples, shows little change following a surprise inclusion on the list. Panel B reports the intensive margin results as well, using Poisson specifications, indicating that a surprise make corresponds to an uptick in the number of successful investments of about 11% relative to the regression sample mean (or 0.16 new successful investments).

The identifying assumption of our DiD specification is parallel trends: surprise makes would have investing histories that evolve in parallel to the surprise misses but for the timing of their surprise midas list inclusion. While not directly testable, Figure 6 allows us to visually examine and inspect for any pre-trends denoting an obvious violation. Importantly, across our main outcome variable of interest, the pre-trend coefficients are jointly and visually indistinguishable from zero. Dynamically, the increase in subsequently successful investments occurs most clearly in the first year following a surprise make. Visually, results again appear to be driven by increases in the propensity to generate exits with high multiples. Figure IA2 reports visual results on the intensive margin, again failing to generate any visual violations of the parallel trends assumption.

4.2.2 Counterfactual #2: Near Makes Versus Near Misses.

Our replication of the Midas list rankings also allows us to estimate the effect of inclusion on the list by comparing those that just made the list to those that barely missed the list. To this end, we compare the lowest five and 15 ranked professionals on the list to, respectively, the first five and 15 professionals who we predicted to be on the list but were not. We again estimate stacked DiD regressions, as in (1), forming cohorts and stacks around each iteration of the Midas List publication. For instance, the 2008 cohort ($g = 2008$) with a "bandwidth" of five includes all VCs ranked 96-100 and those ranked 101-105 that we estimate to have just missed the list. The identifying assumption is, again, parallel trends, which we visually inspect.

Table 9 presents our results. Compared to the counterfactuals based on the surprise misses and makes, the results are somewhat weaker, but point in the same direction. In the five person bandwidth (Panel A), the effect of barely making the list is an 5% increase in the propensity to complete a successful deal, corresponding to about an 12% increase relative to the regression sam-

ple mean. This coefficient is not statistically significant. However, the positive results are driven, again by a higher propensity to make investments with valuations exceeding high thresholds, showing economically and statistically significant increases in the propensity to invest in, for instance, unicorns and decacorns. The subsequent panels using broader bandwidths report similar results, showing 5 to 10 percent increases in the propensity to make investments with high valuations, but limited evidence of changes in the propensity to achieve other types of successful outcomes. Figure IA2 reports dynamic specifications for each window. The evidence is weaker compared to the first counterfactual, but nonetheless shows upticks in successful investments while failing to demonstrate visual or statistical violations of the parallel trends assumptions.

Taken together, the results in this section provide evidence that inclusion on the Midas list results in a higher propensity to generate successful investments. These results run counter to what has been documented for the effects of superstardom on CEO performance (e.g., Malmendier and Tate (2009)). Inclusion on the Midas list is unlikely to confer additional investment skills for the VC. These results, instead, are most consistent with a mechanism where the increased media coverage allows the VC to obtain better access to higher quality startups and helps to further attract resources and other investors into the startups in which they invest in the few years following their recognition on the list. However, for our results to be driven primarily by an increase in resources or value-add abilities for the VC – such as capital involving suppliers, customers, employees – VCs marginally included on the list would have to direct these new resources only to their new investments but not their pre-existing investments. This result underscores prior results of persistency in return outcomes at the individual VC level, providing evidence of a new channel through which the ability to make successful investments is accessed (e.g., Ewens and Rhodes-Kropf (2015) and Nanda et al. (2020)).

5 Conclusion

In this paper we have investigated to what extent individual differences among investment professionals in the venture capital industry can explain investment deal outcomes, life-time investment performance, VCs' career progression, and fund-level returns. To do so, we assemble the largest and most comprehensive dataset of individual U.S. VCs to date, by using a novel method, tracking

their entire careers, deals, outcomes, as well as collecting data on their individual characteristics and relevant biographical details. We further utilize the publication of the Midas List of the most successful VCs to study to what extent appearance on the list improves further investment success. Our results clearly show that individual characteristics matter for outcomes at multiple levels. Given the importance of the VC industry for broader economic outcomes, understanding better the economic mechanisms behind our results presents a fruitful area for further research.

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Figure 1: Example Archived Webpages Over Time

Panel A: New Enterprise Associates 2005 Team Page



Panel B: New Enterprise Associates 2025 Team Page

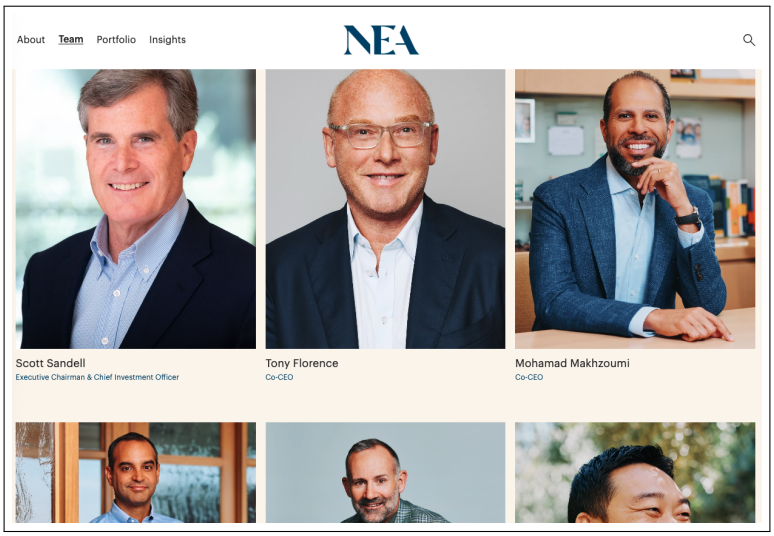


Figure 1: Displays partial snapshots of example webpages archived from the Wayback Machine used to construct the dataset of PE investment professionals. Panel A shows the 2005 team page for New Enterprise Associates (linked here). Panel B displays the 2025 team page for New Enterprise Associates (linked here).

Figure 2: Sources of VC Investment Level Outcomes

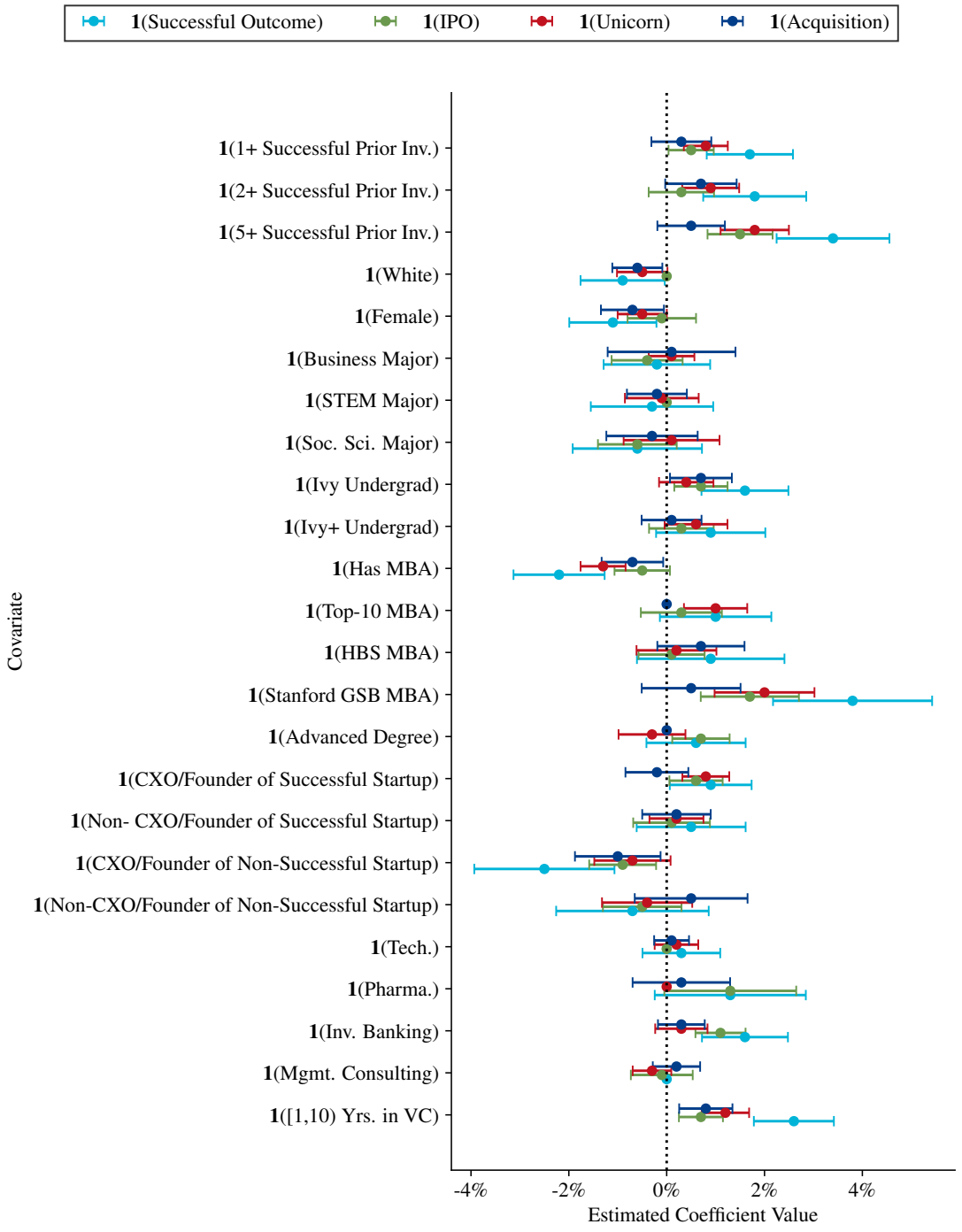


Figure 2: Plots coefficients from four separate regressions of indicators for the success of a VC deal on characteristics of the VC that made the deal. All specifications include fixed effects for: the year of the investment, the state of the target company, the industry of the target company, the age of the target company as of the investment, and the source of the VC-company affiliation. Standard errors are clustered at the individual VC level. Horizontal bars display 95% confidence intervals. Table 5 displays the coefficient values.

Figure 3: Sources of Cumulative VC Investment Success

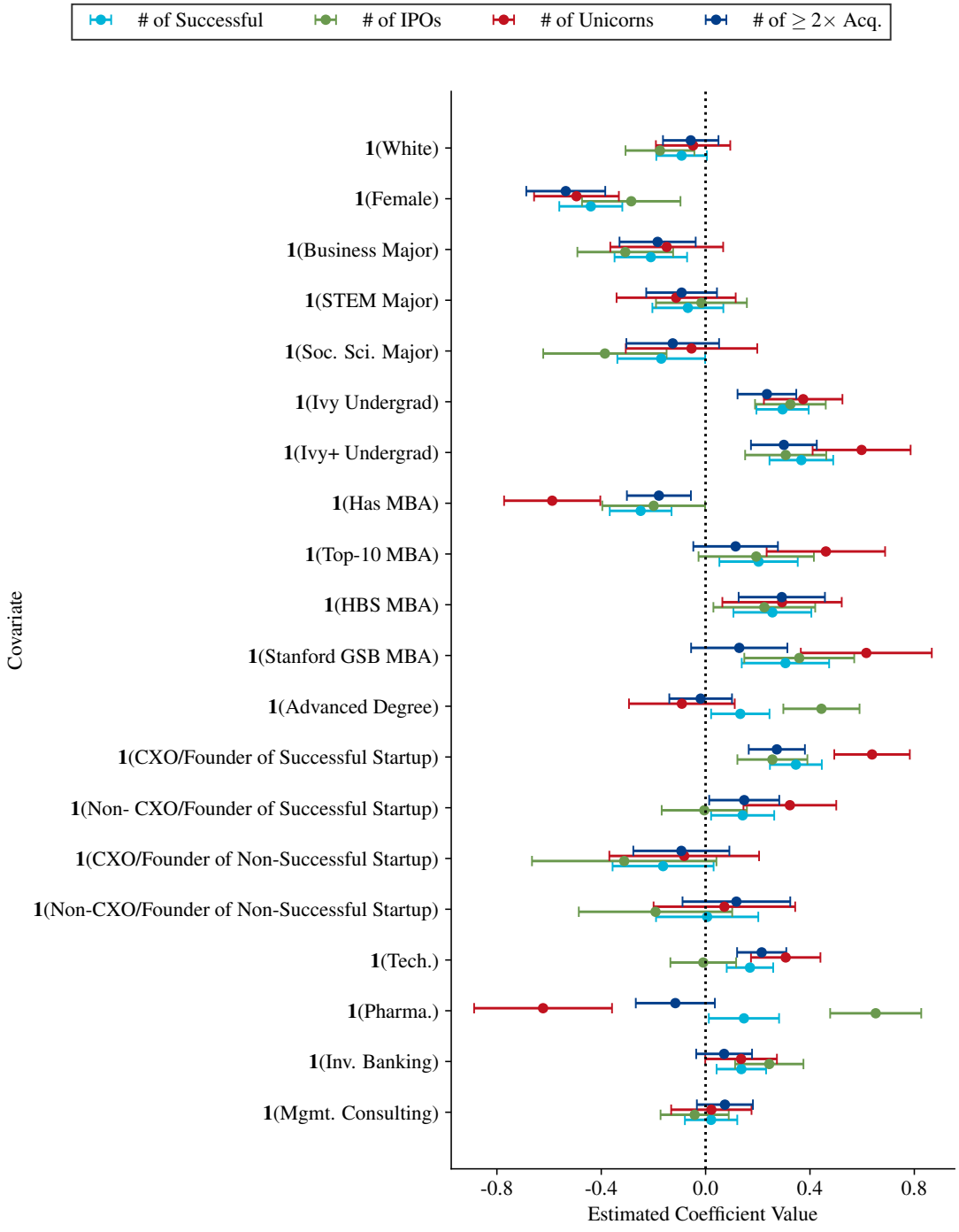


Figure 3: Plots coefficients from four separate Poisson regressions of the total number of successful investments that each individual VC in our sample has made. All specifications include fixed effects for the year the VC first was employed by an institutional U.S. VC firm. Standard errors are clustered at the individual VC level. Horizontal bars display 95% confidence intervals. Table 6 displays the estimated coefficient values.

Figure 4: Sources of VC Fund Returns

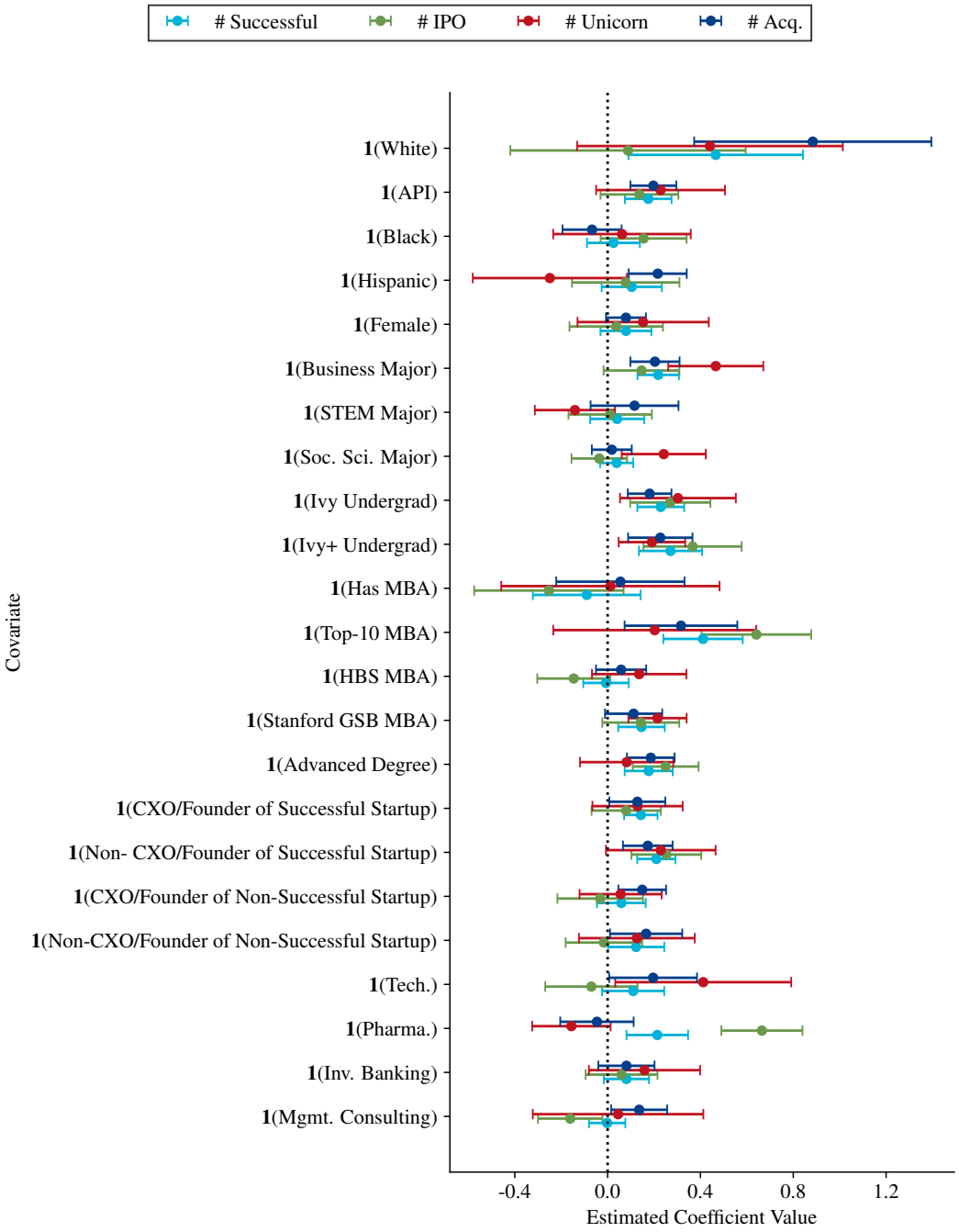
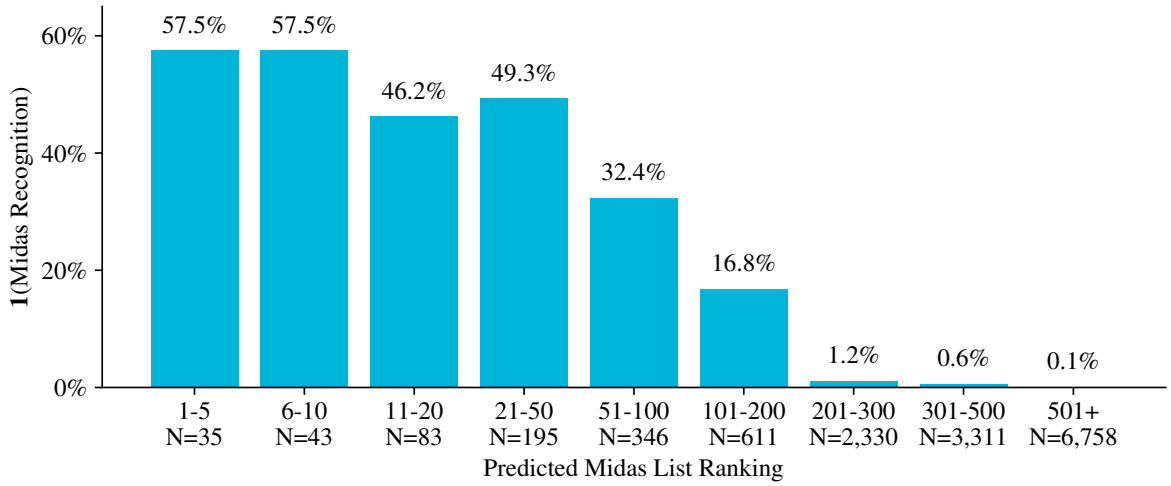


Figure 4: Plots coefficients from separate regressions of the returns of each fund on the characteristics of the professional most involved with the fund via our data. All specifications include controls for the log size of the fund and fixed effects for the vintage of the fund and the category of the fund in PitchBook. Regression samples require that all characteristics are observed. The sample includes VC funds that are denominated in USD, closed, liquidated, or invested as of 2025 and have a vintage of 2020 or earlier, and raised at least $10 million in capital commitments. Standard errors are clustered at the vintage year level. Horizontal bars display 95% confidence intervals. Table 7 displays the estimated coefficient values.

Figure 5: Midas List Predictions

Panel A: Inclusion on the Midas List by Predicted Rank



Panel B: Predicted Rank by Observed Midas Ranking

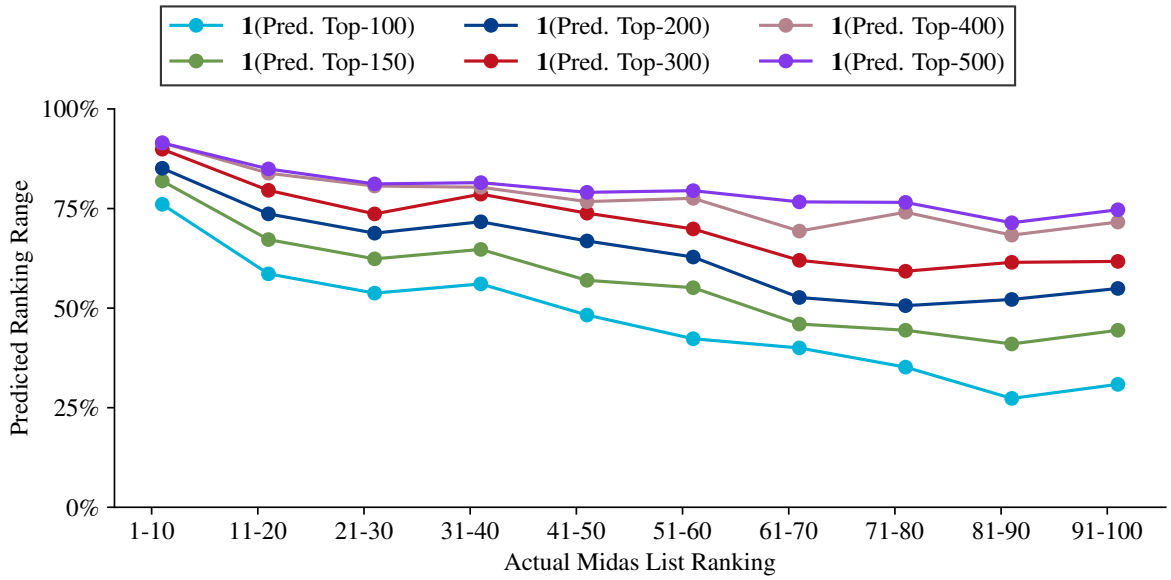


Figure 5: Panel A displays the likelihood for whether a VC professional is included on the Midas list in a given year based on the predicted likelihood that the VC professional will be included on the list for that year. The unit of observation is the VC professional × year. "N" refers to the number of people where a predicted ranking in the interval is observed. Panel B reports the fraction of professionals on the Midas list with a given ranking that have a predicted ranking less than or equal to 100, 150, 200, 300, 400, and 500 in the year they are observed at a given rank.

Figure 6: Midas List Surprise Makes Versus Surprise Misses

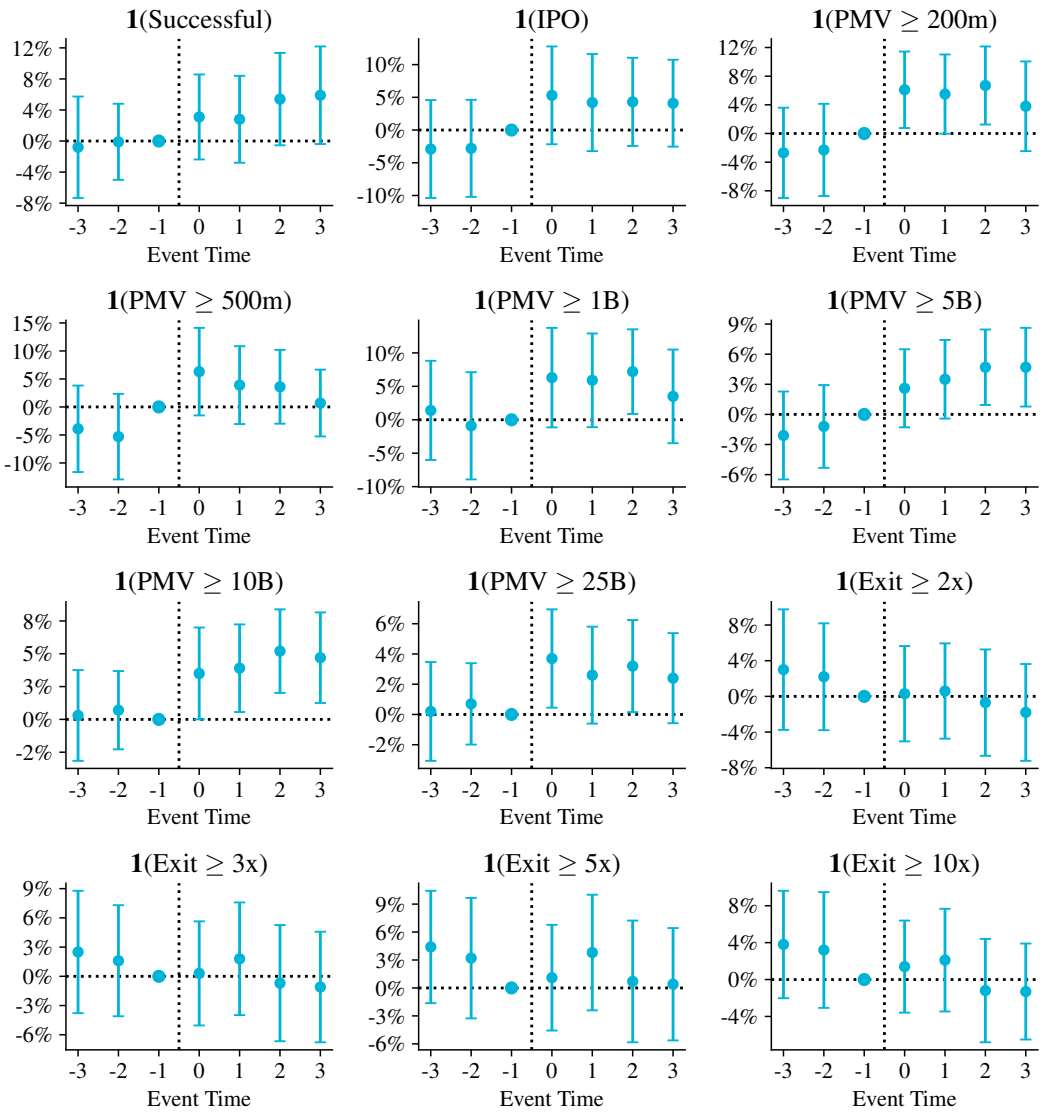


Figure 6: Plots dynamic stacked difference-in-differences estimates of the effect of Midas List recognition on individual VCs' investing activity each calendar year. The unit of observation is the individual VC×calendar year. Indicators denote whether a professional made an investment of a given type each year relative to the Midas List treatment event. Regressions employ stacked datasets for each event (i.e., recognition on the Midas List in each calendar year) and the three years before and after each annual ranking. Each stack only includes VCs that are predicted to be on the Midas list that year but did not receive recognition ("Surprise Misses") and VCs that were not predicted to be on the Midas list that year but did receive recognition ("Surprise Makes"). The treated group are the "Surprise Makes" in the stack and the control group include the "Surprise Misses." All specifications include controls for whether the person was recognized on the Midas list in any of the two prior years. Following Baker, Larcker, and Wang (2022), we include fixed effects for each VC-by-stack and each stack-by-year. Standard errors are independently double clustered at the VC-by-stack and stack-by-year levels. Vertical bars denote 95% confidence intervals.

Table 1: Venture Capitalist Characteristics

		# Successful Involvements				
	All IPs	w/ 1+ Inv.	0	1–2	3–5	6+
# Professionals from Websites	84,796					
# Investment Professionals	30,568	16,600	10,070	4,024	1,423	1,085
w/ Demographics	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
w/ Education	73.8%	86.5%	84.6%	87.7%	91.4%	93.5%
w/ Work Exp	67.8%	77.1%	74.2%	79.1%	83.6%	87.9%
Panel A: Demographics						
1(White)	69.0%	75.0%	73.2%	77.0%	77.8%	79.1%
1(Female)	24.0%	16.5%	20.0%	13.3%	8.4%	5.6%
Panel B: Pre-VC Education						
1(Ivy Undergrad)	16.6%	17.2%	15.1%	18.1%	21.5%	26.6%
1(Ivy+ Undergrad)	10.2%	10.1%	8.7%	10.9%	11.4%	17.3%
1(Business Major)	41.2%	36.4%	39.4%	34.0%	31.3%	25.2%
1(STEM Major)	35.5%	39.6%	35.8%	43.4%	45.5%	51.7%
1(Soc. Sci. Major)	10.6%	10.7%	11.3%	10.0%	10.8%	8.4%
1(Humanities/Arts Major)	8.8%	9.4%	9.6%	8.9%	8.4%	10.5%
1(Has MBA)	32.2%	38.1%	34.3%	41.5%	44.0%	49.5%
1(Top-10 MBA)	15.0%	20.8%	16.4%	24.4%	29.5%	37.2%
1(HBS MBA)	4.2%	5.9%	4.3%	6.6%	9.7%	13.5%
1(Stanford GSB MBA)	2.7%	3.9%	2.3%	4.9%	6.5%	11.2%
1(Advanced Degree)	10.5%	14.5%	13.0%	15.4%	18.0%	19.8%
Panel C: Pre-VC Experience						
1(CXO/Founder of Successful Startup)	7.2%	14.7%	12.5%	16.0%	20.2%	23.4%
1(Non- CXO/Founder of Successful Startup)	7.7%	9.7%	9.4%	9.2%	10.0%	14.3%
1(CXO/Founder of Non-Successful Startup)	3.0%	4.7%	5.4%	3.7%	3.9%	3.2%
1(Non-CXO/Founder of Non-Successful Startup)	3.8%	3.6%	4.0%	3.2%	2.9%	2.6%
1(Tech.)	28.1%	35.3%	34.3%	35.5%	39.0%	38.1%
1(Inv. Banking)	27.2%	23.2%	23.4%	22.8%	22.7%	24.4%
1(Mgmt. Consulting)	21.2%	21.2%	21.1%	20.6%	22.6%	21.8%
1(Pharma.)	6.5%	9.0%	7.9%	10.6%	10.5%	10.4%
1(Hedge Fund)	2.4%	2.4%	2.3%	2.4%	2.4%	2.6%
1(Private Equity)	7.7%	7.5%	7.1%	7.4%	8.9%	9.8%
1(Other Fin. Firm)	14.8%	14.8%	15.6%	14.4%	13.4%	11.7%
1(Govt.)	7.6%	8.4%	8.6%	8.5%	7.9%	6.6%
1(Law Firm)	2.8%	3.4%	3.4%	3.9%	2.8%	2.9%
1(Other)	34.1%	35.9%	39.1%	31.9%	31.5%	29.7%
Panel D: VC Experience						
1(Enter at Junior Level)	41.6%	18.3%	18.4%	17.7%	19.5%	17.0%
1(Enter at Middle Level)	18.5%	11.6%	11.8%	11.5%	11.0%	10.9%
1(Enter at Senior Level)	32.3%	35.5%	29.9%	40.3%	48.1%	55.3%
1([1,10) Yrs. in VC)	75.9%	69.5%	85.5%	60.8%	28.3%	6.8%
1([10,20) Yrs. in VC)	17.6%	23.1%	12.7%	32.4%	53.5%	45.4%
1(20+ Yrs. in VC)	6.5%	7.5%	1.8%	6.8%	18.3%	47.7%
1(Ever Midas List)	1.2%	2.5%	0.3%	1.1%	4.0%	26.3%
1(1-2 Inv.)	11.7%	39.4%	56.5%	21.1%	0.0%	0.0%
1(3-5 Inv.)	8.5%	21.7%	24.4%	25.7%	8.0%	0.0%
1(6+ Inv.)	18.1%	38.9%	19.0%	53.3%	92.0%	100.0%
Avg. # of Successful Inv.	0.6	1.3	0	1.3	3.7	10.5

Table 1: Tabulates characteristics of firm investment professionals sorted by the number of successful companies they have lead a deal in or sat on the board of.

Table 2: Portfolio Company Characteristics by Outcome

	All	Successful	Not Successful
# Companies	64,391	7,818	58,415
w/ Founding Year	95.4%	97.1%	95.2%
w/ Industry	97.8%	99.2%	97.7%
w/ Geography	97.8%	99.2%	97.7%
Panel A: Founding Years			
1(Founded: [0, 2000)])	10.3%	23.3%	8.8%
1(Founded: [2000,2010))	19.1%	34.7%	17.3%
1(Founded: [2010,2020))	53.1%	40.1%	54.8%
1(Founded: [2020,2025])	17.5%	1.8%	19.1%
Panel B: Company Industry			
1(Software)	42.6%	36.7%	43.6%
1(Cmcl. Services)	8.9%	6.8%	9.1%
1(Pharma/BioTech)	7.9%	16.3%	6.9%
1(Healthcare Devices)	4.2%	6.1%	4.0%
1(Media)	3.1%	2.3%	3.2%
Panel C: Company Country			
1(United States)	74.8%	81.8%	74.3%
1(United Kingdom)	4.0%	2.4%	4.1%
1(China)	2.2%	3.5%	1.9%
1(France)	1.1%	0.7%	1.1%
Panel D: Company State			
1(California)	28.7%	36.2%	28.3%
1(New York)	9.0%	7.7%	9.2%
1(Massachusetts)	6.0%	9.6%	5.6%
1(Texas)	4.0%	4.0%	4.0%
1(Washington)	2.6%	2.7%	2.6%

Table 2: Tabulates characteristics of companies in our sample based on whether a VC professional in our sample made an investment in the company that was successful. The unit of observation is the company level. Characteristics of the companies are from PitchBook.

Table 3: Investment Characteristics by Outcome

	Outcome					
	All	IPO	Unicorn	Acq. ≥ 2× Entry	Successful	Not Successful
# Professionals × Companies	133,600	7,744	4,670	10,595	21,941	111,672
# Companies	64,391	2,764	1,246	4,119	7,818	58,415
# Professionals	16,600	3,224	2,391	4,660	6,532	16,064
# VC Firms	3,261	911	971	1,444	1,816	3,236
Panel A: Investment Timing						
1(Pre-2000)	2.7%	17.1%	1.0%	4.4%	8.3%	1.6%
1(2001-2009)	17.8%	36.6%	7.5%	39.4%	32.8%	14.9%
1(2010-2019)	46.2%	43.0%	75.9%	52.7%	52.9%	44.9%
1(2020+)	33.3%	3.3%	15.7%	3.5%	6.0%	38.7%
Panel B: Investment Stage						
1(w/in 1-Yr. of Founding)	20.5%	17.5%	20.2%	22.3%	20.3%	20.5%
1(w/in 2-5 Yrs. of Founding)	45.8%	38.9%	48.1%	44.0%	43.0%	46.3%
1(w/in 6-10 Yrs. of Founding)	14.1%	17.1%	14.6%	12.1%	14.4%	14.1%
1(10+ Yrs. of Founding)	5.9%	7.5%	2.1%	4.0%	4.8%	6.1%
Panel C: VC Prior Success						
1(Prev. Midas Recognition)	5.5%	7.7%	12.6%	7.3%	8.3%	4.9%
1(0 Prior Successful Inv.)	46.7%	36.1%	31.9%	39.4%	37.0%	48.7%
1(1+ Successful Inv.)	53.3%	63.9%	68.1%	60.6%	63.0%	51.3%
1(2+ Successful Inv.)	37.5%	45.9%	53.5%	43.3%	45.9%	35.8%
1(5+ Successful Inv.)	18.4%	22.9%	30.9%	20.5%	23.1%	17.4%

Table 3: Tabulates characteristics of investments sorted by the outcome of the investment. The unit of observation is the company × person involvement. The combined data include the union of deals from all other sources.

Table 4: VC Career Outcomes and VC Characteristics

	1(Senior Level)		**1**(≥ 1 Deal)		**1**(≥ 5 Deals)	
	(1)	(2)	(3)	(4)	(5)	(6)
1(Start Junior)	-0.805***	-0.689***	-0.261***	-0.267***	-0.178***	-0.258***
	(-134.27)	(-51.30)	(-28.52)	(-16.06)	(-21.40)	(-14.80)
1(White)	0.011**	0.020*	0.026***	0.023	0.012	0.015
	(2.20)	(1.76)	(3.09)	(1.37)	(1.60)	(0.84)
1(Female)	-0.029***	-0.061***	-0.063***	-0.144***	-0.054***	-0.129***
	(-5.67)	(-4.57)	(-6.62)	(-6.41)	(-6.68)	(-5.81)
1(Business Major)	0.004	-0.020	-0.020	-0.067***	-0.013	-0.066***
	(0.59)	(-1.43)	(-1.57)	(-2.96)	(-1.12)	(-2.58)
1(STEM Major)	0.005	0.008	-0.004	-0.031	-0.002	-0.036
	(0.83)	(0.58)	(-0.32)	(-1.44)	(-0.13)	(-1.47)
1(Soc. Sci. Major)	0.007	-0.018	-0.024	-0.041	-0.001	-0.041
	(0.92)	(-1.12)	(-1.51)	(-1.46)	(-0.09)	(-1.31)
1(Ivy Undergrad)	0.006	-0.015	0.050***	0.031*	0.050***	0.077***
	(1.02)	(-1.25)	(4.84)	(1.74)	(5.01)	(3.98)
1(Ivy+ Undergrad)	0.023***	0.017	0.030**	0.056***	0.050***	0.088***
	(2.98)	(1.21)	(2.40)	(2.79)	(4.13)	(3.91)
1(Has MBA)	0.026***	0.040***	0.058***	0.055***	0.031***	0.051**
	(4.10)	(3.19)	(4.99)	(2.88)	(2.77)	(2.51)
1(Top-10 MBA)	0.010	0.009	0.028*	0.052**	0.024*	0.027
	(1.20)	(0.57)	(1.91)	(2.21)	(1.70)	(1.07)
1(HBS MBA)	0.023*	0.018	0.035*	-0.000	0.045**	0.040
	(1.89)	(0.99)	(1.87)	(-0.00)	(2.28)	(1.31)
1(Stanford GSB MBA)	0.022	0.011	0.031	0.036	0.072***	0.092***
	(1.51)	(0.53)	(1.44)	(1.28)	(3.13)	(2.67)
1(Advanced Degree)	0.028***	0.056***	0.073***	0.094***	0.033***	0.050**
	(4.36)	(4.80)	(6.27)	(5.16)	(2.76)	(2.24)
1(CXO/Founder of Successful Startup)	0.034***	0.056***	0.152***	0.158***	0.159***	0.191***
	(5.30)	(5.23)	(12.87)	(9.56)	(11.53)	(8.83)
1(Non- CXO/Founder of Successful Startup)	0.042***	0.061***	0.083***	0.104***	0.063***	0.086***
	(5.28)	(4.03)	(6.61)	(5.09)	(5.14)	(3.64)
1(CXO/Founder of Non-Successful Startup)	0.053***	0.092***	0.108***	0.164***	0.056***	0.219***
	(5.24)	(4.26)	(5.77)	(5.37)	(2.94)	(5.32)
1(Non-CXO/Founder of Non-Successful Startup)	0.019**	0.036	0.064***	0.083**	0.070***	0.094**
	(1.99)	(1.43)	(3.91)	(2.22)	(4.78)	(2.18)
1(Tech.)	0.031***	0.032***	0.083***	0.077***	0.065***	0.078***
	(5.70)	(3.35)	(8.68)	(5.05)	(6.81)	(4.30)
1(Pharma.)	0.014	0.022	0.062***	0.071***	0.016	0.040
	(1.50)	(1.35)	(3.80)	(2.81)	(0.93)	(1.29)
1(Inv. Banking)	0.008	0.016	0.019**	0.011	0.015*	0.018
	(1.55)	(1.50)	(2.02)	(0.63)	(1.74)	(0.95)
1(Mgmt. Consulting)	0.011**	0.024**	0.030***	0.023	0.026***	0.044**
	(2.01)	(2.12)	(3.06)	(1.35)	(2.84)	(2.35)
Sample	All	Pre-2011	All	Pre-2011	All	Pre-2011
Y-mean	0.597	0.751	0.535	0.706	0.310	0.512
Year Entered the VC Industry	x	x	x	x	x	x
Adj. R^2	0.776	0.652	0.279	0.195	0.250	0.170
N	12,627	3,855	12,627	3,855	12,627	3,855

Table 4: Tabulates coefficients from regressions of indicators of career progressions on characteristics of the VC investment professionals. The sample is restricted to investment professionals that entered the industry at either a junior-level or a middle-level seniority. Standard errors are clustered at the individual VC level. *t*-stats are in parentheses and */**/*** respectively denote significance at the 10, 5, and 1 % levels.

Table 5: Investment Outcomes and VC Characteristics

	Outcome			
	(1) Successful	(2) IPO	(3) Unicorn	(4) ≥ 2× Acq.
1(1+ Successful Prior Inv.)	0.017***	0.006**	0.008***	0.003
	(3.81)	(2.33)	(3.45)	(0.98)
1(2+ Successful Prior Inv.)	0.015***	0.002	0.006**	0.007*
	(2.85)	(0.74)	(2.29)	(1.90)
1(5+ Successful Prior Inv.)	0.036***	0.015***	0.020***	0.005
	(6.10)	(4.39)	(5.73)	(1.37)
1(White)	-0.008*	0.000	-0.004*	-0.006**
	(-1.94)	(0.17)	(-1.79)	(-2.31)
1(Female)	-0.010**	-0.001	-0.004*	-0.007**
	(-2.25)	(-0.25)	(-1.74)	(-2.10)
1(Business Major)	-0.003	-0.004	0.000	0.001
	(-0.52)	(-1.08)	(0.15)	(0.16)
1(STEM Major)	-0.002	-0.000	-0.001	-0.002
	(-0.43)	(-0.12)	(-0.23)	(-0.63)
1(Soc. Sci. Major)	-0.008	-0.006	-0.001	-0.003
	(-1.18)	(-1.44)	(-0.35)	(-0.61)
1(Ivy Undergrad)	0.017***	0.007**	0.004*	0.007**
	(3.74)	(2.50)	(1.71)	(2.18)
1(Ivy+ Undergrad)	0.008	0.003	0.006*	0.001
	(1.52)	(0.89)	(1.74)	(0.31)
1(Has MBA)	-0.021***	-0.005*	-0.012***	-0.007**
	(-4.44)	(-1.74)	(-5.32)	(-2.19)
1(Top-10 MBA)	0.009	0.003	0.008**	0.000
	(1.46)	(0.73)	(2.56)	(0.10)
1(HBS MBA)	0.008	0.001	0.000	0.007
	(1.03)	(0.29)	(0.07)	(1.55)
1(Stanford GSB MBA)	0.036***	0.017***	0.018***	0.005
	(4.44)	(3.33)	(3.68)	(0.95)
1(Advanced Degree)	0.006	0.007**	-0.003	0.000
	(1.20)	(2.31)	(-0.93)	(0.01)
1(CXO/Founder of Successful Startup)	0.008*	0.006**	0.007***	-0.002
	(1.88)	(2.28)	(2.95)	(-0.58)
1(Non- CXO/Founder of Successful Startup)	0.003	0.000	0.002	0.002
	(0.65)	(0.07)	(0.54)	(0.53)
1(CXO/Founder of Non-Successful Startup)	-0.026***	-0.009**	-0.008**	-0.010**
	(-3.81)	(-2.56)	(-2.41)	(-2.25)
1(Non-CXO/Founder of Non-Successful Startup)	-0.005	-0.006	-0.002	0.005
	(-0.71)	(-1.23)	(-0.60)	(0.86)
1(Tech.)	0.002	-0.000	0.002	0.001
	(0.64)	(-0.23)	(0.75)	(0.56)
1(Pharma.)	0.013*	0.013*	-0.000	0.003
	(1.66)	(1.88)	(-0.12)	(0.59)
1(Inv. Banking)	0.017***	0.011***	0.004*	0.003
	(3.91)	(4.21)	(1.73)	(1.23)
1(Mgmt. Consulting)	0.000	-0.001	-0.002	0.002
	(0.11)	(-0.33)	(-1.01)	(0.82)
1(1-9 Yrs. in VC)	0.026***	0.007***	0.011***	0.008***
	(6.18)	(3.07)	(4.63)	(2.89)
Y-mean	0.163	0.050	0.041	0.081
Invest Year FE	x	x	x	x
State FE	x	x	x	x
Industry FE	x	x	x	x
Company Age FE	x	x	x	x
Data Source FE	x	x	x	x
Adj. R^2	0.138	0.148	0.044	0.070
N	63,634	63,634	63,634	63,634

Table 5: Tabulates coefficients from regressions of indicators for the success of a VC deal on characteristics of the venture capitalists that made the deal. Standard errors are clustered at the individual VC level. *t*-stats are in parentheses and */**/*** respectively denote significance at the 10, 5, and 1 % levels.

Table 6: Cumulative Investment Success and VC Characteristics

	Cumulative # of:			
	(1) Successful	(2) IPOs	(3) Unicorns	(4) ≥ 2× Acq.
1(White)	-0.091*	-0.174***	-0.040	-0.056
	(-1.81)	(-2.59)	(-0.52)	(-1.04)
1(Female)	-0.449***	-0.284***	-0.550***	-0.536***
	(-7.16)	(-2.95)	(-6.24)	(-6.94)
1(Business Major)	-0.219***	-0.309***	-0.179	-0.185**
	(-3.08)	(-3.29)	(-1.57)	(-2.47)
1(STEM Major)	-0.072	-0.015	-0.139	-0.092
	(-1.03)	(-0.16)	(-1.15)	(-1.34)
1(Soc. Sci. Major)	-0.186**	-0.386***	-0.096	-0.127
	(-2.15)	(-3.20)	(-0.73)	(-1.40)
1(Ivy Undergrad)	0.297***	0.324***	0.395***	0.234***
	(5.77)	(4.69)	(4.94)	(4.09)
1(Ivy+ Undergrad)	0.362***	0.308***	0.606***	0.300***
	(5.77)	(3.87)	(6.11)	(4.66)
1(Has MBA)	-0.243***	-0.198**	-0.589***	-0.179***
	(-3.99)	(-1.98)	(-5.96)	(-2.86)
1(Top-10 MBA)	0.194**	0.194*	0.431***	0.114
	(2.51)	(1.73)	(3.54)	(1.39)
1(HBS MBA)	0.256***	0.224**	0.288**	0.291***
	(3.32)	(2.26)	(2.36)	(3.46)
1(Stanford GSB MBA)	0.302***	0.361***	0.632***	0.128
	(3.52)	(3.36)	(4.77)	(1.37)
1(Advanced Degree)	0.136**	0.443***	-0.130	-0.019
	(2.37)	(5.95)	(-1.17)	(-0.31)
1(CXO/Founder of Successful Startup)	0.336***	0.262***	0.621***	0.273***
	(6.55)	(3.83)	(8.06)	(4.97)
1(Non- CXO/Founder of Successful Startup)	0.130**	-0.018	0.311***	0.148**
	(2.07)	(-0.22)	(3.26)	(2.14)
1(CXO/Founder of Non-Successful Startup)	-0.175*	-0.314*	-0.157	-0.094
	(-1.77)	(-1.74)	(-1.00)	(-1.00)
1(Non-CXO/Founder of Non-Successful Startup)	0.010	-0.192	0.085	0.120
	(0.10)	(-1.27)	(0.59)	(1.13)
1(Tech.)	0.167***	-0.008	0.320***	0.215***
	(3.65)	(-0.13)	(4.52)	(4.47)
1(Pharma.)	0.152**	0.651***	-0.757***	-0.116
	(2.20)	(7.31)	(-5.01)	(-1.50)
1(Inv. Banking)	0.145***	0.244***	0.173**	0.071
	(2.96)	(3.65)	(2.37)	(1.30)
1(Mgmt. Consulting)	0.023	-0.043	0.046	0.074
	(0.45)	(-0.65)	(0.56)	(1.35)
Model	Poi	Poi	Poi	Poi
Y-mean	1.480	0.510	0.339	0.737
Year Entered the VC Industry	x	x	x	x
Pseudo R^2	0.301	0.315	0.149	0.269
N	9,277	8,946	9,269	9,143

Table 6: Tabulates coefficients from regressions of the total number of successful investments that each individual VC in our sample has made. All specifications include fixed effects for the year the VC first was employed by an institutional U.S. VC firm. Regression samples require that all characteristics are observed. All regressions are Poisson regressions. Standard errors are clustered at the individual VC level. *t*-stats are in parentheses and */**/*** respectively denote significance at the 10, 5, and 1 % levels.

Table 7: Fund Returns and VC Characteristics

	(1) # Successful	(2) # IPO	(3) # Unicorn	(4) # Acq.	(5) IRR	(6) TVPI
1(White)	0.466**	0.088	0.441	0.884***	-0.019	-0.031
	(2.43)	(0.34)	(1.51)	(3.39)	(-0.64)	(-0.12)
1(API)	0.175***	0.137	0.228	0.197***	0.004	-0.051
	(3.41)	(1.60)	(1.61)	(3.90)	(0.23)	(-0.33)
1(Black)	0.025	0.155	0.062	-0.067	-0.008	-0.101
	(0.43)	(1.64)	(0.41)	(-1.03)	(-0.28)	(-0.55)
1(Hispanic)	0.104	0.078	-0.249	0.216***	0.001	0.132
	(1.57)	(0.66)	(-1.47)	(3.39)	(0.02)	(0.55)
1(Female)	0.079	0.037	0.153	0.079*	-0.029	-0.227
	(1.41)	(0.36)	(1.06)	(1.80)	(-1.68)	(-1.67)
1(Business Major)	0.218***	0.146*	0.466***	0.204***	0.044**	0.171
	(4.79)	(1.75)	(4.46)	(3.77)	(2.69)	(1.07)
1(STEM Major)	0.041	0.011	-0.141	0.116	-0.021	-0.237
	(0.69)	(0.12)	(-1.60)	(1.20)	(-0.94)	(-1.47)
1(Soc. Sci. Major)	0.039	-0.036	0.242***	0.018	-0.026	-0.271*
	(1.07)	(-0.59)	(2.62)	(0.41)	(-1.63)	(-1.86)
1(Ivy Undergrad)	0.229***	0.270***	0.303**	0.181***	0.005	0.176
	(4.44)	(3.06)	(2.38)	(3.77)	(0.23)	(1.27)
1(Ivy+ Undergrad)	0.271***	0.366***	0.191***	0.227***	0.014	-0.054
	(3.90)	(3.39)	(2.61)	(3.21)	(0.76)	(-0.32)
1(Has MBA)	-0.090	-0.253	0.012	0.055	0.008	0.156
	(-0.76)	(-1.54)	(0.05)	(0.39)	(0.27)	(0.51)
1(Top-10 MBA)	0.411***	0.641***	0.203	0.316**	-0.000	-0.358
	(4.71)	(5.32)	(0.91)	(2.55)	(-0.01)	(-1.17)
1(HBS MBA)	-0.007	-0.146*	0.136	0.058	0.003	0.023
	(-0.14)	(-1.82)	(1.31)	(1.05)	(0.15)	(0.18)
1(Stanford GSB MBA)	0.146***	0.143*	0.215***	0.112*	0.027	0.224
	(2.85)	(1.69)	(3.36)	(1.78)	(1.30)	(1.53)
1(Advanced Degree)	0.177***	0.250***	0.082	0.186***	0.023	0.020
	(3.35)	(3.45)	(0.80)	(3.55)	(1.58)	(0.18)
1(CXO/Founder of Successful Startup)	0.143***	0.080	0.129	0.128**	-0.006	-0.230
	(3.89)	(1.05)	(1.30)	(2.08)	(-0.33)	(-1.54)
1(Non- CXO/Founder of Successful Startup)	0.210***	0.253***	0.229*	0.173***	0.025	0.180
	(5.00)	(3.30)	(1.90)	(3.17)	(1.34)	(1.13)
1(CXO/Founder of Non-Successful Startup)	0.059	-0.032	0.056	0.149***	-0.028	0.110
	(1.10)	(-0.34)	(0.62)	(2.84)	(-1.27)	(0.56)
1(Non-CXO/Founder of Non-Successful Startup)	0.123**	-0.016	0.126	0.166**	-0.054***	-0.357**
	(1.99)	(-0.19)	(0.99)	(2.09)	(-2.86)	(-2.65)
1(Tech.)	0.110	-0.070	0.412**	0.196**	0.020	0.386
	(1.61)	(-0.69)	(2.13)	(2.03)	(0.84)	(1.58)
1(Pharma.)	0.214***	0.665***	-0.156*	-0.046	-0.005	-0.165
	(3.16)	(7.46)	(-1.81)	(-0.57)	(-0.27)	(-1.19)
1(Inv. Banking)	0.081	0.060	0.159	0.081	0.012	0.244
	(1.63)	(0.76)	(1.30)	(1.31)	(0.70)	(1.44)
1(Mgmt. Consulting)	-0.002	-0.161**	0.045	0.136**	0.004	-0.310*
	(-0.05)	(-2.27)	(0.24)	(2.21)	(0.28)	(-1.94)
Model	Poi	Poi	Poi	Poi	OLS	OLS
Y-mean	4.346	1.687	0.741	2.168	0.144	2.098
Vintage FE	x	x	x	x	x	x
Fund Type FE	x	x	x	x	x	x
Fund Status FE	x	x	x	x	x	x
Adj. R^2					0.255	0.176
Pseudo R^2	0.439	0.358	0.459	0.370		
N	1,308	1,308	1,232	1,300	1,146	1,217

Table 7: Tabulates coefficients from regressions of the returns of VC funds on whether any of the VCs credited with deploying capital for a given fund possess a particular characteristic. All specifications include controls for the log size of the fund, the percent of capital drawn down, and the number of VCs and companies affiliated with the fund. Specifications also include fixed effects for the vintage of the fund and the category and status of the fund in PitchBook. Regression samples require that all characteristics are observed. The sample includes U.S. VC funds that are denominated in USD, closed, liquidated, or invested as of 2025 and have a vintage of 2019 or earlier, and raised at least $10 million in capital commitments. Standard errors are clustered at the vintage year level. *t*-stats are in parentheses and */**/*** respectively denote significance at the 10, 5, and 1 % levels.

Table 8: Midas List Recognition and Investment Success: Comparing Surprise Makes to Surprise Misses

	Y-Var.	Surprise × Post		Y-mean	Controls	R^2	N
			Panel A: Indicators (Extensive Margin)				
(1)	**1**(Successful)	0.045**	(2.27)	0.611	x	0.267	12,224
(2)	**1**(IPO)	0.064***	(3.00)	0.228	x	0.155	12,224
(3)	**1**(PMV ≥ 200m)	0.070***	(3.59)	0.441	x	0.282	12,224
(4)	**1**(PMV ≥ 500m)	0.068***	(2.88)	0.348	x	0.272	12,224
(5)	**1**(PMV ≥ 1B)	0.055***	(2.62)	0.265	x	0.274	12,224
(6)	**1**(PMV ≥ 5B)	0.047***	(3.74)	0.110	x	0.203	12,224
(7)	**1**(PMV ≥ 10B)	0.039***	(3.82)	0.071	x	0.171	12,224
(8)	**1**(PMV ≥ 25B)	0.027***	(2.72)	0.043	x	0.163	12,224
(9)	**1**(Exit ≥ 2x)	-0.020	(-1.11)	0.220	x	0.213	12,224
(10)	**1**(Exit ≥ 3x)	-0.012	(-0.64)	0.210	x	0.205	12,224
(11)	**1**(Exit ≥ 5x)	-0.009	(-0.49)	0.195	x	0.196	12,224
(12)	**1**(Exit ≥ 10x)	-0.018	(-1.03)	0.170	x	0.172	12,224
			Panel B: Counts (Intensive Margin)				
(13)	# Successful	0.110**	(2.04)	1.476	x	0.311	11,836
(14)	# IPO	0.285**	(2.57)	0.411	x	0.204	9,249
(15)	# PMV ≥ 200m	0.159**	(2.20)	0.942	x	0.271	10,830
(16)	# PMV ≥ 500m	0.205***	(2.75)	0.723	x	0.278	10,071
(17)	# PMV ≥ 1B	0.259**	(2.21)	0.588	x	0.276	8,871
(18)	# PMV ≥ 5B	0.434***	(2.91)	0.337	x	0.237	5,130
(19)	# PMV ≥ 10B	0.796***	(4.58)	0.275	x	0.212	3,753
(20)	# PMV ≥ 25B	1.006***	(3.03)	0.281	x	0.209	2,137
(21)	# Exit ≥ 2x	0.075	(0.79)	0.469	x	0.209	7,915
(22)	# Exit ≥ 3x	0.109	(1.15)	0.457	x	0.204	7,697
(23)	# Exit ≥ 5x	0.082	(0.87)	0.421	x	0.207	7,520
(24)	# Exit ≥ 10x	0.110	(1.05)	0.379	x	0.197	7,100

Table 8: Tabulates stacked difference-in-differences estimates of the effect of Midas List recognition on individual VCs' investing activity each year. The unit of observation is the individual VC×Year. Regressions employ stacked datasets for each event (i.e., recognition on the Midas List in each calendar year) and the three years before and after each annual ranking. Each stack only includes VCs that are predicted to be on the Midas list that year but did not receive recognition ("Surprise Misses") and VCs that were not predicted to be on the Midas list that year but did receive recognition ("Surprise Makes"). The treated group are the "Surprise Makes" in the stack and the control group include the Surprise Misses. All specifications include controls for whether the person was recognized on the Midas list in any of the two prior years. Following Baker, Larcker, and Wang (2022), we include fixed effects for each VC-by-stack and each stack-by-year. Standard errors are independently double clustered at the VC-by-stack and stack-by-year levels. Panel A reports the results of estimating OLS regressions and adjusted R^2. Panel B reports the results of estimating Poisson regressions and Pseudo-R^2. t-stats are in parentheses and */**/*** respectively denote significance at the 10, 5, and 1 % levels.

Table 9: Midas List Recognition and Investment Success: Comparing Near Makes to Near Misses

	(1) **1**(Successful)	(2) **1**(IPO)	(3) **1**(PMV ≥ 200m)	(4) **1**(PMV ≥ 500m)	(5) **1**(PMV ≥ 1B)	(6) **1**(PMV ≥ 5B)	(7) **1**(PMV ≥ 10B)	(8) **1**(PMV ≥ 25B)	(9) **1**(Exit ≥ 2x)	(10) **1**(Exit ≥ 3x)	(11) **1**(Exit ≥ 5x)	(12) **1**(Exit ≥ 10x)
						Panel A: ± 5						
Surprise × Post	0.055	0.085	-0.016	0.027	0.047	0.122***	0.099***	0.086**	0.004	0.012	0.037	0.009
	(0.93)	(1.48)	(-0.31)	(0.50)	(0.75)	(3.24)	(2.79)	(2.48)	(0.08)	(0.28)	(0.88)	(0.20)
Y-mean	0.605	0.225	0.433	0.300	0.245	0.115	0.082	0.060	0.234	0.223	0.202	0.165
Adj. R^2	0.239	0.120	0.307	0.331	0.259	0.234	0.139	0.127	0.229	0.212	0.181	0.143
N	1,275	1,275	1,275	1,275	1,275	1,275	1,275	1,275	1,275	1,275	1,275	1,275
						Panel B: ± 15						
Surprise × Post	0.004	0.049	0.052*	0.032	0.078**	0.062***	0.071***	0.073***	-0.013	-0.003	0.005	-0.032
	(0.13)	(1.48)	(1.71)	(0.93)	(2.36)	(3.13)	(3.20)	(3.43)	(-0.49)	(-0.11)	(0.17)	(-1.18)
Y-mean	0.617	0.231	0.446	0.340	0.268	0.120	0.075	0.055	0.227	0.216	0.198	0.174
Adj. R^2	0.239	0.183	0.296	0.282	0.268	0.229	0.159	0.155	0.212	0.211	0.193	0.170
N	3,913	3,913	3,913	3,913	3,913	3,913	3,913	3,913	3,913	3,913	3,913	3,913

Table 9: Tabulates stacked difference-in-differences estimates of the effect of Midas List recognition on individual VCs' investing activity each year. The unit of observation is the individual VC×Year. Regressions employ stacked datasets for each event (i.e., recognition on the Midas List in each calendar year) and the three years before and after each annual ranking. Each stack only includes VCs that are predicted to be on the Midas list that year but did not receive recognition and VCs that were not predicted to be on the Midas list that year but did receive recognition. The treated group includes the lowest ranked professionals on the Midas list in a given year. The control group includes the professionals with the highest predicted odds of receiving Midas list recognition that did not. The group "±5", for instance, includes professionals ranked 96-100 and the five highest professionals most likely to be on the list that were not included. The size of this comparison group varies by panel. All specifications include controls for whether the person was recognized on the Midas list in any of the two prior years. Following Baker, Larcker, and Wang (2022), we include fixed effects for each VC-by-stack and each stack-by-year, and also fixed effects for the VC firm employing the professional each year. Standard errors are independently double clustered at the VC-by-stack and stack-by-year levels. *t*-stats are in parentheses and */**/*** respectively denote significance at the 10, 5, and 1 % levels.

Internet Appendix for:
Human Capital in Venture Capital:
Evidence From 100,000 Venture Capitalists

March 19, 2026

IA.1 Assembling Data on Venture Capitalists

This section details the steps taken to compile a database of venture capital investment professionals. We collect the data primarily by prompting a Large Language Model (LLM) to iterate through each firm's archived website hosted on the wayback machine (or live website), locate the team and personal pages of each professional displayed on the website, and then return the biographical information about each person contained in the underlying HTML. We subsequently combine these data with several commercial datasets. The process is similar to that employed by Jackson (2025). We further augment this process with large-scale manual collections of historical website data.

IA.1.1 VC Firm Website Collections

VC firm sample construction. We construct our sample of institutional U.S. venture capital firms by including all PitchBook and VentureSource investors that satisfy each of the following criteria:

1. They are headquartered in the United States.
2. They satisfy at least one of the following criteria:
   (a) They invested in at least one VC-backed company that achieved a "unicorn" valuation of at least $1 billion and they did so before it became a unicorn according to PitchBook, VentureSource, and manual reconciliations.
   (b) They invested in a randomly selected VC-backed company in PitchBook that was chosen to mirror the timing and industries of unicorn investments.
   (c) They raised at least $10 million for a closed or liquidated VC fund in 1995 or later according to PitchBook or VentureSource.
3. They are determined by us to be institutional VC funds by excluding not-for-profit VC firms, accelerators, and firms that mostly sponsor fund of funds or hedge funds.

This results in the sample of 4,402 institutional U.S. venture capital firms. This sample omits many non-VC firms, such as BlackRock, KKR, or Blackstone, that have made VC investments, but primarily sponsor other types of funds. Corporate venture capital firms, which typically

invest from the balance sheets of parent companies rather than manage stand-alone venture funds (Strebulaev and Wang 2021), are also omitted. Note that the use of VentureSource, although now-defunct, helps include data that PitchBook may not cover in earlier years. We use the Pitchbook data feed as of May 1, 2025.

Historical websites retrieval: We retrieve historical website data for each of these firms from 1996 to 2025 from the Wayback Machine hosted by the Internet Archive. The Internet Archive is a nonprofit digital library that retains and provides free access to, among other digital media, historical websites starting in 1996. The Wayback Machine scrapes information using web scrawlers which do not have a fixed pattern of deciding which websites they visit and how often they do so, but are more likely to capture a site more frequently if a website is more frequently visited or linked to by other websites (e.g., Eskandar and Murray (2019)). We also scrape the live website for each firm active in 2025 if it exists. All the live websites are accessed in September and October 2025. We retrieve website addresses using iterations of PitchBook historical data feeds starting from 2017. In addition, we manually retrieve older website addresses for all firms where the URLs from PitchBook do not fully extend back to the earliest date of operation for each VC firm. This can arise for defunct firms and for firms that changed URLs. This manual process accounts for approximately 10% of the final URLs in our sample. In total, we access 5,821 unique URLs, approximately 159,000 unique firm-year URLs, and retrieve more than 600 GB of data resulting from more than three million URL requests.

Each year a firm is active, we extract website data from two main pages: team pages and personal pages. Team pages list professionals working at the firm. Personal pages may include additional information about the person not available on the team page. We extract these data in two parallel tracks. We refer to the first as the "LLM" track, wherein an LLM is prompted to search over the directory of pages on the website, identify the team page, extract information from the team page, and repeat the process for personal pages. The prompts specify common features of team pages to identify (e.g., based on key words often contained in the URL or characteristics of the underlying HTML) and rules for progressing through the directory of pages on the website each year. After retrieving team and personal pages, the LLM is then prompted to extract names and biographical information (e.g., education and prior work experience). For the LLM track, we use the google/gemini2.5-flash-preview model.

This method allows us to access data for at least one professional for 3,335 of the 4,402 firms comprising the institutional U.S. VC industry. For the remaining 1,067 firms we were not able to automatically collect professionals from the historical websites: 444 are excluded because we are unable to identify a historical website for the firm, and the remaining 623 either do not list professionals on their website or have website formats that do not allow for automatic parsing of the HTML. Using our second track of data collection (discussed below) we are able to collect data for an incremental 39 firms not collected by LLM parsing, bringing the final sample to 3,374 institutional U.S. VC firms. While not a function of our VC firm selection criteria, Table IA.B1 indicates that we are more likely to have collected website data for more successful (and thereby longer surviving) VC firms. Nonetheless, the resulting sample represents the overwhelming fraction of the U.S. VC industry, accounting for 96% of capital raised by the 4,402 institutional U.S. VC funds and having sponsored 95% of all U.S. VC funds in the 1996-2025 period (based on PitchBook data).

Table IA.B1: Firm Characteristics by Website Availability

	Collected	No Website Data
1(Out of Business)	16.6%	23.9%
1(0 Unicorns)	42.3%	54.0%
1(1-9 Unicorns)	52.1%	43.9%
1(10+ Unicorns)	5.6%	2.1%
1(0-1 VC Funds)	60.5%	88.0%
1(2-4 VC Funds)	29.2%	9.6%
1(5+ VC Funds)	10.3%	2.4%
1($1B+ VC capital)	6.9%	1.1%

Table IA.B1: Tabulates characteristics of U.S. VC firms with collected data versus those without.

Addressing potential hallucinations: A well-known important concern with automated collections via LLMs is the potential for hallucinations. We take four steps to address this. First, we set the temperature to zero on the LLM, which ensures outputs are the same across runs of the prompt, and specify in the prompts to extract only data that is precisely from the underlying webpage HTML. Second, we require that the exact text parsed about the professional (name, title, biographical data, and so on) appears verbatim on the underlying HTML. Once the first steps are implemented, only 1.6% of subsequent person-firm-year cells are affected by this requirement,

indicating the LLM mostly parses data as it appears. Third, we manually check all LLM extractions which could plausibly be flagged as hallucinations: those where a name appears only once, a first name is repeated, or a last name is repeated for multiple people in the same firm. Doing so removes 0.23% of our observations, further suggesting the hallucination rate is fairly low.

Fourth, and most comprehensively, we also employ a second "manual" track for collecting the webpage data, wherein one or more data assistants manually copy and paste all available person, title, and biographical data each year for the firm as of that year. The manual track benefits from human intuition for navigating webpages and is not affected by hallucinations. Of the 3,374 firms in the sample, professionals from 1,570 are collected using both the LLM and manual track, 39 are collected using the manual track alone, and 1,765 are collected using the LLM track alone. We implement the manual track, given its costliness, only for all the U.S. VC firms that invested in at least one unicorn or a matched random sample firm. Our dual collection method further allows us to benchmark our collections. We find that, for an average firm in the historical sample period where professionals are collected by both the LLM and the manual track, 91.4% of professionals are retrieved by the LLM compared to 92.0% by the manual track. Similar coverage implies the two are interchangeable, although the LLM track is more efficient. We further randomly sampled professionals collected by the LLM and not by the data assistants and found no hallucinations throughout the random sample (after the other three steps are applied). The sample of professionals collected by LLMs (but not manually) primarily includes advisory professionals listed outside of central team pages.

Table IA.B2 provides summary statistics for the resulting sample of 3,374 firms. An average VC firm has 9.5 years of internet archival or live presence, is associated with 30 professionals (not all of whom are investment professionals, as detailed below), reports 24 unique titles, and 53 unique biographies for its professionals.

IA.1.2 Variable Construction and Statistics

Merging across datasets: We collect biographical data on each professional from historical websites. We further supplement these archived data with information from commercial datasets Revelio, PitchBook, VentureSource, and LinkedIn (via scrapin.io). Whenever possible, we merge each

Table IA.B2: Data Point Counts by Firm

	Nobs.	Avg.	25p	50p	75p
# Years	3,374	9.46	5	8	13
# Names	3,374	33.93	6	15	35
# People	3,374	30.18	6	13	31
# Titles	3,374	24.25	4	11	25
# Bios.	3,374	52.56	7	20	56
# Bios. $\geq$ 250 Chars.	3,374	47.52	5	17	49
# Bios. $\geq$ 500 Chars.	3,374	40.41	3	13	42

Table IA.B2: Tabulates the distribution of data points collected from websites across firms.

professional collected from websites to a profile in these datasets – using a sequence of matches based on names and affiliations and then manually reviewing unmatched professionals. The merge sequence iterates over potential matches of exact names within the same firm; cleaned names within the same firm; and then "standout" names within the same firm (e.g., if the website and LinkedIn data for firm A both contain only one person with the name "Blake"). Names are further cross-matched and standardized across each dataset. In total, 80% of investment professionals are successfully mapped to at least one of these datasets.

Investment Teams: Our sample of all the professionals affiliated with US-headquartered VC firms consists of 84,796 unique people. These professionals can be broadly classified into full-time investment professionals (those working on sourcing, due diligencing, negotiating, and managing investments) and non-investment professionals or those that do not work full-time. In addition, websites may list additional people, such as founders of portfolio companies. We are primarily interested in full-time investment professionals. To this end, we identify whether each professional is on the investment team in every year they are observed based on their title reported on the website. Those on the investment team have a title containing one of 16 phrases typically assigned to investment professionals that does not contain any of 309 phrases or word stems that typically correspond to a non-investment role.

For example, a title containing "Associate" or a title containing "Partner" is flagged as likely an investment team professional for further analysis. Conversely, titles that contain "Operating",

"Emeritus", "Compliance", and "Counsel" clearly indicate that a person is not on the investment team. We demand that all titles should contain at least one stem, such as Associate or Partner, that indicates a likely investment team inclusion and contain no non-investment stems. The resulting titles are further reviewed. For example, while "General Partner" is on the full-time investment team, "Venture Partner" is not and thus excluded. If the listed title is uninformative or missing, we further parse the title from the biography extracted from the website. This process results in 30,568 full-time investment professionals, for which we have 182,735 annual observations.

Table IA.B3 reports the number of professionals with a title containing each of the 16 investment-team phrases for at least one year in our dataset. The second column reports the number of investment professionals with a title including each phrase (those with a title that did not also correspond to a non-investment role). The third column reports the number of non-investment professionals with a title including each phrase (those with a title that also corresponds to a non-investment role).

Non-Investment Teams: The remaining professionals listed on the website include the "non-investment" professionals. Table IA.B4 reports the number of professionals with a title containing several of the more common stems found among people that are not a part of VC firms' investment teams. The second column reports the number of investment professionals with a title including each phrase (those with a title that did not also correspond to a non-investment role). The third column reports the number of non-investment professionals with a title including each phrase (those with a title that also corresponds to a non-investment role). Several phrases such as "Operating" help to distinguish the two roles, but several less distinctive substrings such as "IR" (which can be found in both "Director" and as an abbreviation for "investor relations") fail to. Many with the title "chief" do not have a C-suite role at the VC firm itself, but are instead C-suite professionals of portfolio companies also listed on the VC firm websites.

Figure IA.B1 reports the fraction of VC firms that have at least one professional with one of several different title-stems denoting their position on the Legal team, Investor Relations team or a position of Venture Partner, CFO, or COO. The prevalence of these internal operations positions has increased over time for all firms, and is significantly more pronounced in levels among larger firms – those with at least 15 unique people listed on the website, roughly the top-quartile for firm size by people. These patterns are generally consistent with the institutionalization of VC firms and the industry over time and a tendency for VC firms to internalize firm management. Firms that

Table IA.B3: Frequency Distribution of Investment Team Title Stems

Title Stem	All (N = 84,796)		Investment (N = 30,568)		Non-Investment (N = 56,496)	
Partner	20,851	24.6%	13,100	15.4%	9,708	11.4%
Director	9,464	11.2%	4,998	5.9%	4,854	5.7%
Associate	9,454	11.1%	7,848	9.3%	1,791	2.1%
Principal	4,713	5.6%	4,296	5.1%	497	0.6%
Investment	4,195	4.9%	3,575	4.2%	701	0.8%
Analyst	3,747	4.4%	3,035	3.6%	783	0.9%
Managing Director	3,729	4.4%	3,309	3.9%	561	0.7%
Vice President	3,623	4.3%	2,147	2.5%	1,580	1.9%
cofounder	3,490	4.1%	1,774	2.1%	600	0.7%
Investor	2,697	3.2%	1,570	1.9%	1,153	1.4%
Investment Team	655	0.8%	642	0.8%	14	0.0%
Investing	303	0.4%	265	0.3%	39	0.0%
Investment Committee	237	0.3%	205	0.2%	38	0.0%
CIO	230	0.3%	131	0.2%	105	0.1%
Chief Investment Officer	163	0.2%	151	0.2%	18	0.0%
copresident	21	0.0%	13	0.0%	9	0.0%

Table IA.B3: Tabulates the frequency of each title stem among professionals in years when the are observed on the investment team versus if they are not. Percentages are reported as a fraction of all professionals. Counts do not sum as some professionals are observed on both the investment team and not on the investment team in our sample. Further, professionals can have multiple titles over time.

are smaller, and plausibly less successful, are less likely to exhibit such patterns.

Seniority: Using the title stems, we further assign investment professional to one of three layers in each year they are observed reflecting the hierarchy observed in practice: a junior-level, a middle-level, and a senior-level investment professional. Doing so allows investment professionals' career progressions to be reasonably comparable across firms and over time. The senior-level always includes managing partners, general partners, and active VC firm founders. If none of these positions are listed on the website, partners are included in the senior-level. This allows for firms to distinguish between more senior general partners and more junior investment partners. A notable example is Andreessen Horowitz, which uses "General Partner" to distinguish the most senior professionals at the firm, calling almost every other investment professional "Partner." As a result, our classification method allows for the same title to belong to different seniority categories across VC firms.

Table IA.B4: Frequency Distribution of Non-Investment Team Title Stems

Title Stem	All (N = 84,796)		Investment (N = 30,568)		Non-Investment (N = 56,496)	
IR	11,713	13.8%	5,303	6.3%	6,879	8.1%
Venture	8,330	9.8%	781	0.9%	7,602	9.0%
Founder	6,571	7.7%	2,635	3.1%	2,892	3.4%
Chief	3,995	4.7%	308	0.4%	3,686	4.3%
CEO	3,743	4.4%	500	0.6%	2,794	3.3%
Operations	2,909	3.4%	0	0.0%	2,906	3.4%
Assistant	2,694	3.2%	0	0.0%	2,694	3.2%
Market	2,086	2.5%	0	0.0%	2,082	2.5%
Operating	1,781	2.1%	0	0.0%	1,779	2.1%
Business	1,427	1.7%	0	0.0%	1,422	1.7%
Financial	1,299	1.5%	0	0.0%	1,298	1.5%
Admin	1,248	1.5%	0	0.0%	1,248	1.5%
Fund	1,236	1.5%	253	0.3%	993	1.2%
Account	982	1.2%	0	0.0%	982	1.2%
Relation	940	1.1%	0	0.0%	938	1.1%
Portfolio	668	0.8%	130	0.2%	545	0.6%
Legal	572	0.7%	0	0.0%	572	0.7%
Compliance	378	0.4%	0	0.0%	378	0.4%
Emeritus	292	0.3%	0	0.0%	292	0.3%
Emeritus	292	0.3%	0	0.0%	292	0.3%
Human	234	0.3%	0	0.0%	234	0.3%
Resources	152	0.2%	0	0.0%	152	0.2%
Tax	94	0.1%	0	0.0%	94	0.1%
Payroll	20	0.0%	0	0.0%	20	0.0%

Table IA.B4: Tabulates the frequency of each title stem among professionals in years when the are observed on the investment team versus if they are not. Percentages are reported as a fraction of all professionals. Counts do not sum as some professionals are observed on both the investment team and not on the investment team in our sample. Further, professionals can have multiple titles over time.

If none of these previous positions are listed on the website, managing directors are included in the senior-level. If still none of these previous positions are listed on the website, principals are included in the senior-level. The junior-level always includes analysts and associates. The middle-level includes vice presidents and any other positions not included in the junior- or senior-levels based on the previously discussed hierarchy. We do not allow for demotions within firms, which occur artificially if a firm changes the titling it uses to refer to professionals of a different seniority over time.

Table IA.B5 reports the number of professionals with a title containing each of the 16

Figure IA.B1: Fraction of Firms with Non-Investment Professionals

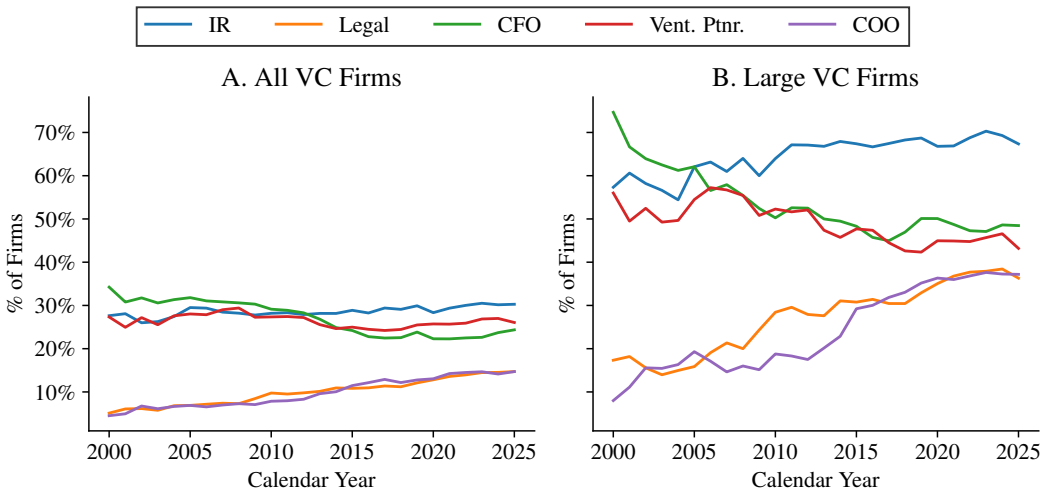


Figure IA.B1: Tabulates the fraction of VC firms with non-investment professionals assuming a particular role over time. Large VC firms list 15+ professionals on their website, roughly the 75th percentile among firm-year cells.

investment-team phrases for at least one year in our dataset. Differing columns report the number of investment professionals with a title including each phrase that also corresponds to the seniority grouping listed in the header (junior, middle, or senior).

Figure IA.B2 reports counts of investment professionals based on which seniority layers they were observed at. 14,933 investment professionals are observed at the senior level at least once. Out of these, 11,918 are only ever observed as senior VCs. Meanwhile, 707 are also present in junior-level positions in other years (and potentially other VC firms), 1,584 in middle-level, and 724 are present in all three seniority levels in our data. Figure IA.B3 summarizes time trends in the seniority at which investment professionals entered the VC industry.

Additionally, Table IA.B6 summarizes the rates at which professionals that assumed different roles at startups join VC firms at junior, middle, and top-level seniorities. 70% of successful startup founders and C-suite level professionals of successful startups join at the partner level. Some of the 30% that do not include Vineet Buch (BlueRun) who co-founded Ojos and Karient (linked here) and Michael Segal who co-founded StudentBusinesses.com that was sold to the Kauffman Foundation in 2009 before joining Bessemer Venture Partners as a VC analyst in 2009. Another example is Kevin Bitterman who joined Polaris as an associate in 2004 after cofounding Sirtris Pharmaceuticals (linked here).

Table IA.B5: Frequency Distribution of Investment Team Title Stems by Seniority

Title Stem	Junior-Level (N = 12,324)		Middle-Level (N = 8,864)		Senior-Level (N = 14,933)	
Associate	7,600	9.0%	0	0.0%	0	0.0%
Analyst	3,015	3.6%	0	0.0%	0	0.0%
Investment	2,108	2.5%	585	0.7%	1,030	1.2%
Investor	1,455	1.7%	38	0.0%	88	0.1%
Investment Team	489	0.6%	41	0.0%	120	0.1%
Investing	145	0.2%	54	0.1%	81	0.1%
Vice President	0	0.0%	2,102	2.5%	0	0.0%
Director	0	0.0%	2,032	2.4%	3,247	3.8%
Principal	0	0.0%	3,855	4.5%	504	0.6%
Managing Director	0	0.0%	604	0.7%	2,813	3.3%
Partner	0	0.0%	1,857	2.2%	11,846	14.0%
Chief Investment Officer	0	0.0%	0	0.0%	148	0.2%
CIO	0	0.0%	0	0.0%	130	0.2%
Investment Committee	0	0.0%	0	0.0%	205	0.2%
cofounder	0	0.0%	0	0.0%	1,750	2.1%
copresident	0	0.0%	0	0.0%	13	0.0%

Table IA.B5: Tabulates the frequency of each title stem among professionals in years when the are observed on each seniority group (junior, middle, or senior). Percentages are reported as a fraction of all investment professionals. Counts do not sum as some professionals are observed across multiple seniority groups. Further, professionals can have multiple titles over time, even within the same seniority.

Table IA.B6: Frequency Distribution of Initial Investment Team Title by Startup Experience

		Entry-Seniority		
	# Professionals	Junior	Middle	Senior
All IPs	26,404	45.8%	20.1%	34.1%
Successful Startup CEO/Founder	1,359	18.8%	15.7%	65.5%
Successful Startup Other CXO	494	16.2%	19.6%	64.2%
Successful Startup Non-CXO/Founder	2,049	42.8%	23.4%	33.8%
Unsuccessful Startup CEO/Founder	613	24.5%	17.9%	57.6%
Unsuccessful Startup Other CXO	174	23.0%	25.3%	51.7%
Unsuccessful Startup Non-CXO/Founder	1,053	54.9%	19.5%	25.6%

Table IA.B6: Tabulates the frequency that investment professionals who previously worked at startup companies join the VC industry in each seniority group (junior, middle, or senior).

Figure IA.B2: Investment Professional Counts by Seniority

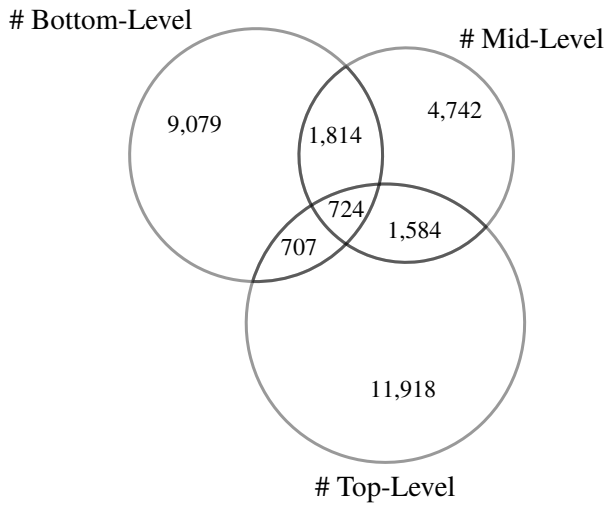


Figure IA.B2: Tabulates the count of investment professionals that appear in each seniority layer.

Figure IA.B3: Seniority Trends by Entry Cohort

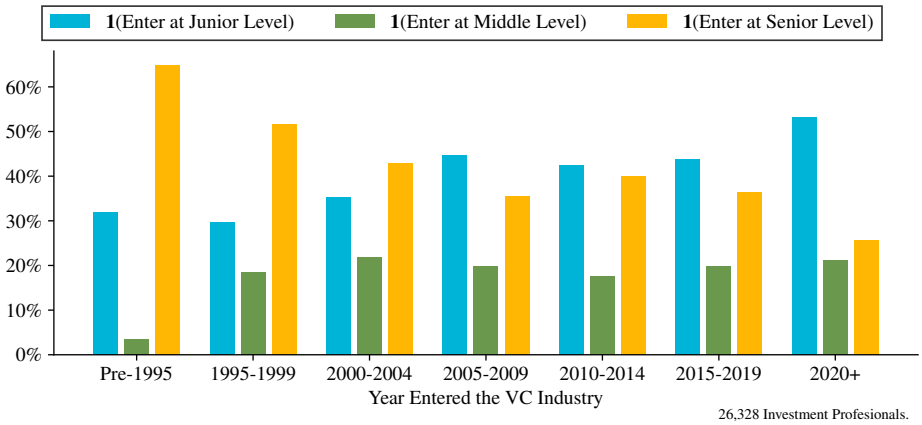


Figure IA.B3: Tabulates the fraction of investment professionals joining the industry at a given seniority.

Employment Spells: End years with the firm, if any, equal the latest year the person is observed at the firm. For each person i working at firm j, this is the maximum value contained in the set of: {last year observed on the website, last year affiliated with the firm on LinkedIn, last year affiliated with the firm on PitchBook, last year affiliated with the firm on VentureSource}. In effect, person i is said to separate from firm j in year t if there is evidence that they are not working at firm j in year $t+1$. Otherwise, they are considered to still be with firm j.

Conversely, a professional is said to start at firm j in the earliest year the person is observed

at the firm or said to be working at firm j based on their biography. For each person i working at firm j, this is the minimum value contained in the set of: {first year observed on the website, first year affiliated with the firm on LinkedIn, first year affiliated with the firm on PitchBook, joining year mentioned in the biography}. Only years observed on or after the founding year of firm j and before the professional separates from firm j (if at all) are retained in the set.

Professionals may have gaps in employment spells within firm j given (a) a legitimate break in employment with the firm, often to pursue an MBA or work at a startup or (b) if the historical webpages for a firm were not comprehensively archived in a given year. Person i is said to have a legitimate gap in their employment spell with firm j in year t if they are missing from the website but 90% or more of the other investment team members are not. For other gaps in employment spells within firm j that are instead due to lapses in archival data, we backfill seniority data so long as year t is within a person's employment spell within the firm. Figure IA.B4 summarizes trends in the number of years investment professionals have worked in the VC industry. Gaps in employment are not counted.

Figure IA.B4: Years Working in VC Over Time

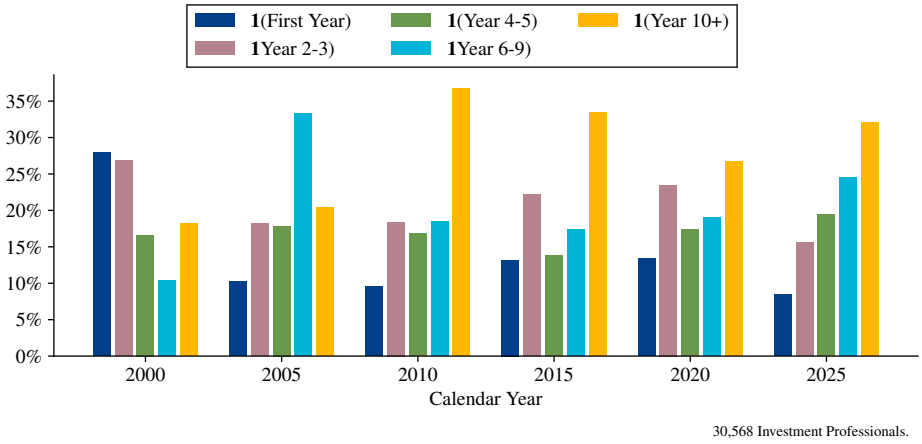


Figure IA.B4: Tabulates trends in the number of years investment professionals have worked in the VC industry for snapshots of six years. Gaps in employment are not counted.

Gender & Race/Ethnicity: Gender is estimated based on the gender reported in LinkedIn or extracted from website biographies. Gender estimates from biographies on websites assume a person to be of a female gender if their biographical data in any year includes pronouns associated with the female gender ("Mrs.", "Ms.", "Miss", "her", or "she") but not the male gender ("Mr.",

"Mister", "he", or "him"). For remaining cases where the gender could not be determined based on biographical data, we use the `gender_guesser.detector` package in Python to subsequently infer the person's gender based on their first name. In cases where the datasets differ in their gender classification (mostly due to androgynous names), we manually reconcile the two based on manual lookups of the professional.

We further estimate the race/ethnicity of each professional using the `RaceBERT` package in Python. This is a transformer based model trained on the Florida voter registration dataset that predicts race and ethnicity from names. Doing so maps each professional to one of five U.S. census race categories: White, Black, Hispanic, Asian Pacific Islander, and American Indian Alaskan Native. We focus on interactions of those classified as "White" or "Non-White" and "Male" or "Female" (Not-Male). Figure IA.B5 summarizes time trends in these demographics. White males comprise the majority of investment professionals and are omitted from this plot for scale.

Figure IA.B5: Demographic Trends by Entry Cohort

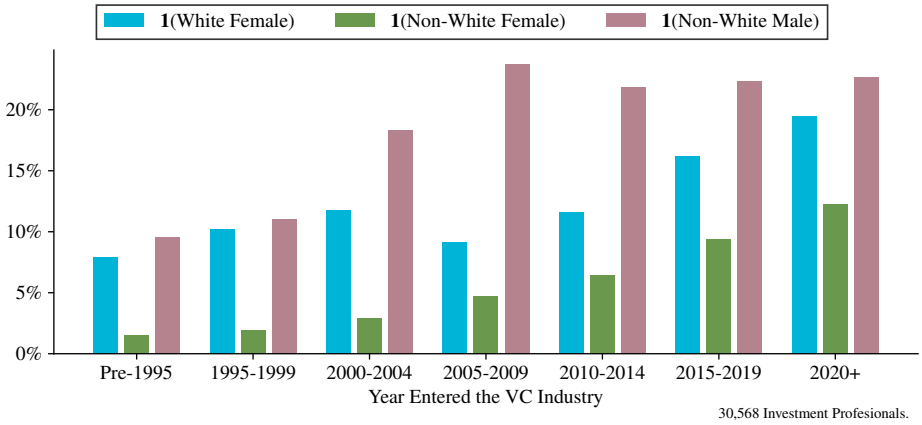


Figure IA.B5: Tabulates the fraction of investment professionals joining the industry of a given demographic.

Education: Education is parsed from website biographies by prompting LLMs and further extracted from educational data available on LinkedIn and other commercial datasets. We manually standardize each raw school name in the sample. For example, "Stanford Business School" and "Stanford GSB" are both treated as the "Stanford University Graduate School of Business." We also manually standardize raw extracted degree names and group degrees from each school into three main categories: undergraduate, master's, and post-master's. MBA degrees are in the master's degree group and are often reported separately given their higher frequency. We exclude

degrees or affiliations falling outside of these groups (e.g., certificates, high school, executive education).

At the undergraduate level, we categorize schools into four main types. Ivy League schools include Brown University, Columbia University, Cornell University, Dartmouth College, Harvard University, Princeton University, University of Pennsylvania, and Yale University. Ivy-plus schools is the group of other top-private schools, including Stanford University, MIT, CalTech, Duke University, Johns Hopkins University, Northwestern University, and University of Chicago. The remaining Top-30 schools are the 15 other schools listed in the 2024 U.S. News Top-30 schools: Carnegie Mellon University; Emory University; Georgetown University; New York University; Rice University; University of California, Berkeley; University of California, Los Angeles; University of California, San Diego; University of Michigan; University of North Carolina, Chapel Hill; University of Notre Dame; University of Southern California; University of Virginia; Vanderbilt University; and Washington University in St. Louis. Figure IA.B6 summarizes trends in education by school and degree type.

Figure IA.B6: Education Trends by Entry Cohort

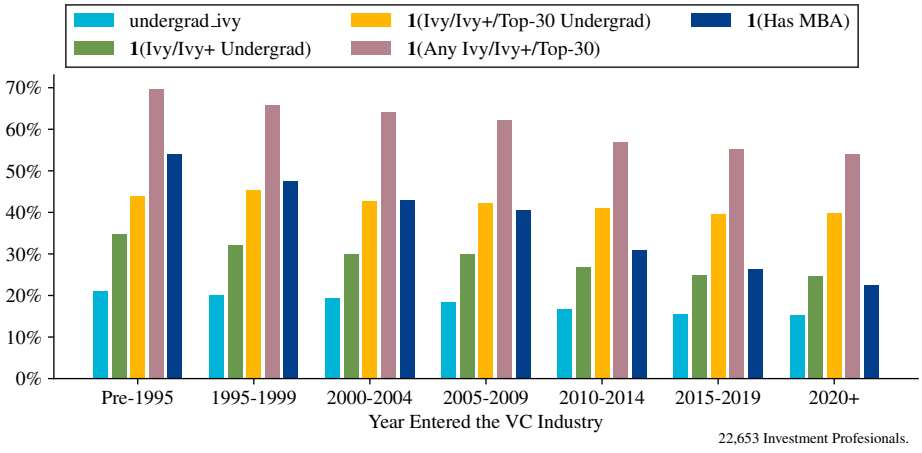


Figure IA.B6: Tabulates trends in education among investment professionals upon entering the VC industry.

At the undergraduate level, we also extract each professional's main field of study, again by parsing website biographies that we supplement with LinkedIn and Revelio data. We standardize each extracted field into the following five primary major categories:

1. STEM (Mathematics, Statistics, Computer Science, Biology, Chemistry, Physics, Astron-

omy, Earth Sciences, Engineering);

2. Humanities & Arts (Philosophy, Literature, History, Languages, Religious Studies, Arts, Pedagogy, Environmental Science, Health Science);

3. Social Sciences (Anthropology, Psychology, Political Science, Sociology, Geography, Legal Studies, Journalism, Design);

4. Business (Economics, Business);

5. Other.

Less than 5% of majors fall outside of the four major groups into "Other," including, for instance, majors such as "Symbolic systems" or "Science, technology, and society." We assign specific fields of study to groups based on on key-phrases in the extracted majors. For example, a Business major includes key phrases such as "finance," "accounting", or "marketing," while an Engineering major includes substrings such as "electrical engineering" or "systems control." Figure IA.B7 summarizes trends in fields of study.

Figure IA.B7: Undergraduate Major Trends by Entry Cohort

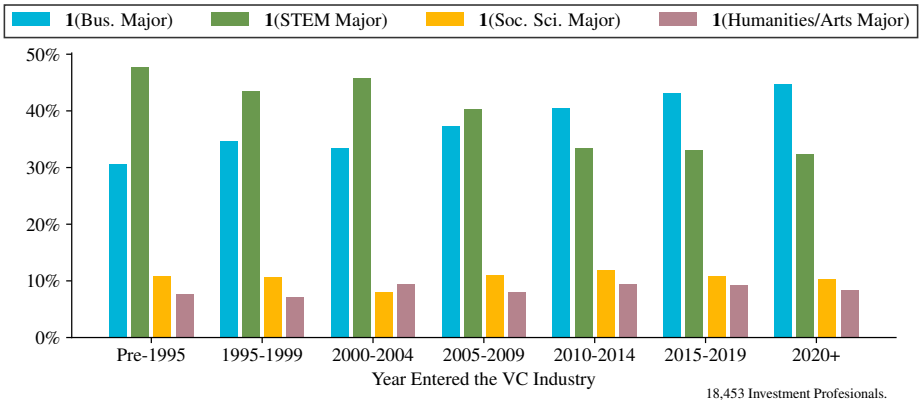


Figure IA.B7: Tabulates trends in undergraduate major types among investment professionals upon entering the VC industry.

For analysis at the MBA level, we often group professionals into those with: (1) a top-10 MBA, (2) a non top-10 MBA, or (3) no MBA. MBA rankings are based on those reported in the 2025 U.S. News rankings. The Top-10 includes: University of Pennsylvania Wharton; Northwestern Kellogg; Stanford GSB; University of Chicago Booth; MIT Sloan; Dartmouth Tuck; Harvard

Business School; New York University Stern; Columbia Business School; and Yale School of Management. Note that only standard MBA degrees are included in the MBA category. Other degrees that business schools may give (such as MIT Sloan degree) are assigned to non-MBA master's degrees.

Pre-VC and Post-VC Work Experience: Work experience is parsed from website biographies by prompting LLMs. We further extract work experiences from data available on LinkedIn and Revelio, and cross-merge datapoints across all sources. We define pre-VC work experience as all full-time positions a professional had before they first were employed by a VC firm in our sample. We exclude affiliations from internships or those that lasted for a year or less. We further exclude LinkedIn/Revelio work experiences where the professional was an investor board member, observer, chair, advisor, or mentor based on their reported titles.

Based on prior employers, we group experience into the following categories: startup, consulting, investment banking, hedge fund, private equity firm, law firm, government, more general finance, or other unclassified experiences. To form such groupings, we manually classify every firm that employed 50 or more professionals in the sample (and a few thousand other randomly selected firms) as one of the above firm types. We then extrapolate classifications assigned in this subsample to other firms with the same NAICs code not in the manually reviewed sample.

An important classification is that of startup experience. We consider professional i's work experience at company k to be considered startup experience if each of the following three conditons are met:

1. Company k has raised VC capital according to PitchBook or VentureSource;

2. Professional i began working at company k before it went first went public or was acquired, which also includes experience at startup companies that never went public or were acquired;

3. The company is not manually identified as an investment bank, private equity firm, VC firm, law firm, hedge fund, or consulting firm.

Biographies rarely list the start year of prior work experiences, which would fail to satisfy the above condition (1) for startup experiences extracted from biographies. Therefore, to include these experiences, we adjust condition (1) to also include all companies founded within five years

of when the professional entered the VC industry. For example, if professional i joined a U.S. VC firm in 2015, any work experience at companies founded in 2010 or later extracted from their biography are flagged as startup experience for this professional. For startup experience, we further use the extracted titles affiliated with each experience to classify professionals as a founder or a C-suite level executive ("CXO") at a startup company. We apply the same classifications for pre-VC work experience to identify and classify experiences for professionals after they leave the VC industry using positions listed on their LinkedIn profiles. Figure IA.B8 summarizes time trends in pre-VC work experience. Figure IA.B9 summarizes time trends in post-VC work experience, which is calculated using LinkedIn profiles as these professionals are those that leave the sample.

Figure IA.B8: Work Experience Trends by Entry Cohort

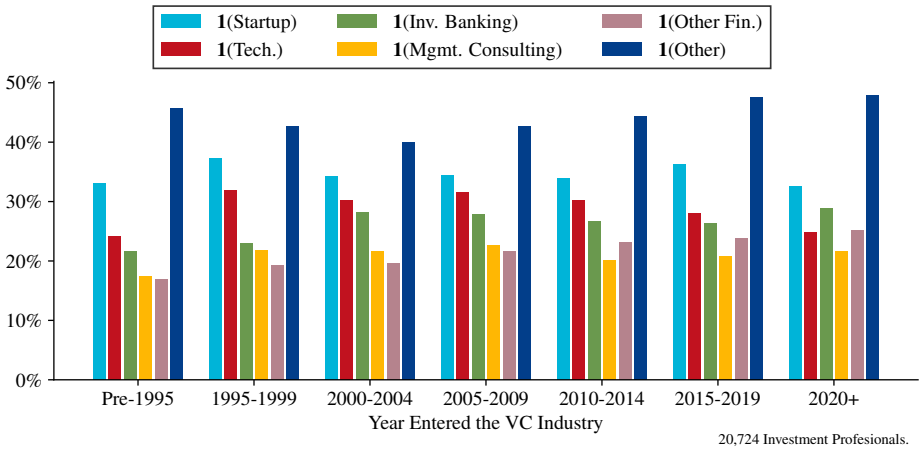


Figure IA.B8: Tabulates trends in pre-VC work experience among investment professionals. Numbers can exceed one for professionals with multiple pre-VC work experiences.

IA.1.3 Investment Data

We utilize information on PitchBook deals, PitchBook boards, VentureSource boards, historical website boards, and historical website deals data to identify companies that professional i worked on throughout their VC careers. Affiliations based on archival website data are parsed from website biographies by prompting LLMs using the same LLM track process detailed above. Professional i is credited with an investment in portfolio company c if they (i) sat on the board of company c (according to PitchBook, VentureSource, or historical websites), (ii) led an investment in company c (according to PitchBook or historical websites), or (iii) were actively involved in an investment

Figure IA.B9: Post-VC Work Experience Trends by Entry Cohort

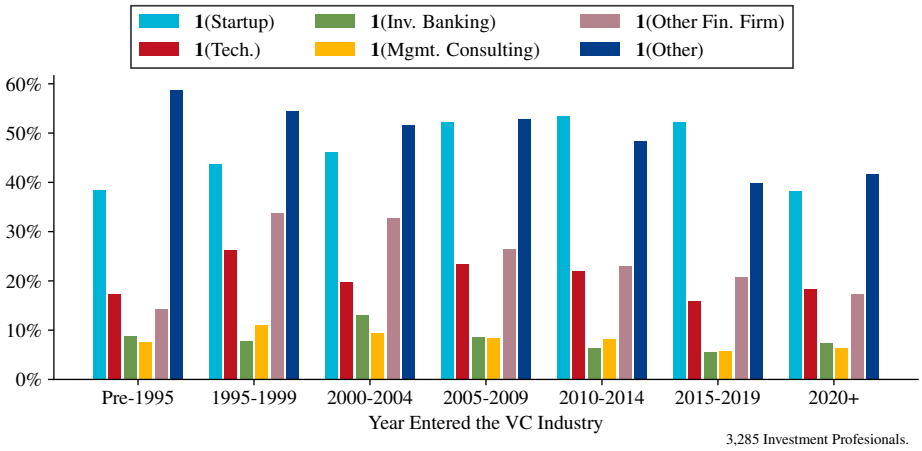


Figure IA.B9: Tabulates trends in post-VC work experience among investment professionals. Numbers can exceed one for professionals with multiple post-VC work experiences.

in company c (according to historical websites). Importantly, this approach allows us to recover affiliations between professionals and companies beyond what is available in commercial datasets alone, which is important for tracking partners' full investing activity.

We further require that professional i entered the VC industry on or after the year that the firm employing them (denoted j) first invested in portfolio company c. The year that VC firm j is first credited with investing in company c is the first year we identify an investment credited to this firm based on the full suite of our data: (a) the first year firm j invested in company c according to PitchBook; (b) the first year firm j invested in company c according to VentureSource; (c) the first year a professional working at firm j took a board position in company c according to PitchBook; (d) the first year a professional working at firm j took a board position in company c according to VentureSource; (e) the first year a professional working at firm j has a biography mentioning that they invested in, worked on, or had a board seat in company c.

Company-professional relationships extracted from website data require a few additional steps. First, we remove affiliations with entities arising from "service," which is typically a volunteer relationship or fellowship, and not as part of a VC firm investment set. The excerpted 2025 biography of Scott Sandell of New Enterprise Associates provides an example, with the service boards in bold:

Scott is Executive Chairman and Chief Investment Officer of NEA. He previously held

the role of CEO, and prior to that, of Managing General Partner. Since joining the firm in 1996, Scott has led investments in a wide range of technology companies and has played a role in many industry-transforming businesses, including Bloom Energy, Cloudflare, Robinhood, Salesforce, Tableau, and Workday. Outside of NEA, Scott is actively involved with the ***National Venture Capital Association*** *and is a founding director of the organization's nonprofit,* ***Venture Forward****. . . .*

We flag such service boards if the name of the company the professional is involved with includes any one of phrases typically associated with such positions, such as "Foundation," "University," and "Orchestra." 6.3% of person-company affiliations are flagged and removed by this filter.

As a second step, we also require that the year of the person's website biography including the company name precedes any IPO exit, the year the company first obtained a unicorn valuation, or was otherwise exited. Person-company affiliations without successful outcomes are not affected. Doing so helps limit positive selection in affiliation that can come from using the website biographies to recover company involvements. Applying this filter removes 18.7% of person-company pairings recovered from website biographies.

For example, the most extreme case in our sample is SpaceX, which first achieved a unicorn valuation in 2010 (8 years after its founding). It has otherwise not gone public or been acquired. We recover 28 professionals that are affiliated with SpaceX as either a lead partner investor, a board member, or having invested in the commpany. 10 of these professionals have a SpaceX affiliation via PitchBook or VentureSource. The remaining 18 professionals did not list an affiliation with SpaceX in their biographies between its founding in 2002 and its first unicorn valuation in 2010. The earliest mention we recover comes from Peter Theil's biography in 2012. His excerpted biography from Founder's Fund in 2010, for instance, mentions affiliations with several other companies, but not with SpaceX. It reads:

As a venture capitalist and entrepreneur, Peter has been involved with some of the most dynamic companies to emerge from Silicon Valley in the past decade. Peter's first start-up wasPayPal, which he co-founded in 1998, and led as Chairman and CEO. Peter's tenure culminated in PayPal's sale to eBay for $ 1.5 billion in 2002. After the eBay acquisition, Peter founded Clarium Capital Management, a global macro hedge fund that manages several billion dollars for institutions and individuals. Peter also helped launch Palantir Technologies, an analytical software company, and serves as the chairman of that company's board. Before launching Founders Fund with his PayPal partners Ken Howery and Luke Nosek, Peter was an active venture

capitalist in his personal capacity, funding companies like Facebook, where Peter was that company's first outside investor and director. Peter's contributions to technology, entrepreneurship, and finance have been widely recognized, including by the World Economic Forum (which honored Peter as a Young Global Leader) and by Business-Week, which named him one of the 25 most influential people on the web. Peter is also involved with a variety of philanthropic, academic, and cultural pursuits. . . .

We subsequently remove the SpaceX affiliations for Peter Theil and the 17 other professionals associated with it. This is, however, the most extreme example and could presumably still remove some affiliations with successful companies that just are reported later. The average target company has 1.5 people recovered from biographical information on websites, of which nearly 15% (0.3 people) are removed by applying this biography timing filter. After dropping these successful mentions, the average biography mentioning an affiliation with a subsequently successful company does so 4.1 years before the company has its successful outcome.

Table IA.B7 shows the descriptive statistics on person-company affiliations. Panel A shows the distribution of the number of companies each professional is affiliated with and Panel B shows the distribution of the number of people affiliated with each company. Including the website data increases the average number of involvements for each person from five to eight, leading to the inclusion of just above 4,000 more professionals in our data.

Table IA.B7: Companies Per Person and People Per Company

	Nobs.	Avg.	Std.	25p	50p	75p	Max.
Panel A: Companies Per Person by Source							
Combined Data	16,569	8.18	13.94	1	4	10	469
1(Only PB/VS)	12,550	5.74	12.59	1	2	6	469
1(Only Websites)	6,747	3.23	3.45	1	2	4	60
1(Websites & PB/VS)	7,691	5.41	6.36	1	3	7	67
Panel B: People Per Company by Source							
Combined Data2	66,127	2.05	1.77	1	1	2	26
1(Only PB/VS)	46,525	1.55	1.12	1	1	2	19
1(Only Websites)	15,945	1.37	0.78	1	1	1	14
1(Websites & PB/VS)	25,576	1.63	1.04	1	1	2	11

Table IA.B7: Tabulates the distribution of the number of companies each professional is affiliated with in Panel A, and the distribution of the number of people affiliated with each company in Panel B. Counts will not sum to one another as the sources vary affiliations between people and companies, not the unique people or companies.

Table IA.B8 displays statistics about the person-company affiliations in our data based on the source of the data. Relative to data that is only available through commercial sources, data that is available only from historical website biographies is more likely to include deals from before 2010 (the year PitchBook started), is more likely to precede a successful outcome, and is less likely to come from a professional that has a more established track record (as proxied by either recognition on the Midas list or many prior successful investments). An example of a company involvement we extract from websites but not from PitchBook or VentureSource is Mary Meeker's investment in Airbnb while she worked at Kleiner Perkins in 2015. Commercial data identify that Kleiner Perkins invested in Airbnb's 2015 Series E,[1] five years before Airbnb went public and four years after it first became a unicorn. Commercial data, however, do not capture which partner(s) at Kleiner Perkins were responsible for the investment. Her Airbnb investment is mentioned in her 2017 biography while at Kleiner Perkins, predating Airbnb's 2020 IPO, reproduced and bolded below:

> *Mary Meeker joined Kleiner Perkins Caufield & Byers in December 2010. She focuses on investments in the firm's digital practice and helps lead KP's Digital Growth Funds, targeting high-growth Internet companies that have achieved rapid adoption and scale. Mary serves on the boards of Square, Lending Club and DocuSign and has been involved in KP's investments in Ring,* ***Airbnb****, Pinterest, Stance, Instacart, Slack, Snap, NextDoor, Houzz, SoundCloud, Trendyol, Spotify, LegalZoom, Jawbone and Affectiva. She also led KPCB's investments in Bitstrips (acquired by Snap), Waze (acquired by Google/Alphabet), JD.com (NASDAQ: JD), Groupon (NASDAQ: GRPN) and Facebook (NASDAQ: FB). . . .*

IA.1.3.1 Investment Return Outcomes

We characterize the success of each investment based on whether the investment subsequently (a) had an initial public offering (IPO); (b) achieved a unicorn valuation; or (c) was acquired for a total sale that value was more than twice the amount invested (following Ewens and Rhodes-Kropf (2015)).

An important component of our measurement of success is that the person's investment must have occurred before the successful event. Doing so helps avoid flagging cases where the

[1] See, e.g., here: WSJ Article Airbnb 2015 Series E

Table IA.B8: Investment Statistics by Data Source

	All	Only Web	Only Cmcl.	PB - Board	PB - Deal	VS - Board	Web - Board	Web - Deal
# Professionals × Companies	135,487	21,812	72,043	43,000	92,108	24,477	43,954	31,149
# Companies	66,127	15,945	46,525	26,289	52,305	14,656	26,874	19,442
# Professionals	16,569	6,747	12,550	9,381	12,042	4,303	8,545	5,538
# VC Firms	3,259	1,691	3,088	2,488	3,083	1,247	2,315	1,477
Panel A: Data Sources								
1(Only PB/VS)	53.2%	-	100.0%	33.0%	67.6%	33.0%	-	-
1(Only Websites)	16.1%	100.0%	-	-	-	-	20.4%	47.5%
1(Websites & PB/VS)	30.7%	-	-	67.0%	32.4%	67.0%	79.6%	52.5%
1(PitchBook Deal)	68.0%	-	86.4%	74.4%	100.0%	49.3%	56.5%	37.7%
1(PitchBook Board)	31.7%	-	19.7%	100.0%	34.7%	46.3%	59.6%	29.8%
1(VentureSource Board)	18.1%	-	11.2%	26.4%	13.1%	100.0%	32.4%	24.1%
1(Website Deal)	23.0%	67.9%	-	21.6%	12.8%	30.6%	26.5%	100.0%
1(Website Board)	32.4%	41.2%	-	60.9%	27.0%	58.2%	100.0%	37.4%
Panel B: Investment Outcomes								
1(Successful Outcome)	16.6%	19.9%	10.4%	20.8%	13.6%	33.6%	23.2%	28.5%
1(IPO)	5.9%	8.8%	2.9%	7.0%	3.8%	13.8%	8.9%	11.5%
1(Unicorn)	3.5%	3.6%	2.7%	4.6%	3.7%	3.7%	3.9%	5.8%
1(Acquisition)	8.0%	8.3%	5.3%	10.3%	6.8%	17.3%	11.5%	12.7%
Panel C: Investment Timing								
1(Pre-2000)	2.6%	3.8%	1.4%	0.8%	0.7%	9.8%	4.4%	4.6%
1(2001-2009)	18.0%	29.4%	9.6%	15.8%	9.8%	51.0%	29.9%	27.5%
1(2010-2019)	46.2%	37.6%	48.6%	56.2%	50.4%	39.1%	42.4%	45.4%
1(2020+)	33.2%	29.3%	40.5%	27.2%	39.0%	0.1%	23.3%	22.6%
Panel D: Investment Stage								
1(w/in 1-Yr. of Founding)	20.4%	18.6%	21.8%	18.0%	21.4%	20.4%	18.2%	20.1%
1(w/in 2-5 Yrs. of Founding)	45.8%	46.4%	45.7%	45.4%	46.4%	44.9%	45.8%	46.0%
1(w/in 6-10 Yrs. of Founding)	14.1%	16.7%	12.9%	15.0%	13.3%	13.7%	15.6%	15.1%
Panel E: Geography/Industry								
1(California)	34.8%	35.1%	33.8%	32.8%	34.7%	41.1%	34.4%	39.3%
1(New York)	9.6%	8.6%	10.9%	9.0%	10.6%	5.9%	7.6%	8.8%
1(Massachusetts)	7.2%	8.9%	5.2%	9.2%	6.0%	11.1%	10.3%	8.9%
1(Software)	43.6%	40.2%	46.6%	41.0%	46.6%	37.5%	38.0%	43.6%
1(Cmcl. Services)	8.3%	7.8%	8.7%	7.4%	8.4%	8.2%	7.6%	7.9%
1(Pharma/BioTech)	8.9%	10.8%	6.2%	13.1%	7.3%	12.2%	14.1%	9.0%
Panel F: GP Prior Success								
1(Prev. Midas Recongition)	5.4%	2.9%	5.4%	6.8%	6.3%	8.1%	5.5%	5.7%
1(0 Prior Successful Involvements)	46.5%	56.9%	47.1%	43.7%	43.4%	34.5%	44.3%	44.6%
1(1-2 Prior Successful Involvements)	24.4%	23.6%	23.0%	25.1%	24.0%	29.5%	26.7%	26.0%
1(3-5 Prior Successful Involvements)	13.7%	10.5%	13.0%	15.3%	14.5%	19.2%	15.2%	14.7%
1(6+ Prior Successful Involvements)	15.4%	9.0%	16.9%	15.9%	18.1%	16.8%	13.8%	14.7%

Table IA.B8: Tabulates statistics about investments in our sample by the source of the person-company affiliation. The unit of observation is the person-company.

professional took a position in the company after it had already achieved a successful outcome. 21% of successful companies in our sample have at least one person who took a board seat or is credited with investing in the company only after (but not before) it had achieved a successful outcome. 2.1% of total person-company relationships are affected by this requirement. In practice, companies that achieve any one of these measures of success can often achieve another; companies

that have IPOs often previously have achieved a unicorn valuation of $1 billion. In assigning these classifications, we prioritize IPOs, then unicorns, and then acquisitions. If, for instance, a company had all three – achieved a unicorn valuation, was acquired, subsequently spun-out, and then went public – we classify this as an IPO outcome and the person's relationship with the company as successful in one of the three ways so long as they invested before the IPO. However, for our main outcome measurement, this distinction is immaterial because we classify an investment as successful it achieved any of the three measures of investment success.

To illustrate, Zynga (the video game developer and publisher), was founded in 2007, and received investments from several notable VCs in 2008, such as John Doerr, who also served on its board. In 2009, Zynga achieved a unicorn valuation and received VC from Yuri Milner, who did not serve on its board. Zynga then subsequently went public in 2011. Sunil Paul is subsequently identified as serving on the board of Zynga starting in 2012. John Doerr and Yuri Milner (among others) are credited as investing in Zynga pre-IPO. John Doerr also invested pre-unicorn, but the IPO classification supersedes the unicorn classification. Sunil Paul, by contrast, was affiliated with Zynga after the IPO, so his relationship is not characterized as occurring before a successful outcome.

Internet Appendix References

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IA.2 Additional Figures and Tables

Figure IA1: Composition of Midas Recognition Over Time

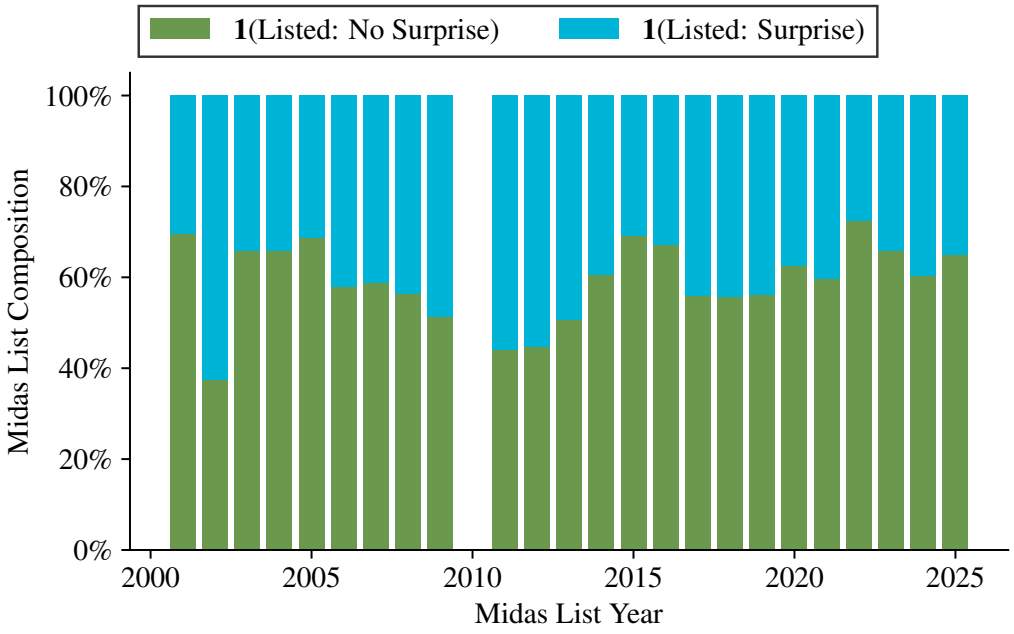


Figure IA1: Plots the composition of the Midas List each year based on whether the listed VC professional was predicted to be in the list versus whether they were not. A VC professional is said to predicted to be included in the Midas list in year t if their estimated coefficients over the rolling previous five years $[t-1, t-5]$ produce odds for recognition in year t that are in the top-100. Exceptions are 2002, where our historical lists only contain 25 people, 2003-2005 where our lists only contain 50 people, and 2010, where no list was published. Our sample of VC professionals includes all those affiliated with a company at least once in our sample.

Figure IA2: Midas List Surprise Makes Versus Surprise Misses Extensive Margin

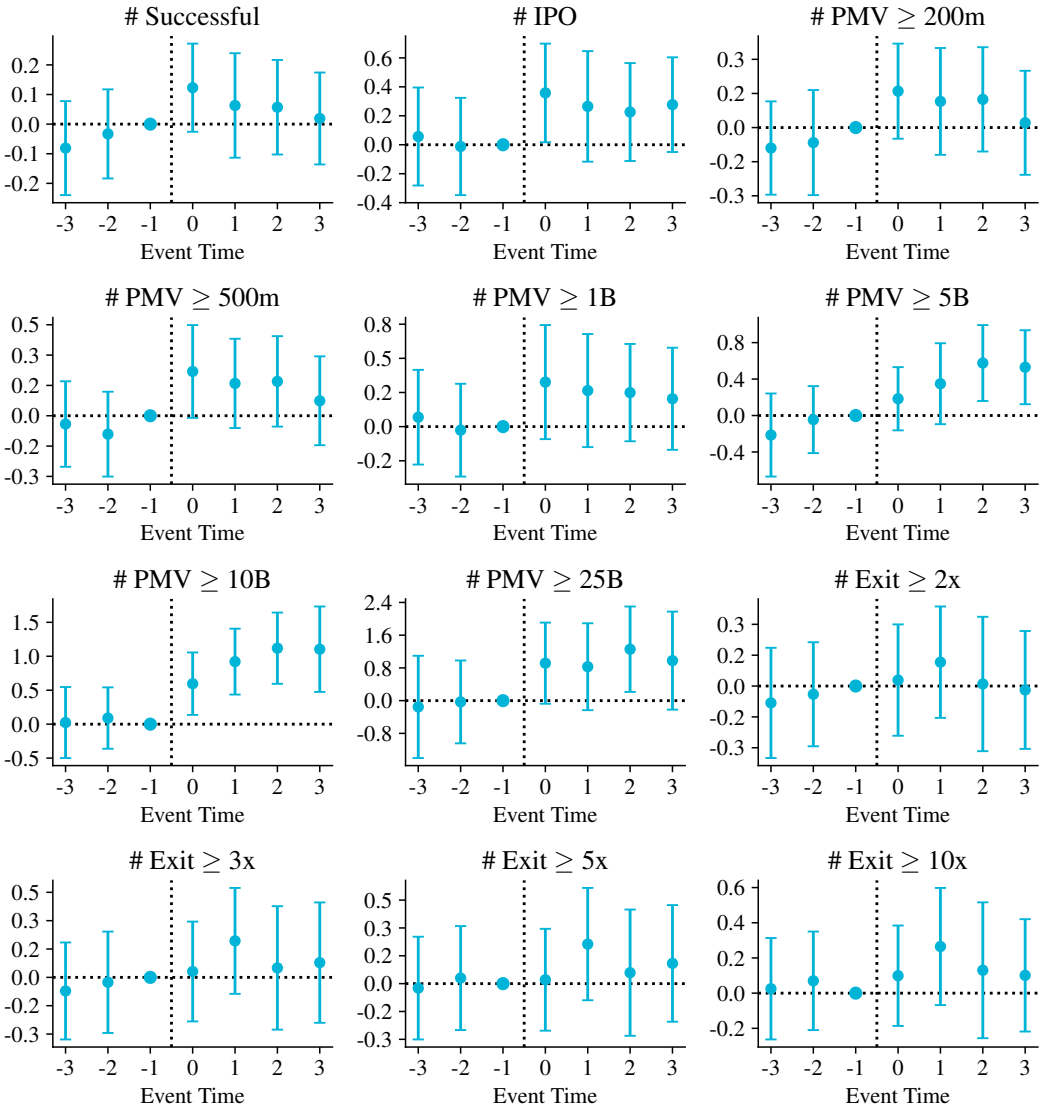


Figure IA2: Plots dynamic stacked difference-in-differences estimates of the effect of Midas List recognition on individual VCs' investing activity each year. The unit of observation is the individual VC×Year. Outcome variables are the number of investments a professional makes satisfying a particular criteria denoted in the title of the subplot each year. Regressions employ stacked datasets for each event (i.e., recognition on the Midas List in each calendar year) and the three years before and after each annual ranking. Each stack only includes VCs that are predicted to be on the Midas list that year but did not receive recognition and VCs that were not predicted to be on the Midas list that year but did receive recognition. The treated group includes the lowest ranked professionals on the Midas list in a given year. The control group includes the professionals with the highest predicted odds of receiving Midas list recognition that did not. The group "±5", for instance, includes professionals ranked 96-100 and the five highest professionals most likely to be on the list that were not included. All specifications include controls for whether the person was recognized on the Midas list in any of the two prior years. Following Baker, Larcker, and Wang (2022), we include fixed effects for each VC-by-stack and each stack-by-year. Standard errors are independently double clustered at the VC-by-stack and stack-by-year levels. Vertical bars denote 95% confidence intervals.

Figure IA3: Midas List Near Makes Versus Nears Misses

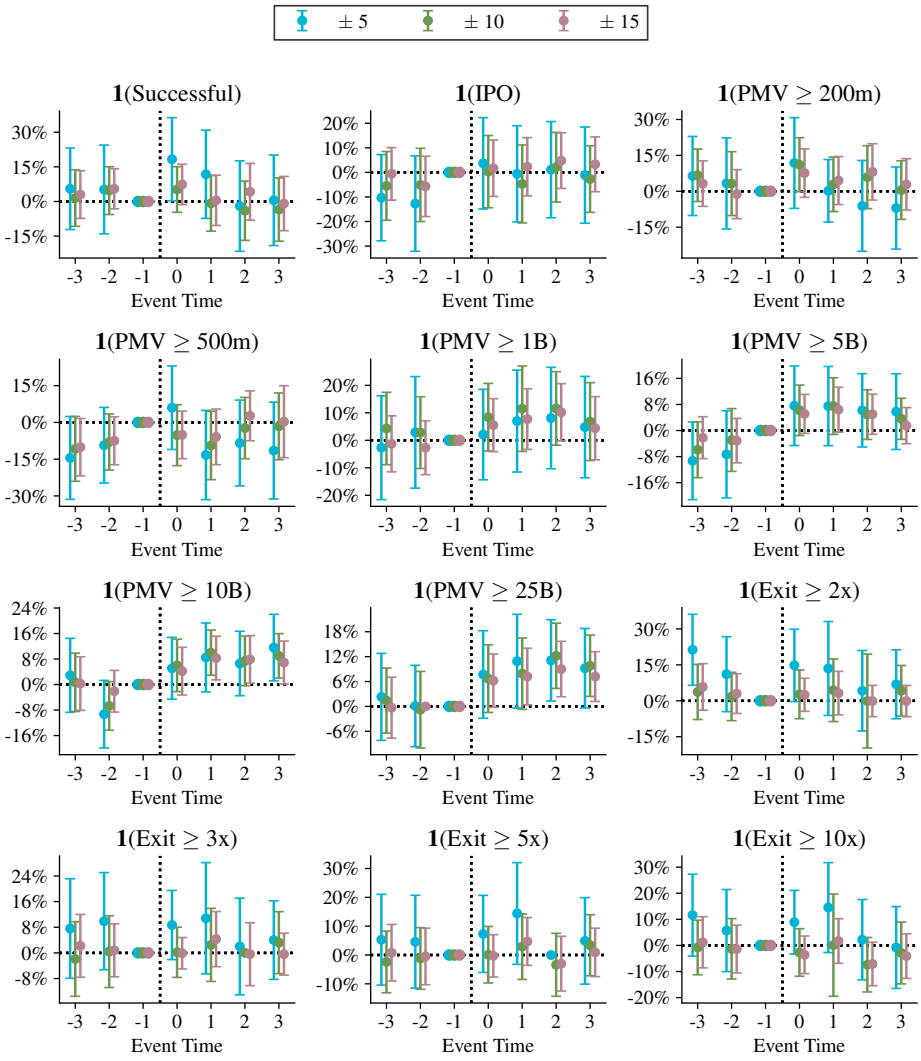


Figure IA3: Plots dynamic stacked difference-in-differences estimates of the effect of Midas List recognition on individual VCs' investing activity each calendar year. The unit of observation is the individual VC×calendar year. Indicators denote whether a professional made an investment of a given type each year relative to the Midas List treatment event. Regressions employ stacked datasets for each event (i.e., recognition on the Midas List in each calendar year) and the three years before and after each annual ranking. Each stack only includes VCs that are predicted to be on the Midas list that year but did not receive recognition and VCs that were not predicted to be on the Midas list that year but did receive recognition. The treated group includes the lowest ranked professionals on the Midas list in a given year. The control group includes the professionals with the highest predicted odds of receiving Midas list recognition that did not. The group "±5", for instance, includes professionals ranked 96-100 and the five highest professionals most likely to be on the list that were not included. All specifications include controls for whether the person was recognized on the Midas list in any of the two prior years. Following Baker, Larcker, and Wang (2022), we include fixed effects for each VC-by-stack and each stack-by-year. Standard errors are independently double clustered at the VC-by-stack and stack-by-year levels. Vertical bars denote 95% confidence intervals.

Table IA1: Affiliations by Data Source

	Outcome					
	All	IPO	Unicorn	Acq. ≥ 2× Entry	Successful	Not Successful
# Professionals × Companies	133,600	7,744	4,670	10,595	21,941	111,672
1(Only PB/VS)	53.3%	26.1%	41.2%	35.2%	33.2%	57.3%
1(Only Websites)	15.6%	23.2%	15.7%	16.1%	18.6%	15.0%
1(Websites & PB/VS)	31.1%	50.7%	43.1%	48.7%	48.2%	27.7%
1(PitchBook Deal)	68.8%	45.0%	73.6%	59.0%	56.7%	71.1%
1(PitchBook Board)	32.1%	38.8%	42.1%	41.8%	40.7%	30.4%
1(VentureSource Board)	17.8%	42.7%	19.4%	39.0%	36.6%	14.1%
1(Website Deal)	22.9%	45.8%	37.9%	36.7%	39.9%	19.6%
1(Website Board)	32.7%	50.7%	36.2%	47.2%	46.4%	30.0%

Table IA1: Denotes the composition of our sample by the source of the person-company affiliation. The unit of observation is the company × person involvement. The combined data include the union of deals from all other sources.

Table IA2: Investments Sample Coverage Improvements

	All	Web & PB/VS	Only PB/VS	Only Webs	PB/VS - Web
# Professionals	16,599	7,682	12,491	6,712	
# Companies	64,391	25,489	45,818	15,001	
# Professionals × Companies	133,583	41,536	71,224	20,836	
Panel A: Investment Outcomes					
1(Successful Outcome)	16.8%	25.8%	10.7%	20.1%	-9.4%***
1(IPO)	5.8%	9.5%	2.8%	8.6%	-5.8%***
1(Unicorn)	3.9%	5.2%	3.2%	4.1%	-0.9%***
1(Acquisition)	7.9%	12.4%	5.2%	8.2%	-2.9%***
Panel B: Investment Relationships					
1(Early Stage)	61.4%	60.8%	63.0%	57.1%	5.9%***
1(Board Seat)	49.6%	93.2%	26.8%	40.6%	-13.8%***
Panel C: Investment Timing & Characteristics					
1(Pre-2000)	2.7%	4.3%	1.3%	4.1%	-2.7%***
1(2001-2009)	17.8%	26.5%	9.1%	30.1%	-21.0%***
1(2010-2019)	46.2%	46.7%	48.6%	36.9%	11.8%***
1(2020+)	33.3%	22.5%	40.9%	29.0%	11.9%***
1(California)	34.9%	36.4%	33.9%	35.1%	-1.2%***
1(New York)	9.7%	8.1%	10.9%	8.6%	2.3%***
1(Massachusetts)	7.1%	9.8%	5.1%	8.7%	-3.6%***
1(Software)	43.7%	40.3%	46.7%	40.3%	6.5%***
1(Cmcl. Services)	8.3%	7.6%	8.7%	8.0%	0.7%***
1(Pharma/BioTech)	8.8%	12.7%	6.1%	10.3%	-4.1%***
Panel D: Demographics					
1(White)	76.0%	78.9%	74.8%	73.9%	0.9%**
1(Female)	11.0%	10.1%	10.6%	14.6%	-4.1%***
Panel E: Pre-VC Education					
1(Ivy Undergrad)	20.4%	21.7%	19.2%	21.5%	-2.3%***
1(Ivy+ Undergrad)	13.7%	14.0%	13.6%	13.1%	0.5%*
1(Business Major)	32.9%	31.8%	32.9%	35.2%	-2.3%***
1(STEM Major)	42.1%	46.2%	39.1%	43.4%	-4.3%***
1(Soc. Sci. Major)	10.9%	9.6%	12.3%	8.9%	3.3%***
1(Humanities/Arts Major)	10.0%	8.6%	11.3%	8.8%	2.5%***
1(Has MBA)	43.0%	48.5%	38.6%	45.7%	-7.1%***
1(HBS MBA)	8.9%	10.9%	7.5%	10.0%	-2.6%***
1(Stanford GSB MBA)	6.1%	8.4%	4.5%	7.0%	-2.5%***
1(Advanced Degree)	14.4%	17.1%	13.3%	13.1%	0.2%
Panel F: Pre-VC Experience					
1(CXO/Founder; Successful Startup)	20.3%	19.1%	22.5%	14.9%	7.6%***
1(Non- CXO/Founder; Successful Startup)	11.5%	12.5%	10.7%	12.5%	-1.8%***
1(CXO/Founder; Non-Successful Startup)	4.7%	4.0%	5.3%	3.7%	1.6%***
1(Non-CXO/Founder; Non-Successful Startup)	3.3%	3.2%	3.1%	3.9%	-0.7%***
1(Tech.)	40.4%	38.6%	43.2%	34.8%	8.4%***
1(Inv. Banking)	23.1%	24.4%	21.0%	27.2%	-6.2%***
1(Mgmt. Consulting)	22.3%	23.0%	21.6%	23.2%	-1.6%***
1(Pharma.)	7.0%	9.1%	5.2%	8.3%	-3.1%***
Panel G: VC Experience					
1(Enter at Junior Level)	15.7%	16.5%	10.9%	29.4%	-18.4%***
1(Enter at Middle Level)	10.4%	11.8%	8.7%	13.5%	-4.9%***
1(Enter at Senior Level)	49.8%	53.8%	51.6%	36.4%	15.2%***
1(Ever Midas List)	10.6%	14.5%	9.2%	8.1%	1.1%***
1(1-2 Inv.)	21.6%	18.4%	19.9%	33.5%	-13.5%***
1(3-5 Inv.)	19.4%	20.7%	16.9%	25.2%	-8.3%***
1(6+ Inv.)	59.0%	60.9%	63.1%	41.3%	21.8%***

Table IA2: Tabulates characteristics of investments at the Person×Company level based on whether the affiliation is recovered from PitchBook/VentureSource or instead from parsing archived website biographies. */**/*** respectively denote significance in the difference in sample means at the 10/5/1 percent levels.

Table IA3: Most Common Schools Among VC Professionals

By # of Successful Involvements:

Panel A. Undergraduate Schools

Rank	All (N = 13,336)	0 (N = 7,802)	1–2 (N = 3,294)	3–5 (N = 1,248)	6+ (N = 992)
1	Stanford (4.7%)	Stanford (3.7%)	Stanford (5.4%)	Harvard (5.9%)	Stanford (9.2%)
2	Harvard (4.2%)	Harvard (3.6%)	Harvard (4.1%)	Stanford (5.8%)	Harvard (6.8%)
3	UPenn (3.2%)	UPenn (3.1%)	UC-Berkeley (3.0%)	UC-Berkeley (4.0%)	Princeton (4.4%)
4	UC-Berkeley (2.8%)	UC-Berkeley (2.4%)	UPenn (2.9%)	UPenn (3.9%)	Dartmouth (4.2%)
5	Yale (2.1%)	Yale (1.9%)	Yale (2.4%)	Princeton (3.3%)	MIT (3.7%)
6	Princeton (2.0%)	UMichigan (1.7%)	MIT (2.3%)	Cornell (2.4%)	UC-Berkeley (3.6%)
7	MIT (1.9%)	Cornell (1.7%)	Princeton (2.1%)	Duke (2.3%)	UPenn (3.4%)
8	Cornell (1.9%)	Princeton (1.5%)	Dartmouth (1.9%)	UMichigan (2.2%)	Cornell (2.6%)
9	UMichigan (1.7%)	MIT (1.5%)	Cornell (1.8%)	MIT (2.0%)	Yale (2.3%)
10	Dartmouth (1.7%)	Duke (1.4%)	Duke (1.7%)	Yale (1.9%)	Brown (1.7%)
11	Duke (1.6%)	Dartmouth (1.3%)	UMichigan (1.7%)	Dartmouth (1.8%)	Duke (1.6%)
12	Brown (1.3%)	Columbia (1.2%)	Brown (1.6%)	BYU (1.6%)	Northwestern (1.4%)
13	Columbia (1.2%)	UVA (1.1%)	Columbia (1.4%)	Brown (1.4%)	UVA (1.3%)
14	UVA (1.1%)	Georgetown (1.1%)	UIUC (1.1%)	UVA (1.1%)	UCLA (1.2%)
15	Georgetown (1.1%)	UT-Austin (1.1%)	UT-Austin (1.1%)	Tufts (1.1%)	UMichigan (1.2%)
16	UT-Austin (1.0%)	NYU (1.0%)	Georgetown (1.1%)	Columbia (1.0%)	Boston College (1.1%)
17	Northwestern (1.0%)	Brown (1.0%)	UVA (1.0%)	UCLA (1.0%)	Columbia (1.1%)
18	UCLA (0.9%)	UIUC (0.9%)	Northwestern (1.0%)	Northwestern (0.9%)	Georgetown (1.0%)
19	UIUC (0.9%)	Univ. South. Cal. (0.9%)	UCLA (0.9%)	Georgetown (0.9%)	UIUC (0.9%)
20	NYU (0.8%)	UCLA (0.9%)	Tufts (0.8%)	Williams (0.8%)	Johns Hopkins (0.8%)

Panel B. MBA Schools

Rank	All (N = 5,110)	0 (N = 2,688)	1–2 (N = 1,373)	3–5 (N = 556)	6+ (N = 493)
1	HBS (19.3%)	HBS (16.1%)	HBS (19.4%)	HBS (25.0%)	HBS (29.6%)
2	Stanford GSB (12.6%)	Stanford GSB (8.6%)	Stanford GSB (14.5%)	Stanford GSB (16.5%)	Stanford GSB (24.7%)
3	UPenn-Wharton (9.2%)	UPenn-Wharton (8.0%)	UPenn-Wharton (11.2%)	UPenn-Wharton (10.8%)	UPenn-Wharton (7.9%)
4	Columbia (5.0%)	Columbia (5.2%)	UChicago Booth (5.0%)	Northwestern (4.7%)	Columbia (4.5%)
5	UChicago Booth (4.8%)	UChicago Booth (4.9%)	Northwestern Kellogg (5.0%)	Columbia (4.5%)	Northwestern (4.5%)
6	Northwestern (4.7%)	Northwestern (4.7%)	Columbia(4.9%)	UChicago Booth (4.1%)	UChicago Booth (3.9%)
7	MIT Sloan (3.0%)	MIT Sloan (3.5%)	MIT Sloan (2.8%)	UC-Berkeley (2.7%)	Dartmouth Tuck (2.6%)
8	UC-Berkeley (2.4%)	UC-Berkeley (2.8%)	UCLA Anderson (2.1%)	Dartmouth Tuck (2.2%)	UMichigan Ross (2.0%)
9	UCLA Anderson (1.9%)	UMichigan Ross (1.9%)	UC-Berkeley (1.9%)	Yale SOM (2.0%)	MIT Sloan (1.8%)
10	UMichigan Ross (1.8%)	NYU Stern (1.9%)	UMichigan Ross (1.7%)	MIT Sloan (1.8%)	UC-Berkeley (1.6%)
11	Dartmouth Tuck (1.8%)	UCLA Anderson (1.9%)	NYU Stern (1.6%)	UCLA Anderson (1.8%)	UCLA Anderson (1.4%)
12	NYU Stern (1.7%)	INSEAD (1.9%)	Dartmouth Tuck (1.5%)	INSEAD (1.4%)	Cornell Johnson (0.8%)
13	INSEAD (1.5%)	Dartmouth Tuck (1.7%)	UVA Darden (1.3%)	UMichigan Ross (1.4%)	NYU Stern (0.8%)
14	Cornell Johnson (1.2%)	Cornell Johnson (1.5%)	INSEAD (1.2%)	NYU Stern (1.3%)	Duke Fuqua (0.6%)
15	UVA Darden (1.2%)	UVA Darden (1.3%)	Cornell Johnson (1.1%)	Duke Fuqua (1.3%)	UT-Austin McCombs (0.6%)
16	Duke Fuqua (1.1%)	Duke Fuqua (1.3%)	Duke Fuqua (0.9%)	Boston University (1.1%)	Babson (0.4%)
17	Yale SOM (1.0%)	UT-Austin McCombs (1.0%)	UNC-Keenan Flagler (0.9%)	UVA Darden (0.9%)	Boston University (0.4%)
18	UT-Austin McCombs (0.9%)	Yale SOM (1.0%)	USC Marshall (0.8%)	BYU (0.7%)	IIT-Ahmedabad (0.4%)
19	Babson (0.7%)	Babson (0.9%)	Yale SOM (0.8%)	UT-Austin McCombs (0.7%)	UVA Darden (0.4%)
20	UNC-Keenan Flagler (0.7%)	UNC-Keenan Flagler (0.7%)	Santa Clara University (0.8%)	Indiana Kelley (0.5%)	York University (0.4%)

Table IA3: Tabulates top schools among VC firm investment professionals sorted by the number of successful involvements. "N" reports the number of professionals described in the column from which percentages are calculated. Panel A reports undergraduate education. Panel B reports MBA education.

Table IA4: Most Common Prior Employers of VC Professionals

Rank	# of Successful Involvements				
	All (N = 14,391)	0 (N = 8,654)	1–2 (N = 3,503)	3–5 (N = 1,250)	6+ (N = 984)
1	McKinsey (3.9%)	McKinsey (3.3%)	McKinsey (4.2%)	McKinsey (5.0%)	McKinsey (6.4%)
2	Goldman Sachs (3.0%)	Goldman Sachs (3.1%)	Morgan Stanley (3.1%)	IBM (3.1%)	Goldman Sachs (3.9%)
3	Morgan Stanley (2.7%)	Morgan Stanley (2.5%)	Goldman Sachs (2.7%)	Bain & Co. (2.8%)	Morgan Stanley (3.8%)
4	Google (2.2%)	Google (2.3%)	PwC (2.5%)	Morgan Stanley (2.7%)	Bain & Co. (3.3%)
5	PwC (2.0%)	Merrill Lynch (2.1%)	Microsoft (2.3%)	Microsoft (2.6%)	IBM (2.9%)
6	Microsoft (2.0%)	J.P. Morgan (2.0%)	IBM (2.2%)	Goldman Sachs (2.5%)	BCG (2.3%)
7	Merrill Lynch (2.0%)	PwC (1.9%)	Google (2.1%)	PwC (2.2%)	Microsoft (2.2%)
8	IBM (1.9%)	Microsoft (1.8%)	Merrill Lynch (2.1%)	BCG (2.0%)	Compaq (2.2%)
9	J.P. Morgan (1.8%)	Deloitte (1.6%)	BCG (1.8%)	Merrill Lynch (1.8%)	Cisco (2.1%)
10	Bain & Co. (1.7%)	IBM (1.5%)	Credit Suisse (1.8%)	Google (1.8%)	Alex. Brown (2.1%)
11	BCG (1.6%)	Bain & Co. (1.5%)	Deloitte (1.7%)	Oracle (1.7%)	Apple (2.0%)
12	Deloitte (1.5%)	BCG (1.4%)	Accenture (1.4%)	Cisco (1.7%)	J.P. Morgan (1.9%)
13	Credit Suisse (1.5%)	Accenture (1.4%)	Citi (1.4%)	J.P. Morgan (1.6%)	Sun Microsystems (1.8%)
14	Accenture (1.4%)	Credit Suisse (1.4%)	J.P. Morgan (1.4%)	AT&T (1.5%)	General Electric (1.7%)
15	Citi (1.2%)	Citi (1.3%)	Oracle (1.3%)	Deloitte (1.5%)	Robertson Stephens (1.7%)
16	General Electric (1.1%)	General Electric (1.1%)	Bain & Co. (1.3%)	Credit Suisse (1.4%)	Google (1.7%)
17	Oracle (1.1%)	UBS (1.0%)	Apple (1.2%)	Intelliseek (1.4%)	PwC (1.7%)
18	UBS (1.0%)	Yahoo! (0.9%)	UBS (1.2%)	Lehman Brothers (1.2%)	Accenture (1.7%)
19	Cisco (1.0%)	Oracle (0.9%)	Cisco (1.2%)	Nokia (1.2%)	Yahoo! (1.6%)
20	Yahoo! (1.0%)	Compaq (0.9%)	Yahoo! (1.1%)	UBS (1.1%)	Silicon Graphics (1.6%)

Table IA4: Tabulates top prior employers among VC firm investment professionals sorted by whether they were *ever* observed at each seniority. Column counts do not sum to the "All" column if professionals are observed at more than one seniority. "N" reports the number of professionals described in the column from which percentages are calculated. For example, 10% indicates that 10% of all professionals worked at the firm. Individuals can have worked at more than one firm. The Table only includes employer firms before the professional began working in VC. Firm names are as reported based on a cross-merge between LinkedIn, PitchBook, and website data.

Table IA5: Portfolio Company Characteristics Over Time

	Investment Year						
	All	Pre-2000	2001-2005	2006-2010	2011-2015	2016-2020	2021+
# Companies	61,247	1,802	4,400	6,829	13,918	20,798	22,113
Panel A: Outcomes							
1(Successful Outcome)	12.6%	51.8%	30.1%	25.7%	18.2%	10.6%	1.9%
1(IPO)	4.2%	36.2%	10.8%	9.1%	5.7%	2.5%	0.3%
1(Unicorn)	2.3%	1.3%	0.8%	1.7%	3.7%	4.2%	1.3%
1(Acquisition)	6.6%	15.0%	18.8%	15.7%	10.0%	4.6%	0.4%
Panel B: Affiliation Types							
1(Early Stage)	68.7%	74.8%	60.7%	61.2%	68.9%	62.6%	58.8%
1(Board Seat)	55.7%	91.0%	90.5%	83.3%	60.2%	51.6%	35.2%
Panel C: Company Industry							
1(Software)	42.8%	29.9%	33.2%	33.2%	43.8%	43.6%	48.7%
1(Cmcl. Services)	8.8%	9.9%	9.2%	11.1%	9.9%	7.5%	7.7%
1(Pharma/BioTech)	7.9%	9.9%	11.6%	10.5%	6.7%	8.2%	7.4%
1(Healthcare Devices)	4.2%	7.4%	7.4%	7.8%	4.5%	4.2%	2.7%
1(Media)	3.1%	2.4%	2.0%	5.0%	4.9%	2.7%	1.9%
Panel D: Company Country							
1(United States)	74.9%	95.1%	90.7%	84.0%	78.7%	73.3%	70.9%
1(United Kingdom)	4.0%	1.2%	1.9%	2.5%	3.1%	4.2%	4.9%
1(China)	2.1%	0.3%	0.8%	2.8%	2.6%	2.3%	1.3%
1(France)	1.1%	0.3%	0.9%	0.5%	0.6%	1.2%	1.3%
Panel E: Company State							
1(California)	28.8%	40.6%	37.9%	34.6%	32.6%	28.5%	26.4%
1(New York)	9.0%	3.2%	2.9%	6.7%	9.4%	10.2%	10.6%
1(Massachusetts)	6.0%	12.7%	11.2%	8.3%	5.9%	5.6%	4.8%
1(Texas)	4.0%	6.3%	5.5%	4.6%	4.0%	3.5%	3.8%
1(Washington)	2.6%	4.2%	3.7%	3.2%	2.6%	2.5%	2.4%

Table IA5: Tabulates characteristics of companies in our sample based on whether a VC professional in our sample made an investment in the company in a particular time period. The unit of observation is the company level. Characteristics of the companies are from PitchBook.

Table IA6: Junior VC Career Outcomes and VC Characteristics

	1(Senior Level)		**1**(≥ 1 Deal)		**1**(≥ 5 Deals)	
	(1)	(2)	(3)	(4)	(5)	(6)
1(White)	0.014*	0.038	0.038***	0.051*	0.018**	0.048*
	(1.68)	(1.53)	(3.32)	(1.80)	(2.08)	(1.91)
1(Female)	-0.038***	-0.117***	-0.059***	-0.169***	-0.046***	-0.115***
	(-4.50)	(-4.33)	(-4.88)	(-4.98)	(-5.69)	(-4.30)
1(Business Major)	0.018	-0.029	-0.005	-0.102**	-0.007	-0.043
	(1.34)	(-0.68)	(-0.30)	(-2.16)	(-0.54)	(-1.03)
1(STEM Major)	0.005	0.021	-0.007	-0.067	-0.004	-0.001
	(0.32)	(0.48)	(-0.37)	(-1.41)	(-0.30)	(-0.03)
1(Soc. Sci. Major)	0.008	-0.069	-0.028	-0.054	-0.004	-0.055
	(0.44)	(-1.29)	(-1.14)	(-0.86)	(-0.24)	(-1.00)
1(Ivy Undergrad)	0.011	-0.031	0.045***	0.003	0.022*	0.011
	(0.93)	(-1.09)	(2.97)	(0.09)	(1.89)	(0.40)
1(Ivy+ Undergrad)	0.053***	0.057	0.045**	0.104***	0.035**	0.082**
	(3.48)	(1.60)	(2.46)	(2.66)	(2.44)	(2.24)
1(Has MBA)	0.056***	0.079**	0.071***	0.076**	0.034**	0.067**
	(3.97)	(2.57)	(3.97)	(2.23)	(2.46)	(2.20)
1(Top-10 MBA)	0.016	0.040	0.034	0.088**	0.041**	0.065*
	(0.92)	(1.12)	(1.55)	(2.17)	(2.39)	(1.84)
1(HBS MBA)	0.076**	0.058	0.124***	0.057	0.105***	0.094*
	(2.51)	(1.14)	(3.69)	(1.06)	(3.45)	(1.80)
1(Stanford GSB MBA)	0.080**	0.054	0.132***	0.095	0.114***	0.079
	(2.14)	(0.82)	(3.41)	(1.51)	(2.97)	(1.18)
1(Advanced Degree)	0.057***	0.156***	0.114***	0.189***	0.057***	0.151***
	(3.41)	(3.48)	(5.60)	(4.30)	(3.50)	(3.34)
1(CXO/Founder of Successful Startup)	0.169***	0.271***	0.287***	0.377***	0.229***	0.373***
	(5.52)	(5.01)	(9.61)	(8.90)	(7.44)	(7.01)
1(Non- CXO/Founder of Successful Startup)	0.066***	0.133***	0.109***	0.148***	0.074***	0.132***
	(4.04)	(3.44)	(5.60)	(3.79)	(4.59)	(3.38)
1(CXO/Founder of Non-Successful Startup)	0.151***	0.397***	0.159***	0.183*	0.080**	0.309***
	(4.18)	(4.17)	(3.97)	(1.88)	(2.55)	(3.13)
1(Non-CXO/Founder of Non-Successful Startup)	0.032**	0.097	0.043**	0.113	0.038**	0.023
	(1.98)	(1.25)	(2.00)	(1.40)	(2.37)	(0.30)
1(Tech.)	0.070***	0.088***	0.113***	0.108***	0.083***	0.093***
	(5.13)	(2.62)	(6.92)	(3.08)	(6.12)	(2.73)
1(Pharma.)	0.045**	0.089	0.080***	0.121**	0.020	0.013
	(2.01)	(1.45)	(2.79)	(1.96)	(0.90)	(0.21)
1(Inv. Banking)	0.016	0.064**	0.047***	0.042	0.025**	0.051*
	(1.64)	(2.33)	(3.55)	(1.36)	(2.54)	(1.85)
1(Mgmt. Consulting)	0.025**	0.061**	0.056***	0.035	0.035***	0.047
	(2.23)	(2.02)	(3.92)	(1.10)	(3.23)	(1.55)
Sample	All	Pre-2011	All	Pre-2011	All	Pre-2011
Y-mean	0.144	0.273	0.322	0.481	0.147	0.291
Year Entered the VC Industry	x	x	x	x	x	x
Adj. R^2	0.143	0.142	0.177	0.149	0.179	0.158
N	5,940	1,313	5,940	1,313	5,940	1,313

Table IA6: Tabulates coefficients from regressions of indicators of career progressions on characteristics of the VC investment professionals. The sample is restricted to *only* include investment professionals that entered the industry at either a junior-level. Standard errors are clustered at the individual VC level. *t*-stats are in parentheses and */**/*** respectively denote significance at the 10, 5, and 1 % levels.

Table IA7: Robustness: Investment Outcomes and VC Characteristics

	Outcome			
	(1) **1**(Successful; 5x)	(2) **1**(Successful; 10x)	(3) **1**(Exit ≥ 5x)	(4) **1**(Exit ≥ 10x)
1(1+ Successful Prior Inv.)	0.014***	0.013***	0.005	0.003
	(3.27)	(3.20)	(1.41)	(1.09)
1(2+ Successful Prior Inv.)	0.015***	0.015***	0.008**	0.006*
	(2.92)	(2.98)	(1.96)	(1.68)
1(5+ Successful Prior Inv.)	0.035***	0.035***	0.013***	0.011***
	(5.92)	(6.15)	(2.94)	(2.83)
1(White)	-0.006	-0.006	-0.004	-0.003
	(-1.46)	(-1.36)	(-1.33)	(-0.96)
1(Female)	-0.012***	-0.011**	-0.009***	-0.009***
	(-2.73)	(-2.57)	(-2.64)	(-3.01)
1(Business Major)	-0.005	-0.003	-0.006	-0.006
	(-0.81)	(-0.63)	(-1.42)	(-1.61)
1(STEM Major)	-0.004	-0.002	-0.007*	-0.006
	(-0.64)	(-0.41)	(-1.71)	(-1.58)
1(Soc. Sci. Major)	-0.010	-0.009	-0.009*	-0.007*
	(-1.55)	(-1.37)	(-1.69)	(-1.70)
1(Ivy Undergrad)	0.015***	0.015***	0.008**	0.008***
	(3.42)	(3.53)	(2.32)	(2.64)
1(Ivy+ Undergrad)	0.007	0.008	0.001	0.001
	(1.25)	(1.51)	(0.20)	(0.42)
1(Has MBA)	-0.022***	-0.024***	-0.013***	-0.014***
	(-4.67)	(-5.40)	(-3.70)	(-4.29)
1(Top-10 MBA)	0.011*	0.012**	0.006	0.006
	(1.90)	(2.17)	(1.39)	(1.55)
1(HBS MBA)	0.004	0.005	0.001	0.002
	(0.56)	(0.67)	(0.27)	(0.48)
1(Stanford GSB MBA)	0.039***	0.036***	0.015**	0.011*
	(4.82)	(4.61)	(2.54)	(1.96)
1(Advanced Degree)	0.006	0.007	0.003	0.002
	(1.21)	(1.38)	(0.74)	(0.71)
1(CXO/Founder of Successful Startup)	0.009**	0.009**	0.005	0.005
	(2.12)	(2.28)	(1.61)	(1.62)
1(Non- CXO/Founder of Successful Startup)	0.004	0.003	0.004	0.002
	(0.81)	(0.58)	(1.14)	(0.62)
1(CXO/Founder of Non-Successful Startup)	-0.025***	-0.027***	-0.012**	-0.015***
	(-3.80)	(-4.18)	(-2.44)	(-3.41)
1(Non-CXO/Founder of Non-Successful Startup)	-0.008	-0.010	-0.001	-0.001
	(-1.09)	(-1.42)	(-0.08)	(-0.28)
1(Tech.)	0.001	-0.001	0.002	0.000
	(0.38)	(-0.20)	(0.72)	(0.10)
1(Pharma.)	0.015*	0.009	0.008	0.001
	(1.90)	(1.15)	(1.23)	(0.12)
1(Inv. Banking)	0.017***	0.015***	0.010***	0.006**
	(3.89)	(3.72)	(3.20)	(2.16)
1(Mgmt. Consulting)	-0.002	-0.002	0.002	0.001
	(-0.38)	(-0.56)	(0.52)	(0.27)
1(1-9 Yrs. in VC)	0.024***	0.022***	0.012***	0.009***
	(5.97)	(5.71)	(3.97)	(3.31)
Y-mean	0.151	0.137	0.098	0.076
Invest Year FE	x	x	x	x
State FE	x	x	x	x
Industry FE	x	x	x	x
Company Age FE	x	x	x	x
Data Source FE	x	x	x	x
Adj. R^2	0.132	0.124	0.110	0.087
N	63,634	63,634	63,634	63,634

Table IA7: Tabulates coefficients from regressions of indicators for the success of a VC deal on characteristics of the venture capitalists that made the deal. These specifications use higher cutoffs for the exit valuations of 5x and 10x, rather than the baseline of 2x. Standard errors are clustered at the individual VC level. *t*-stats are in parentheses and */**/*** respectively denote significance at the 10, 5, and 1 % levels.

Table IA8: Heterogeneity: Investment Outcomes and VC Characteristics

	1(Successful Outcome)			
	(1)	(2)	(3)	(4)
Sample	Board	No Board	Early Stage	Later Stage
1(1+ Successful Prior Inv.)	0.015**	0.018***	0.018***	0.015**
	(2.26)	(3.28)	(3.23)	(2.38)
1(2+ Successful Prior Inv.)	0.020**	0.010	0.014**	0.015*
	(2.57)	(1.44)	(2.07)	(1.95)
1(5+ Successful Prior Inv.)	0.053***	0.023***	0.040***	0.030***
	(6.52)	(3.12)	(5.74)	(3.58)
1(White)	-0.018***	-0.001	-0.009*	-0.008
	(-3.02)	(-0.12)	(-1.72)	(-1.23)
1(Female)	-0.018***	-0.005	-0.012**	-0.009
	(-2.62)	(-0.94)	(-2.11)	(-1.29)
1(Business Major)	-0.009	0.001	-0.002	-0.005
	(-1.19)	(0.10)	(-0.31)	(-0.57)
1(STEM Major)	-0.007	-0.001	0.001	-0.008
	(-0.97)	(-0.12)	(0.20)	(-1.00)
1(Soc. Sci. Major)	-0.016	-0.005	-0.006	-0.011
	(-1.56)	(-0.67)	(-0.70)	(-1.17)
1(Has MBA)	-0.023***	-0.017***	-0.024***	-0.017**
	(-3.41)	(-2.73)	(-4.14)	(-2.51)
1(Top-10 MBA)	0.009	0.007	0.011	0.007
	(1.13)	(0.86)	(1.43)	(0.86)
1(HBS MBA)	0.008	0.004	0.011	0.000
	(0.85)	(0.42)	(1.27)	(0.03)
1(Stanford GSB MBA)	0.042***	0.028**	0.039***	0.029**
	(3.81)	(2.49)	(3.92)	(2.41)
1(Advanced Degree)	0.008	0.002	0.010	-0.000
	(1.16)	(0.27)	(1.59)	(-0.01)
1(CXO/Founder of Successful Startup)	0.012*	0.003	0.009*	0.004
	(1.86)	(0.64)	(1.88)	(0.67)
1(Non- CXO/Founder of Successful Startup)	0.009	-0.000	-0.002	0.013*
	(1.20)	(-0.05)	(-0.30)	(1.66)
1(CXO/Founder of Non-Successful Startup)	-0.032***	-0.020**	-0.032***	-0.017*
	(-3.32)	(-2.29)	(-4.03)	(-1.77)
1(Non-CXO/Founder of Non-Successful Startup)	-0.006	-0.007	0.000	-0.015
	(-0.49)	(-0.87)	(0.04)	(-1.32)
1(Tech.)	0.004	0.002	0.002	0.003
	(0.72)	(0.36)	(0.47)	(0.51)
1(Pharma.)	0.016	-0.006	0.017	0.008
	(1.57)	(-0.49)	(1.50)	(0.70)
1(Inv. Banking)	0.026***	0.006	0.011**	0.024***
	(4.17)	(1.23)	(2.14)	(3.83)
1(Mgmt. Consulting)	0.000	0.000	-0.006	0.009
	(0.01)	(0.06)	(-1.10)	(1.44)
1([1,10) Yrs. in VC)	0.035***	0.020***	0.029***	0.020***
	(5.75)	(3.94)	(5.68)	(3.49)
Y-mean	0.214	0.111	0.166	0.159
Invest Year FE	x	x	x	x
State FE	x	x	x	x
Industry FE	x	x	x	x
Company Age FE	x	x	x	x
Data Source FE	x	x	x	x
Adj. R^2	0.128	0.120	0.146	0.137
N	32,290	31,269	37,430	26,142

Table IA8: Tabulates coefficients from regressions of indicators for the success of a VC deal on characteristics of the venture capitalists that made the deal. Regression samples vary according to the "Sample" listed in each column. Standard errors are clustered at the individual VC level. *t*-stats are in parentheses and */**/*** respectively denote significance at the 10, 5, and 1 % levels.

Table IA9: Robustness: VC Investment Outcomes and VC Characteristics with Differing Selection

	1(Successful Outcome)		
	(1)	(2)	(3)
Sample	Baseline	Missing=0	Missing=1
1(1+ Successful Prior Inv.)	0.017***	0.018***	0.018***
	(3.78)	(4.88)	(4.91)
1(2+ Successful Prior Inv.)	0.018***	0.019***	0.019***
	(3.35)	(4.20)	(4.21)
1(5+ Successful Prior Inv.)	0.034***	0.033***	0.034***
	(5.78)	(6.48)	(6.65)
1(White)	-0.009**	-0.008**	-0.008**
	(-2.05)	(-2.30)	(-2.30)
1(Female)	-0.011**	-0.010**	-0.010**
	(-2.42)	(-2.52)	(-2.40)
1(Business Major)	-0.002	-0.007*	0.005*
	(-0.36)	(-1.69)	(1.67)
1(STEM Major)	-0.003	-0.007*	0.005
	(-0.47)	(-1.88)	(1.47)
1(Soc. Sci. Major)	-0.006	-0.012**	0.003
	(-0.89)	(-2.17)	(0.82)
1(Ivy Undergrad)	0.016***	0.014***	0.011***
	(3.53)	(3.42)	(3.02)
1(Ivy+ Undergrad)	0.009	0.013***	0.009**
	(1.58)	(2.58)	(2.14)
1(Has MBA)	-0.022***	-0.023***	-0.027***
	(-4.63)	(-5.18)	(-6.60)
1(Top-10 MBA)	0.010*	0.013**	0.017***
	(1.72)	(2.34)	(3.23)
1(HBS MBA)	0.009	0.004	0.005
	(1.17)	(0.62)	(0.71)
1(Stanford GSB MBA)	0.038***	0.040***	0.041***
	(4.58)	(5.35)	(5.54)
1(Advanced Degree)	0.006	0.003	0.002
	(1.16)	(0.62)	(0.47)
1(CXO/Founder of Successful Startup)	0.009**	0.010**	0.010**
	(2.11)	(2.47)	(2.53)
1(Non- CXO/Founder of Successful Startup)	0.005	0.001	0.002
	(0.88)	(0.27)	(0.35)
1(CXO/Founder of Non-Successful Startup)	-0.025***	-0.016***	-0.016**
	(-3.42)	(-2.61)	(-2.54)
1(Non-CXO/Founder of Non-Successful Startup)	-0.007	-0.008	-0.009
	(-0.88)	(-1.28)	(-1.31)
1(Tech.)	0.003	0.000	-0.004
	(0.74)	(0.02)	(-1.19)
1(Pharma.)	0.013*	0.007	-0.005
	(1.65)	(1.02)	(-0.97)
1(Inv. Banking)	0.016***	0.017***	0.012***
	(3.57)	(4.31)	(3.25)
1(Mgmt. Consulting)	-0.000	-0.002	-0.006*
	(-0.06)	(-0.45)	(-1.74)
1([1,10) Yrs. in VC)	0.026***	0.027***	0.028***
	(6.23)	(7.84)	(7.95)
Y-mean	0.168	0.171	0.171
Invest Year FE	x	x	x
State FE	x	x	x
Industry FE	x	x	x
Company Age FE	x	x	x
Data Source FE	x	x	x
Adj. R^2	0.129	0.135	0.135
N	63,625	94,739	94,739

Table IA9: Tabulates coefficients from regressions of indicators of investment success on characteristics of the VC investment professionals. "Sample" denotes how missing values for work and education data are treated. Standard errors are clustered at the individual VC level. *t*-stats are in parentheses and */**/*** respectively denote significance at the 10, 5, and 1 % levels.

Table IA10: Midas List Release Dates and Coverage

Midas List Year	Release Date	# of People	Data Source	# Transcribed	# in Our Dataset
2001	February, 19	100	Wayback	100	66
2002	February, 18	100	Library Print	25	17
2003	February, 17	100	Library Print	50	42
2004	February, 16	100	Library Print	50	41
2005	February, 14	100	Library Print	50	39
2006	January, 26	100	Wayback	100	71
2007	January, 25	100	Wayback	100	73
2008	January, 24	100	Wayback	100	74
2009	February, 16	100	Wayback	100	81
2010	No List				
2011	April, 6	100	Wayback	100	92
2012	May, 2	100	Wayback	100	85
2013	May, 8	100	Wayback	100	88
2014	March, 26	100	Wayback	100	87
2015	March, 25	100	Wayback	100	85
2016	March, 23	100	Wayback	100	84
2017	April, 14	100	Wayback	100	86
2018	April, 3	100	Wayback	100	79
2019	April, 2	100	Wayback	100	73
2020	April, 14	100	Wayback	100	72
2021	April, 13	100	Wayback	100	72
2022	April, 12	100	Wayback	100	69
2023	May, 4	100	Wayback	100	70
2024	June, 4	100	Wayback	100	73
2025	May, 27	100	Website	100	75

Table IA10: Tabulates our collections and coverage of the historical Midas List produced by Forbes.

Table IA11: Midas List Composition

Group	# Listings	# People
US VC	**1,641**	**387**
Non-US	325	84
Growth	**55**	**14**
Banker	45	29
Angel	26	14
PE	25	15
Lawyer	19	12
Hedge Fund	18	5
Recruiter	7	6
Executive	5	4
Professor	5	1
Government	2	1
Entrepreneur	1	1
Consultant	1	1
Total	2,175	559
Included	1,696	399

Table IA11: Tabulates the types of professionals includes on the Midas List produced by Forbes. We assign classifications by manually reading each person's listing. Columns separately report the number of unique listings (2005 rank 1 and 2007 rank 3, are, for instance, two separate listings) and the number of people assigned to each classification. Our main sample includes only those classified as U.S. VCs or growth investors (bolded).

Table IA12: Midas List Methodology

Year	Methodology Quote
2001	The rankings for the inaugural Midas List were based on extensive FORBES reporting and surveys sent to several hundred potential list members. For each member, we calculated the performance of all venture-backed companies through December 29, 2000. Companies must have gone public, merged or been acquired after August 1995 to be eligible. We awarded points based on how involved candidates were in each company both before and after the primary liquidity event. We then multiplied scores by the market valuation of the company both at the time of the offering, merger or acquisition and on December 29. The sum of these figures is a fairly accurate measure of a candidate's record of creating wealth.
2002	The Midas list seeks to identify individuals who deploy venture capital to create wealth for investors. Our ranking formula weighs most heavily the market capitalization of a venture-backed company on its first day of trading or the purchase price in an acquisition. Companies must have gone public or been acquired after June 1995 to be considered, and they must be engaged in the field of information technology or life sciences. Placement on the list also depends on a venture capitalist's (or lawyer's or recruiter's) degree of involvement with a startup. Our results are based on extensive reporting and surveys sent to 600 professionals including VCs, angels, lawyers and bankers. This year we also polled limited partners in VC funds. Special thanks go to VentureOne and the National Venture Capital Association.
2004	The Midas List seeks to identify individuals who deploy venture capital to create wealth for their investors. Our ranking formula ignores the original amount invested in a deal (as it is often undisclosed), instead weighing most heavily the market capitalization of a venture-backed company on the close of its first day of trading or the purchase price in an acquisition. A lesser weight is given to the change in value of each investment since going public or being sold. Ranking also depends on a venture capitalist's (or lawyer's, banker's or recruiter's) length of involvement and influence with a startup. Companies must have gone public or been acquired after June 1995 to be considered, and they must be engaged in information technology or life sciences. Our results are based on extensive reporting and surveys sent to 1,000 professionals, including VCs, angels, lawyers, bankers, recruiters and limited partners.
2025	The Midas List is a metrics-driven ranking of the best venture investors in the world. Forbes recognizes investors whose portfolio companies have gone public, completed an M&A transaction, or raised financing at higher valuations. The list is produced annually using public data and submissions from hundreds of investment partners. To qualify, investors are ranked by companies that have gone public or been acquired for at least $200 million in the past five years, or that have doubled their private valuation to $400 million or more.

Table IA12: Tabulates quotes on the described methodology for constructing the Midas List by year.