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

Blake Jackson† Ilya A. Strebulaev‡

June 16, 2026

Abstract

We study human capital in venture capital (VC) using a new dataset covering over 100,000 professionals affiliated with U.S. VC firms. Investment success is extremely concentrated: fewer than 40% of VCs with any investments are ever credited with a successful investment, and 90% of investment profits are generated by 5% of VCs. Differences in education, prior work experience, and demographics predict career progression and investment outcomes, consistent with persistent investor-specific skills. Quasi-experimental variation from marginal inclusions on the Forbes Midas List shows that achieving superstar status increases access to highly-valued startups, complementing other human capital and contributing to concentration.

*For helpful comments and discussions, we thank Liudmila Alekseeva, Mike Ewens, Minmo Gahng, Paul Gompers, Sabrina Howell, and seminar participants at Harvard Business School, the LBS Private Capital Symposium, and the WEFI Fellows Conference. We especially thank Kai Wen Cui for exceptional research assistance. For helpful research assistance, we further thank: Umidjon Abdunabiyev, Faith Adeola, Femi Babatunde, Manfredi Bernardi, Arafat Charakhmetov, Bekzhan Elebesov, Anton Eremin, Akylai Kasymkulova, Alina Kemalova, Svetlana Kim, Shantia Laurenz, Alex Leontaridis, Alin Molchanova, Rahmatullah Nazar, Minh Nguyen, Bakyt Parman, Yana Pavlovskaya, Arlan Rakhmetzhanov, Salimzhan Sagat, Banuir Sansyzbay, Dauirzhan Sansyzbay, Deven Shah, and Kholidakhon Sharifkhanova.

†Fisher College of Business, The Ohio State University, E-mail: jackson.4607@osu.edu

‡Stanford University Graduate School of Business and NBER, E-mail: ilyas1@stanford.edu

The U.S. venture capital industry has had an outsized impact on U.S. innovation, firm creation, and the broader economy over the last fifty years. Venture capital-backed companies account for 41% of total U.S. market capitalization and 62% of public U.S. companies' R&D spending (Gornall and Strebulaev 2021). Seven of the 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 other developed nations outside of the U.S. that historically have lacked a VC industry have not witnessed the same creation of similarly large new companies over this same time period.

Venture capital (VC) investing is also a highly human capital-intensive business, requiring substantial effort on the part of individual VCs to identify promising startups in which to invest and ultimately help contribute to the success of these investments. Michael Moritz, of the VC firm Sequoia, is widely credited for making early investments in Google and PayPal. Marc Andreessen, of yet another VC firm a16z, is well known for highly successful venture investments in Airbnb and Lyft. Existing empirical evidence has shown that the ability of these individual VCs to make successful investments is persistent. For example, the identity of the VC sitting on the board of a startup is far more important for explaining whether an investment in a startup subsequently succeeds or fails than which firm the VC represented or the year they took a board seat, accounting for 12% of cross-sectional variation in whether the startup subsequently goes public (Ewens and Rhodes-Kropf 2015). Further, at the fund level, VC firms with funds in 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, a great deal of empirical work has shown that the VC industry exhibits substantial persistence and economic impact, drawing, in part, on the human capital of individual VCs responsible for managing investments. However, surprisingly little is known about these individual VCs themselves. 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? Insofar as these characteristics and experiences are costly to replicate or acquire, to what extent are returns to investing in the VC industry concentrated among a relatively small number of VC

investment professionals?

In this paper, we aim to answer these questions. Such a research agenda has historically been hampered by incomplete, potentially biased, and opaque data. We, therefore, 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. By our estimates, about 50% of the datapoints we assemble are not available in standard commercial datasets alone. Using these new data, we document significant concentration in persistent investment success in the U.S. VC industry and show that characteristics of these VCs' demographics, education, and work experiences predict whether they are among the small group of persistently successful VCs accounting for most of the industry's profits. We further show that one economic mechanism helping sustain this concentration in VC is the strong positive effect of "superstar" status.

We start by presenting a 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 100,000 VC affiliated professionals we collect, 37,000 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.

One set of statistics that emerges from our dataset is the compositional makeup of the U.S. VC industry. 69.7% of VCs are white. 23.0% are female. 16.4% have an undergraduate degree from an Ivy League school. Nearly one-third have an MBA and 10% have an advanced degree. About 25% worked at a startup. 7.5% were CEOs or founders of a successful startup. Over time, the industry has proportionally started to include more females, fewer STEM degrees, and more business degrees, while the fraction of VCs with startup experience has remained fairly stable.

Our first analysis uses our unique coverage of junior-level investment professionals over time to document how these characteristics relate to successful career progressions in VC. Is it the case that the VC industry only hires professionals from these backgrounds? Or, instead, are professionals with particular backgrounds consistently likely to become more senior VCs?

Our comparisons favor the latter. Female professionals are 2.6 percentage points less likely to 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. Further, individuals entering at a junior associate level are up to 83 percentage points less likely to eventually become VC partners, compared to those that join at a more senior middle-level position. These results show that VC professionals with particular backgrounds, namely, specialized skills, knowledge, networks, or work experience, not necessarily those with junior VC experience, are more likely to become senior-level VCs. 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)).

The resulting dataset also allows us to quantify how much the different experiences of VC investors contribute to the returns of their investments, even after accounting for their prior investing success (e.g., Kaplan and Schoar (2005) and Nanda, Samila, and Sorenson (2020)). 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 what we document to be a 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 missing from other datasets.[1]

Investments made by VCs with one prior successful deal are 2% more likely to have a

[1]Our additions 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, or are made earlier in a venture capitalist's career.

successful outcome. Investments made by VCs with five prior successful deals are about 7% more likely to succeed (a 47% 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 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 from 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, comparable and opposite in magnitude to the role of having made two prior successful investments.

However, the most significant differences in investment success explained by the backgrounds of VCs appear when we use our new data to examine whether the VCs that have had more cumulative 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 37% 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 higher-ranking schools, have degrees from a top MBA program, hold advanced terminal degrees, have held a CEO or founder position in a successful startup, or transitioned from a technology or investment banking firm.

When we further estimate the net profits accruing to VCs from each investment they make, accounting for dilution and the cost of the investment, we find that these differences in investment success translate to consequential differences in economic value across VCs. For instance, the average VC with an MBA from a highly ranked school is estimated to have made investments with net profits that are at least two-times more than the net lifetime profits of an average VC. Given the high selectivity of the admissions and hiring policies for these pedigreed schools and companies in each of the industries where many of the successful VCs are from, the results are consistent with a mechanism where the specialized human capital (acquired, e.g., from startup experience, technology experience, or banking experience) is relevant for specialized VC investments.

An additional result delivered by these analyses is a quantification of the concentration of

success in the VC industry at the individual VC level. While variation in VCs' experiences and demographics provides useful explanatory power for whether VCs fall into the group of highly successful VCs or not, few VCs ultimately do. We find that only 38% of VCs with at least one investment have been credited with at least one successful investment over their careers. Only 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. The results are even more pronounced for the approximately $1.2 trillion in inflation-adjusted net profits we observe. In the aggregate, the investments of the top 1% of VCs in our sample (about 120 VCs) have contributed about 57% of all net profits, while the top 5% have contributed about 90%.

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. This is not unlike, for instance, the distribution of compensation and success among CEOs of U.S. companies. An important question, therefore, is whether such status can contribute to VCs' subsequent investment success. Superstar VCs could plausibly have better access to investments in highly-valued startups or exposure to resources (e.g., suppliers, customers, labor) that less well-known VCs may otherwise not have. However, such a result is not obvious. By contrast, the key finding in studies of superstar CEOs is that achieving superstar status appears to have negative effects on the performance of their firms (e.g., Malmendier and Tate (2009)).

The primary empirical concern in estimating the effects of achieving superstar status 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 institutional feature of the VC industry that allows us to approximate such an experiment is 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 list reports the 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 correctly predicts 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 discussed by Baker, Larcker, and Wang (2022)) to compare those marginally awarded such status to those that were 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 inclusion. These results represent about a 10% increase in investment success relative to the sample mean, equal to an increase of about 0.13 new successful investments. Increased success is driven primarily by new investments in companies that later 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)).

Related Literature and Contribution. A series of important related papers in VC document persistence in VC investment success at the fund level (e.g., Kaplan and Schoar (2005), Harris, Jenkinson, and Kaplan (2014), and Harris et al. (2023)). Relatedly, Ewens and Rhodes-Kropf (2015) show that a key source of persistence in VC relates to the human capital of the VC who sits on the board of a startup; variation in venture investment exits is attributable more so to the individual partner that served on the board of the portfolio company than to the VC firm at which they are a partner. Relative to these papers, our contribution is to provide evidence tracing differences in the persistent success of individual VCs to differences in their backgrounds, namely, differences in their demographics, education, and work experiences.

Our findings further contribute to the literature documenting an important role for VCs' human capital in explaining their investment success (e.g., Gompers, Mukharlyamov, Weisburst, and Xuan (2022), Calder-Wang, Gompers, and Sweeney (2023b), Gompers and Mukharlyamov (2025), and Duevski (2025)). However, a key concern in these prior studies, and studies of VC and private markets more generally, is the ability for potentially limited data to contaminate conclusions about differences in investment success. Relative to these papers, a unique contribution of our new dataset, therefore, is to show that several of the basic correlations presented at the deal-level in prior work are not an artifact of selection bias present purely in commercial data – such as a negative correlation between investment success and whether a VC is female or a positive correlation between investment success and whether a VC previously founded a successful startup. The main economic contribution of our paper, relative to this extant work, is to document distinguishing characteristics of the most successful VCs relative to a broad universe of U.S. VC investors and to study how these characteristics jointly contribute to career progressions and differences in lifetime investment success.

Additionally, our paper is related to the literature studying whether VCs' ability to generate superior investment performance is driven more by their ability to select better companies or their ability to add value to the companies in which they invest (e.g., Lerner (1995), Hellmann and Puri (2002), Sørensen (2007), Bernstein, Giroud, and Townsend (2016), and Gompers, Gornall,

Kaplan, and Strebulaev (2020)). Several studies focus specifically on the role of VCs' access to high quality startups, related to differences in their initial success (e.g., Nanda et al. (2020)) and their networks (e.g., Hochberg, Ljungqvist, and Lu (2007) and Garfinkel, Mayer, Strebulaev, and Yimfor (2025)). Our relative contribution is to use quasi-experimental variation from marginal inclusions on the Forbes Midas List to provide evidence of a new channel through which the ability to access investments in higher-quality startups contributes to their investment success, complementary to other aspects of their human capital.

Our paper is also not the first to document skewness in the returns to equity investing. Prior work has shown that a very small fraction of companies account for virtually all of the returns to equity investors in exited venture-backed companies (e.g., Cochrane (2005)) and in publicly traded companies (e.g., Bessembinder (2018)). Kerr, Nanda, and Rhodes-Kropf (2014) use the full portfolio of one VC fund to show that about 8% of this anonymous VC's investments accounted for about 55% of its gross returns. The relative distinction of our work is to show that the concentration further persists at the individual VC level; looking across the lifetime investing success of individual VCs, only a small fraction have made investments that positively contribute to the overall net profits of the industry.

More broadly, the results in our paper also contribute to a consequential strand of work showing that early career work experiences matter for productivity, wages, and labor market outcomes (e.g., Acemoglu and Pischke (1998)). Several studies of investment fund managers' human capital, outside of venture capital, generally suggest that superior investment performance is related to specialized knowledge and information acquired from multiple channels including past investing experiences, education, early mentors, and differential industry experiences (e.g., Chevalier and Ellison (1999), Coval and Moskowitz (2001), Kacperczyk, Sialm, and Zheng (2005), Kempf, Manconi, and Spalt (2017), Cici, Gehde-Trapp, Göricke, and Kempf (2018), Jackson (2025), and Ivashina, Rotermund, and Wallace-Wright (2026)). The contribution of our work is to highlight the importance of early career experience and education in explaining persistent differences in lifetime investment success and skewness in the aggregate VC industry.

1 Data Sources and Descriptive Statistics

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 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 archival website sample includes historical webpage data for professionals affiliated with 3,430 of the 4,402 U.S. VC firms (78% of firms). The 22% 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, the firms do not list professionals on their website, or firms 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. We further supplement firms covered via historical website data with data on professionals affiliated with any of these firms on PitchBook or VentureSource. This results in a final sample covering professionals across 3,958 of our 4,402 sample firms, accounting for 96% of capital raised by the 4,402 institutional U.S. VC firms and having sponsored 95% of all U.S. VC funds in the 1996-2025 period (based on PitchBook data).

Our resulting sample of professionals affiliated with these US-headquartered VC firms includes just over 103,000 unique people. Many are unique to our website collections. For reference, PitchBook covers about 36,000 of these professionals and VentureSource covers about 15,000.

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 instead a non-investment professional that does not work at the firm full time or primarily works in firm operations, portfolio operations, or is retired.[2] 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 37,290 individuals. 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. We match VCs with portfolio companies using 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 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

[2]Firm operations typically include internal functions such as compliance and human resources. Portfolio operations often includes venture partners and advisors. Venture partners are also often non-full-time investment professionals.

VCs in the Midas list contains their notable investments that we use to complement our other sources.

Our main sample includes investments in 68,010 unique VC-backed companies where at least one VC investment professional has an affiliation with that company. In total, 16,425 U.S. VC investment professionals, or 44% 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.[3] These 16,425 VCs 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 over 20,000 incremental VC investment professionals, and 5,000 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 20,000 person×company affiliations that are otherwise not available in commercial datasets, equal to a coverage improvement of about 15%. 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 summarizes and Section IA.1.3 further discusses our improvements. 55.6% of the person-company involvements we recover are unique to PitchBook or VentureSource and 14.5% are unique to the archived webpages.[4] The remaining 29.9% of involvements are present in both types of sources. An example of a company involvement we extract from websites but

[3] These are usually junior professionals or investment professionals that worked in the industry for only a few years; about 80% of all senior investment professionals that worked in the VC industry for five or more years have at least one portfolio company affiliation.

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

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,[5] 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:

> *. . . 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. Our coverage improvements tend to include more successful later stage startup investments from deals done during earlier years.

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 16,425 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% and pre-VC work experience for 84% of the final sample. We report means for the entire sample of VCs with data on each characteristic, as well as for subsamples that contain VCs that are affiliated with 0, 1–2, 3–5, or 6 or more successful investments.

[5] https://www.wsj.com/articles/airbnb-raises-1-5-billion-in-one-of-largest-private-placements-1435363506

We define an investment to have been successful if the startup subsequently went public or was acquired at a valuation of at least five-times the total capital raised.[6] 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. Furthermore, taking into account unicorns allows us to include successful deals that are still private, thus reducing the bias against more recent investments. Section IA.2 provides additional evidence supporting our use of these investment return outcome measures, showing that they correlate strongly with the net profits of the VCs' involvement in the company.

Characteristics of U.S. VCs. Panel A shows that, demographically, 75% of VCs are white and 16.3% of VCs are female. For the subsample of VCs that are affiliated with at least six successful deals, only 5.4% are females. Panel B focuses on pre-VC education experience and shows that 18% of VCs attended Ivy League schools as undergraduates, while 10% attended Ivy+ school, with Ivy+ including other highly ranked private schools.[7] Overall, 40% attended top-30 undergraduate schools as defined by the US News 2025 ranking. Stanford is the most common undergraduate school (4.8%), 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 36.5%, STEM at 39.5%, social sciences at 10.7%, 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 25.4% while the fraction with a STEM major increases to 52.3%.

[6] Our results are robust to instead using cutoffs of two-times or ten-times the amount invested for acquisition multiples. This definition of success follows Ewens and Rhodes-Kropf (2015) in principle, with the difference that their benchmark is two-times acquisition value.

[7] 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.

More than a third of VCs, 38.0%, and almost half of those with at least six successful deals, 49.6%, 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 School (6% of all VCs and 16% of those with MBAs), followed by Stanford GSB (4% and 10%, respectively) and Wharton (2.8% and 7.4%). Among the VCs with at least six successful deals, the number of Harvard and Stanford MBAs increases substantially, to 12.5% and 11.8%, respectively. Every seventh VC has an advanced degree, such as Ph.D. or MD. Table IA4 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 fifth working at a successful VC-backed startup (one that was acquired, went public or achieved a unicorn valuation after the professional joined). 60% of startup affiliations (or 13.4% of all VCs) were either a founder or a C-suite executive of such startups. Successful startup experience is more pronounced among VCs with at least six successful investments.

Another third (34.4%) 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 buyout (7.4%), hedge fund (2%), law firm (3.5%), or government (8.1%) backgrounds. Note that almost 40% of VCs worked in "other" institutions that are often more general operating companies defying these classifications, such as Procter & Gamble, Boeing, or Nike. The most common prior employer is McKinsey (4.0%), followed by Goldman Sachs (3.1%), and Morgan Stanley (2.8%). Table IA5 lists the 20 most frequent previous employers.

Panel D shows that 40% 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 (69.3%) have worked in the VC industry for 10 or fewer years, 23.2% 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 (47.9%).

A very small fraction of our sample, 2.4%, were named to the Midas list in at least one year.[8] A quarter of VCs with at least six successful deals have been recognized on the Midas list at least once.

As implied by other rows, the final row of Table 1 highlights the skewness in investment success across VCs most directly. The average VC with at least one affiliated company has 1.3, and the average VC with six or more successful investments has about 10.4 successful investments. Table IA3 reports the distribution of total deals affiliated with each VC, averaging 8.17.

Comparisons with Other Samples and Investment Professionals. 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 investment professionals that founded a startup before they worked in the VC industry is similar in our sample and theirs (around 10%). We further focus on startup CEO or founder experience, which is about 15% in our sample. 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 comparison point is with Jackson (2025) who reports a set of similarly sourced 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 in-

[8] A smaller fraction of those without successful affiliations (0.2%) 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.

vestment 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. Further, comparatively fewer VCs enter the industry as an associate. This suggests that the production function of VC investing relies comparatively less on junior investment professionals compared to that of buyout investing, plausibly due to the nature of investing (requiring substantially more financial modeling and due diligence in buyout compared to venture).

Data presented in Ivashina et al. (2026) drawing from LinkedIn further allow us to compare human capital in the VC industry with that in the private credit industry. Consulting experience is less common among private debt professionals (8%), consistent with PE and VC professionals being more involved in the operations of their target companies following an investment. Private debt professionals, instead, are relatively more likely to have broader finance backgrounds (e.g., asset management, insurance), with 34% having such a background compared to only 16% in VC and 20% in PE. More generally, these comparisons suggest that each investment specialization draws on distinctive human capital.

Company Characteristics. Table 2 summarizes characteristics of the 68,010 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, 53.7%, were founded after 2010 and before 2020. 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.[9] 43.6% of companies are software companies. By

[9]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.

location, our sample predominantly includes companies located in the United States (74% for the full sample) with California being the most popular state, accounting for 29.1% of companies compared to only 9.1% for New York, which is the second most popular state. Table IA6 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.

Investment Characteristics. Table 3 summarizes the sample of person-company deals in total and by each outcome achieved. 49% of deals in our sample are based on board affiliations. The professional was the lead investor of the round in PitchBook for 23.3% of deals and invested within three years of the company's founding ("Early Stage") for 61.4% of deals. About two-thirds of investments are from pre-2020. Panel C shows statistics on VCs' successful investments prior to making a deal. While 2.4% of VCs are ever in the Midas list, they made 5.5% of all investments. VCs with at least five successful deals before they make the investment made almost a fifth of all investments. Note that VCs with many successful deals are also observed to have invested in many deals that are not successful. Ritter (2026) reports 3,782 VC-backed IPOs from 1980 through 2025, 3,269 of which occurred in 2000 or later and 472 of which are classified as growth equity backed. Our data includes 2,951 companies that went public, indicating we have recovered at least one pre-IPO investor for the vast majority of all VC-backed IPOs.

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 senior VCs?

We focus our analysis on the 14,420 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.[10]

All specifications include fixed effects for the year the 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 28 percentage points lower as well.

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 up to 12 percentage points less likely to be identified as active deal-makers. Female career progression rates are lower in the earlier part of our sample compared to the later part of our sample, consistent with findings by Calder-Wang et al. (2023b), which documents increasing female hiring in VC following the 2015 Pao versus Kleiner Perkins gender discrimination trial.

[10]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.

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 four 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 eight 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. This result, paired with the higher promotion rates for VCs that join at the middle level, are most 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 a better match for the industry (e.g., Topel and Ward (1992)).

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 or CEOs are all more likely to move up in seniority in the VC industry.

Additional Decomposition. Table IA7 examines career progressions among VCs that entered the industry at the junior level. Within juniors, VCs that joined as analysts are less likely to see career progressions compared to associates or senior associates. 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 subsequently 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

Prior work has found that VC investment success is highly skewed 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 VCs' 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. We then relate individual characteristics to economic value.

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 et al. (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, and a sale for the value at least five-times 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.[11] Specifications all include controls for the stage of the investment and whether the VC led at least one round for the company. We further present these results visually in Figure 2. Standard errors in all deal- and career-level specifications are clustered at the individual VC level.

While, as expected, predicting investment outcomes of VC-backed companies involves 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 1.8% 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 6.7% more likely that the company will subsequently have a successful outcome (1.8% + 1.6% + 3.3%), 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 47% 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 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 et al. (2016), even though our analysis does not allow us to disentangle selection and post-investment investment value additive contribution.

We find that demographic characteristics also correlate with individual deal outcomes, though the overall effect economically is relatively small. Companies affiliated with female VCs

[11] This last fixed effect includes fixed effects for whether (a) the VC sat on the board of the startup or (b) was otherwise a non-board investor in the startup, stratified by the source of the affiliation. Note that these data-source fixed effects also absorb differences in average success rates across provenance.

have a 1% lower chance of a successful investment outcome, similar to the most stringent specification reported by Gompers et al. (2022).

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 1.6% more likely to achieve a successful outcome. Interestingly, deals led by professionals with an MBA degree have a 2.2% 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.

Investments by VCs that were previously the CEO or founder of an unsuccessful startup are 2.7% less likely to have realized a successful outcome compared to other investments in the same year. Of other industry experience, deals led by investment bankers that entered the VC industry are 1.4% more likely to be successful.

Deals led by VCs that entered at a senior level are about 0.7% less likely to have a successful outcome. Deals led by VCs within the first ten years of their VC careers are 3.1% 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.

Heterogeneity and Robustness. 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 having led a round) or whether the VC was an earlier investor in the company (having made an initial investment within three years of the company's founding). Across all variables, the relationship between VCs' characteristics and the financial outcome of the investment tends to be more pronounced within the subsamples of VCs that were lead investors or who sat on the board. Additionally, Table IA9 confirms similar results attain if focusing only on investments in startups with fewer than five affiliated VCs or only investments

made by VCs that have full career progression data.

Missing Data. 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 IA10 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 0.037 in the baseline specification, 0.036 after assuming missing values take a value of zero, and 0.036 if instead assuming missing values have a value of one. More generally, the results presented in Table IA10 are similar to our main results even after assuming extreme selection in either direction, suggesting the missing data are unlikely to change our conclusions.[12]

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, early mentors, and differential industry experiences (e.g., Coval and Moskowitz (2001), Kacperczyk et al. (2005), Kempf et al. (2017), Cici et al. (2018), and Jackson (2025)). One measure of lifetime VC success is the number of success-

[12]Undergraduate major variables are the only exception.

ful 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 -0.47 implies that female VCs, on average, have about 0.82 successful deals over their lifetime, which is a 37% reduction ($= \exp(-0.47) - 1$) relative to the regression sample mean of 1.3. The 95% confidence interval for this count covers 0.70 to 0.96. 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 Nanda (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 21% 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 29% more successful investments. Those with an Ivy+ degree are credited with 43% more. VCs with advanced terminal degrees display a positive, but economically smaller, increase cumulative investing success of 19%. The relationship between investment success and MBA degree varies strikingly by institution. VCs with MBAs have, on average, completed 25% fewer successful deals relative to the mean. By contrast, VCs with a top-10 MBA, a Harvard MBA, or a Stanford MBA, have incrementally completed 27%, 21%, and 36% 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. They are also consistent with 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 et al. (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 CEO or founder of a successful startup. Relative to the sample mean, CEOs or founders of successful startups have made about 35% more successful investments over their careers. By contrast, CEOs or founders of unsuccessful startups have made about 24% fewer successful investments over their careers, relative to the sample mean. Estimated differences are unlikely to be

driven just by an affiliation with a successful or unsuccessful startup, as VCs with rank-and-file startup experience do not see similar swings in their lifetime investing success.

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 unsuccessful previous ventures matter negatively. 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 favor the former.

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, e.g., from technology experience or banking experience) is more relevant for specialized VC investments compared to the relatively more general human capital acquired from experience as a management consultant.

Robustness. Table IA11 presents additional results where regression samples also include investment professionals without any observed lifetime investments. The lifetime success measures for these professionals take a value of zero by construction. Results tend to be stronger across all covariates, both statistically and economically, when the best performing VCs are compared to the universe of professionals that have worked on the investment team at a U.S. VC firm.

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 of 2019 and earlier 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. 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 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), the status of the fund (e.g., fully invested versus liquidated), and the industry focus of the fund. Standard errors are clustered at the vintage year level. 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 person level, affiliations with successful companies tend to have been made in funds where the team members possess particular characteristics. Funds where the team includes a VC with a track record containing 1-, 2-, or 5+ successful investments are incrementally more likely to have more successful investments in the fund. Funds

where the team includes a white VC (94% of funds) tend to invest in about 1.69 times as many ($= e^{0.526}$) companies with a successful outcome (i.e., 69% more) compared to the 6% of funds that do not include any white team members. 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 is also directionally higher on average compared to funds where none of the investors are female, though this difference is not statistically significant.

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 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 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 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) tend to have made more investments in successful companies. The presence of former bankers does not distinguish funds with many successes, while the presence of technologists or consultants is associated with marginally more successful investments. Funds that allow a VC within their first five years in the industry to lead at least one investment also tend to include a higher count of successful investments.

Relation with Net of Fee Returns. In contrast to the prior results at the deal, person, and the fund-count level, the results presented in the last two columns of Table 7, fail to present 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. We examine this possibility in Table IA12 and Table IA13, where we focus on results estimated within funds sponsored by small teams (where the composition of the full team is less likely to wash out the contribution of a single VC) or based on various aggregations of the average characteristics of the team. Within these focused subsamples, human capital also predicts successful deal counts, but interestingly does not predict net of fee fund returns.[13] We interpret these results to mean that the characteristics of the full team are unlikely to attenuate those of a single VC.

Another interpretation of this result 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. Equivalently, deal-level returns may be attenuated when combined into a fund. We investigate this possibility in two ways. First, Section 3.4 directly tests this hypothesis by estimating the economic value of VC investments. The results suggest this explanation is also unlikely as the same human capital characteristics that predict the lifetime success of VCs (by counts of successful investments) also predicts the dollar value of profits they generate. Second, Table IA15 focuses on results estimated within funds where we observe only a few investments (where the effects of other deals are less likely to attenuate the effects of any winners). Within these focused subsamples, and inconsistent with deals canceling one another out completely, human capital also predicts successful deal counts, but not net of fee fund returns.

These results leave two main plausible interpretations. First, VCs are able to capture most of the returns to their human capital without splitting this value with their LPs. More successful VCs are able to charge higher fees by increasing carried interest or changing other contractual terms in their favor such that the presence of particular characteristics may correlate 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. Alternatively, the currently available

[13] Table IA14 presents a similar set of findings based on how similar firm teams on demographic, education, and work experience dimensions, where, for the most part, more diverse teams see a higher count of successful deals, but tend not to deliver higher fund-level IRRs or TVPIs.

commercial data on VC fund returns does not provide sufficient variation and power for us to successfully observe the correlation between fund-level returns and human capital characteristics.

3.4 The Economic Value of VC Investments

Our previous results measure the success of a venture investment primarily based on outcomes at the company-level. But are these investments consequential, translating to large differences in economic value across VCs? Our data further allow us to document the lifetime dollar value generated by US VCs' investments and its relation to their characteristics. The gross value of an investment made by VC i in company c during round d as of exit year T equals the VC's ownership percentage multiplied by the value of the company as of year T:

$$\text{Gross Investment Value}_{i,c,d,T} = \left(\frac{K_{i,c,d}}{V_{c,d}} \left[\prod_{j=d+1}^{N} \left(1 - \frac{K_{c,j}}{V_{c,j}} \right) \right] \times V_{c,T} \right), \tag{1}$$

where $K_{i,c,d}$ denotes the dollar value invested in round d, and $V_{c,d}$ denotes the post-money valuation of company c during round d.

Calculating Gross and Net Values of VC investments. Equation (1) relies on several different inputs. First, this formula dilutes each round's investment based on the money raised in subsequent rounds. Incorporating subsequent dilution takes into account one of the most important features of raising capital with multiple rounds of financing (Gornall and Strebulaev 2023).

Second, the exit value of the company, $V_{c,T}$ is derived from multiple types of financing events. If the company exited via IPO or M&A, we use its pre-money value as of the exit event. If the company has not yet exited, its valuation is not directly comparable with the valuations obtained from exit events given the presence of various contractual features. For these still-private companies, we account for this by multiplying the most recent post-money valuation by $1 - 0.32 = 0.68$ given results reported in Gornall and Strebulaev (2020) showing that the average overvaluation of unicorns is 48% (implying a haircut percentage of $1 - 1/1.48 = 0.32$).[14]

[14] An alternative approach would estimate that Gornall-Strebulaev model to approximate the fair value of individual VC-backed companies whenever possible. This requires backing out contractual terms, as discussed in Gornall and

Third, this calculation requires the investment amount ($K_{i,c,d}$), and post-money valuations per round ($V_{c,d}$). We acquire these data primarily from PitchBook. For companies that went public in the U.S., we further adjust individual ownership data based on hand-collections of regulatory S-1 filings listing beneficial ownership data. In some cases, we impute missing values, discussed in detail in Section IA.2. The main effect of this restriction is that some investments must be excluded because this calculation further requires round level information. This reduces our sample from about 130,000 person-company pairings to about 98,000 person-company pairings. These 98,000 pairings benefit from more detailed data obtained from 143,096 individual investments in 46,372 startups by 12,151 VCs.

Fourth, we further calculate the net profits resulting from each investment by subtracting its cost to VC i, equal to $K_{i,c,d}$. In an additional more conservative calculation, we also adjust the cost of the investment assuming the opportunity cost corresponds to the market returns in excess of the risk-free rate (obtained from Ken French's data library) over the holding period:

$$\text{Investment Cost}_{i,c,d,T} = K_{i,c,d} \prod_{\tau=t(d)}^{\tau=T} (1 + \beta_{i,c,d}(r_\tau^M - r_\tau^f) + r_\tau^f). \tag{2}$$

We set $\beta_{i,c,d} = 1$, which reports the dollar value of the VCs' stake relative to the value of having invested the same amount in the market portfolio entering and exiting at the same time, similar in spirit to the Kaplan and Schoar (2005) Public Market Equivalent. All net profit measures are reported in dollars of 2024 purchasing power.

The exit date, T, equals the date of the IPO or acquisition, which assumes VCs hold their stakes until the first major liquidity event.[15] If the investment is still active and not yet exited, T is set to the earlier of (a) January 31, 2026 or (b) five years after the VC last invested in the company. We assume an investment is active for VC i if it meets the following four conditions: (1) it has raised new financing since 2021; (2) VC i invested in the company since 2016; (3) the company has not gone bankrupt or out of business; and (4a) the company is five years or younger or (4b) it is

Strebulaev (2023).

[15]The development of the secondary market and rise of inter-investor transactions could adjust this assumption. VCs sometimes also do not fully exit their investments until well after an IPO (e.g., Gahng (2026)).

older than five years and has a post-money valuation of at least $10 million. Section IA.2 provides statistics on the underlying rounds, about 6% of which result in an IPO exit, 25% in an M&A exit, 36% that are still active and 32% that are presumed to be expired.

Statistics on Concentration. Table 8 summarizes the distribution of VC investment-level profits after different opportunity cost adjustments. In round numbers, the average investment results in $14 million of gross profits, $8 million in net profits, and $4 million in net profits if the opportunity cost of VC investments is adjusted for contemporaneous market returns assuming β is equal to one. Depending on how conservative the outside return is assumed to be, between 22% and 32% of round-level investments have positive net profits.

Panels B and C of Table 8 describe net profits at the level of startups and VCs respectively, emphasizing that the profits from these investments are concentrated in a relatively small share of the companies and individual VC investors in our sample. Between 15% and 24% of companies are credited with positive net profits. Between 20% and 40% of individual VCs have investments that cumulatively generate positive lifetime profits. Table IA16 summarizes the distribution of investment amounts and profits based on whether the VC×deal relationship is (a) a lead relationship; (b) a board relationship; (c) early stage; or (d) later stage.

Figure 5 further displays the striking concentration in these profits across individual VCs, showing that most of these profits are concentrated in only a few hundred VCs. This figure uses net profits that do not adjust for contemporaneous market returns over the holding period, which results in a more conservative concentration estimate. We calculate the total net profits in our sample across all VCs to be just over 1.2 trillion dollars (in 2024 dollars). Figure 5 then reports the sum of net profits across the lowest-X% of VCs in the sample for varying levels of X, e.g., $\sum_{\text{Lowest-99\%}} \text{Net Profits}_i/\$1.2$ trillion. The lowest 99% of VCs account for only about 43% of sample net profits. Conversely, one percent of VCs (about 120 VCs) account for 56.6% of all net profits in our data, equal to about $680 billion. Five percent of VCs (about 600 VCs) account for 90% of all net profits in our data, equal to roughly $1.08 trillion. The remaining 95% of VCs combine to account for the remaining $120 billion in net profits.

Relation with Characteristics. Table 9 presents regressions of the lifetime profits of these VCs their characteristics, analogous to the person-level results presented in Table 6. Specifications benefit from a fixed effect for the year the VC first joined the industry and cluster standard errors at the entry-year cohort level, though require we observe all covariates for each VC. Figure 6 summarizes the relationship between lifetime economic value and profits visually.

The main finding is that many of the same characteristics that predict the quantity of investments in successful companies a VC makes also predict the lifetime economic value generated by that VC's investments. In terms of demographics, the investments of female VCs tend to have resulted in lifetime gross profits that are about $50 million lower compared to that of male VCs that joined the industry in the same year. Much of the lower value is accounted for by investment timing and amounts, as the gap declines to $18 million and fails to attain statistical significance after adjusting for costs and contemporaneous market returns.

Business majors also tend to have generated less lifetime value compared to non-business majors. VCs from more prestigious undergraduate schools – namely Ivy or Ivy-plus schools – have generated incremental lifetime gross profits of between $80 and $117 million and incremental lifetime net profits of between $56 and $81 million. VCs with MBAs have, on average, generated lower lifetime profits. VCs with an MBA from HBS have generated higher gross and net profits, though not significant market adjusted net profits. One of the most pronounced characteristics of VCs that have generated the highest lifetime profits, including market adjusted net profits, is whether they have an MBA from Stanford GSB.

VCs whose investments have contributed relatively more profits again tend to have had CEO or founder experience at a successful startup. VCs with experience at a technology firm also made investments with higher economic value, equal to $90 million in gross profits or $54 million in market adjusted net profits.

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 that allows us to approximate such an experiment is 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 IA17 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 96 through 100 or 91 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).[16]

Table IA18 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 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 conjunction with an investment manager TrueBridge in recent years) uses.[17] To arrive at rankings, Forbes solicits information on attribution from VCs and their firms directly. Table IA19 reports quotations about the reported methodology. Even though the detailed methodology has never been publicly disclosed and there are some indicators that there are additional factors at play in ranking determination, the available evidence suggests that the methodology as reported 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

[16] 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.

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

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.[18]

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 U.S. VCs credited in our data with being important investors in SpaceX as of 2022 to produce their estimated rankings for 2023. 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 (Ritter 2026).

Our replication then ranks each VC based on the sum of points awarded to them from all companies they are credited with investing in. Pooled across years, 46% of all entries on the Midas List are in our top-100 ranked VCs for the corresponding year. 56% are in our highest scoring 150 VCs and 63% are in our highest scoring 200. These percentages are computed across all Midas List entries, including the non-U.S. and non-venture honorees outside our U.S. VC ranking universe;

[18] As a robustness exercise, we also 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.

among the U.S. venture capitalists we rank, about 60% appear in our top-100. Figure 7 further summarizes our replication results 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 71% 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 33% 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 approximately a 90% 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 31% of the time, and our top-500 approximately 73% of the time.

Taken together, these results indicate that our replication procedure accounts for a large part of the list that Forbes creates, though there are a number of non-trivial misses on both sides. That the Forbes ranking process includes idiosyncratic inclusions and exclusions for unreported reasons strengthens our counterfactual tests in the next section.

4.2 The Effect of Inclusion on the Midas List

4.2.1 Counterfactual #1: Surprise Makes Versus Surprise Misses.

Table 10 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:

$$Y_{i,t} = \beta\left(Post_{i,g,t} \times Treat_{i,g}\right) + \gamma_{i,g} + \delta_{g,t} + \varepsilon_{i,g,t}, \tag{3}$$

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 ($\delta_{g,t}$), and independently double cluster standard errors by VC identity and by year within each stack.

The main outcome variables we focus on in these regressions are measures for whether professional i was able to invest in startups that are otherwise challenging to receive an allocation for. The key idea we test is that inclusion on the Midas list amplifies VCs' performance by improving access to high-quality companies. We employ several measures of perceived and realized startup quality; namely, (i) whether the company achieved a high valuation (stratified by the timing of when the VC first invested in the startup), (ii) whether the company had raised capital from many VCs, or (iii) whether the company achieved an otherwise high value exit. Highly valued and better performing investments are more likely to cluster among high-quality startups. Specifications include indicators for whether the VC made any particular type of higher-quality investment in year t (the extensive margin), alongside additional tests for the count of each type of higher-quality investment they made in year t.

The results presented in Panel A of Table 10 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 subsequently be credited with investments in high-quality startups. Panel A reports that surprise makes and surprise misses are equally likely to invest in the most popular companies (those that are in the top-quartile or decile of the number of VCs from which they have cumulatively received an investment from). Columns 3 and 4 show they are also equally likely to invest in companies after the company had achieved a post-money valuation of $1 billion or $5 billion. Column 5, however, shows that VCs are 5.5% more likely to invest in a company that subsequently

has a successful outcome following a surprise make, an increase which is statistically and economically significant, equaling 10% of the regression sample mean (and substantially higher than the population mean). The increase in successful investments following a surprise make comes primarily from an uptick in investments that are highly valued, which shows a 5% increase in companies that later achieve a valuation of $5 billion or higher. By contrast, the incidence of investments that are exited at high multiples, shows little change following a surprise inclusion on the list.

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 8 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.

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 lowest-ten ranked professionals on the list to, respectively, the first five and first-ten professionals who we predicted to be on the list but were not. We again estimate stacked DiD regressions, as in Equation (3), 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 the five lowest ranked U.S. VCs appearing on the Midas list (ranked 96–100) to those ranked 101–105 that we estimate to have just missed the list. The identifying assumption is parallel trends, which we visually inspect. Relative to the surprise makes comparisons, this group will, by definition, perform comparisons among relatively lower ranked VCs, where access to the Midas list could plausibly be more impactful.

Panels B and C of Table 10 present our results. Compared to the counterfactuals based on the surprise misses and makes, the results are qualitatively similar, but the effect on the composite successful-outcome indicator is not statistically significant in these narrower near-make windows

(0.001 in the ±5 window and 0.072 in the ±10 window). Results are, however, driven by a propensity to invest in companies before they achieve high valuations, proxied by a valuation of at least $5 billion in this specification. In the five-person bandwidth (Panel B), barely making the list raises the likelihood of investing in a company that later reaches a $5 billion valuation by 14.3 percentage points (about 1.1 times the sample mean), the likelihood of a pre-IPO investment by 11.6 percentage points, and the likelihood of a high-multiple exit by 7.2 percentage points. In the ten-person bandwidth (Panel C), the effect on $5 billion valuations is 9.4 percentage points (about 40% of the sample mean), with comparable effects on pre-IPO and high-multiple-exit access. Figure IA2 reports dynamic specifications for each window. The evidence is somewhat stronger compared to the first counterfactual, showing upticks in successful investments while failing to demonstrate visual or statistical violations of the parallel trends assumptions.

Count Outcome Results. Previous results reported the probability of gaining access to a high-quality startup following surprise inclusion on the Midas List. Table IA20 re-estimates regressions using count variables instead, estimated via Poisson Regressions. Results are qualitatively similar, but show larger increases across the various measures of high-quality startups, especially among the frequency with which VCs marginally included on the Midas list invest in highly valued companies, before and after the company first achieves a high valuation.

Economic Value of Midas List Inclusion. Table IA21 presents results estimating the effect of inclusion on the Midas list on the economic value of access to new investments using our main counterfactuals. The main outcome variables are the inflation-adjusted (2024 dollars) net profits of all investments professional i made in year t as of 2026. Section 3.4 details the profits calculation. If round-level information for a given investment is not available, it is treated as missing.

The results across each specification show positive effects of Midas list inclusion when comparing surprise makes to surprise misses or near misses to near makes. Marginal inclusions lead to an increase in the amount invested of about $6 million in a given year, about 40% of the regression sample mean. Compared to professionals that were predicted to be on the list, but were not, the new investments for the surprise makes have gross profits that are about $62 million higher,

translating to incremental net profits of about $56 million. Magnitudes nearly double for the near makes relative to the near misses, again suggesting inclusion is most impactful for lower ranked VCs.

Summarizing Results. 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 the extent to which individual differences among investment professionals in the venture capital industry can explain investment deal outcomes, lifetime investment performance, career progression, and fund-level returns. We do so by assembling the largest and most comprehensive dataset of individual U.S. VCs to date. We use 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 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.

References

Acemoglu, D., & Pischke, J.-S. (1998). Why Do Firms Train? Theory and Evidence. *Quarterly Journal of Economics*, *113*(1), 79–119.

Baker, A., Larcker, D. F., & Wang, C. C. (2022). How Much Should we Trust Staggered Difference-In-Difference Estimates? *Journal of Financial Economics*, *144*(2), 370–395.

Bernstein, S., Giroud, X., & Townsend, R. R. (2016). The impact of venture capital monitoring. *Journal of Finance*, *71*(4), 1591–1622.

Bertrand, M., & Mullainathan, S. (2004). Are Emily and Greg More Employable Than Lakisha and Jamal? A Field Experiment on Labor Market Discrimination. *American Economic Review*, *94*(4), 991–1013.

Bessembinder, H. (2018). Do Stocks Outperform Treasury Bills? *Journal of Financial Economics*, *129*(3), 440–457.

Calder-Wang, S., & Gompers, P. A. (2021). And the children shall lead: Gender diversity and performance in venture capital. *Journal of Financial Economics*, *142*(1), 1–22.

Calder-Wang, S., Gompers, P. A., Huang, K., & Levinson, W. (2023a). Diversity in Venture Capital. *The Palgrave Encyclopedia of Private Equity*.

Calder-Wang, S., Gompers, P. A., & Sweeney, P. (2023b). Venture Capital's 'Me Too' Moment. *NBER Working Paper No. w28679*.

Chen, J., & Ewens, M. (2025). Venture Capital and Startup Agglomeration. *Journal of Finance*, *80*(4), 2153–2198.

Chevalier, J., & Ellison, G. (1999). Are Some Mutual Fund Managers Better Than Others? Cross-Sectional Patterns in Behavior and Performance. *Journal of Finance*, *54*(3), 875–899.

Cici, G., Gehde-Trapp, M., Göricke, M.-A., & Kempf, A. (2018). The Investment Value of Fund Managers' Experience Outside the Financial Sector. *Review of Financial Studies*, *31*(10), 3821–3853.

Cochrane, J. H. (2005). The Risk and Return of Venture Capital. *Journal of Financial Economics*, *75*(1), 3–52.

Cohn, J. B., Liu, Z., & Wardlaw, M. I. (2022). Count (and Count-Like) Data in Finance. *Journal of Financial Economics*, *146*(2), 529–551.

Coval, J. D., & Moskowitz, T. J. (2001). The Geography of Investment: Informed Trading and Asset Prices. *Journal of Political Economy*, *109*(4), 811–841.

Doidge, C., Karolyi, G. A., & Stulz, R. M. (2017). The U.S. listing gap. *Journal of Financial Economics*, *123*(3), 464–487.

Duevski, T. (2025). Human Capital Breadth and the Financing of Innovative Startups [HEC Paris Research Paper No. FIN-2025-1605].

Ewens, M., & Rhodes-Kropf, M. (2015). Is a VC Partnership Greater Than the Sum of Its Partners? *Journal of Finance*, *70*(3), 1081–1113.

Ewens, M., & Townsend, R. R. (2020). Are early stage investors biased against women? *Journal of Financial Economics*, *135*(3), 653–677.

Gahng, M. (2026). Cash or Stock? Agency Frictions in Venture Capital Distributions. *Working Paper*.

Gao, X., Ritter, J. R., & Zhu, Z. (2013). Where Have All the IPOs Gone? *Journal of Financial and Quantitative Analysis*, *48*(6), 1663–1692.

Garfinkel, J. A., Mayer, E. J., Strebulaev, I. A., & Yimfor, E. (2025). Alumni Networks in Venture Capital Financing. *Journal of Financial and Quantitative Analysis*.

Gompers, P., Kovner, A., & Lerner, J. (2009). Specialization and Success: Evidence from Venture Capital. *Journal of Economics & Management Strategy*, *18*(3), 817–844.

Gompers, P. A., Gornall, W., Kaplan, S. N., & Strebulaev, I. A. (2020). How do venture capitalists make decisions? *Journal of Financial Economics*, *135*(1), 169–190.

Gompers, P. A., & Mukharlyamov, V. (2025). Transferable Skills? Founders as Venture Capitalists. *National Bureau of Economic Research Working Paper*.

Gompers, P. A., Mukharlyamov, V., Weisburst, E., & Xuan, Y. (2022). Gender Gaps in Venture Capital Performance. *Journal of Financial and Quantitative Analysis*, *57*(2), 485–513.

Gornall, W., & Strebulaev, I. A. (2020). Squaring Venture Capital Valuations with Reality. *Journal of Financial Economics*, *135*(1), 120–143.

Gornall, W., & Strebulaev, I. A. (2021). The Economic Impact of Venture Capital: Evidence from Public Companies. *SSRN Working Paper*.

Gornall, W., & Strebulaev, I. A. (2023). The contracting and valuation of venture capital-backed companies (B. E. Eckbo, G. M. Phillips, & M. Sorensen, Eds.). *1*(1), 3–76.

Harris, R. S., Jenkinson, T., & Kaplan, S. N. (2014). Private Equity Performance: What Do We Know? *Journal of Finance*, *69*(5), 1851–1882.

Harris, R. S., Jenkinson, T., Kaplan, S. N., & Stucke, R. (2023). Has Persistence Persisted in Private Equity? Evidence from Buyout and Venture Capital Funds. *Journal of Corporate Finance*, *81*.

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

Hochberg, Y. V., Ljungqvist, A., & Lu, Y. (2007). Whom You Know Matters: Venture Capital Networks and Investment Performance. *Journal of Finance*, *62*(1), 251–301.

Howell, S., & Nanda, R. (2024). Networking Frictions in Venture Capital, and the Gender Gap in Entrepreneurship. *Journal of Financial and Quantitative Analysis*, *59*.

Ivashina, V., Rotermund, S.-D., & Wallace-Wright, Z. (2026). Staffing the Private Debt Boom: Skills, Talent, and Consequences. *Working Paper*.

Jackson, B. (2025). How do Barbarians Get to the Gates? Private Equity Careers, Styles, and Returns. *SSRN Working Paper*.

Kacperczyk, M., Sialm, C., & Zheng, L. (2005). On the Industry Concentration of Actively Managed Equity Mutual Funds. *Journal of Finance*, *60*(4), 1983–2011.

Kaplan, S. N., & Schoar, A. (2005). Private Equity Performance: Returns, Persistence, and Capital Flows. *Journal of Finance*, *60*(4), 1791–1823.

Kempf, E., Manconi, A., & Spalt, O. (2017). Learning By Doing: The Value Of Experience And The Origins Of Skill For Mutual Fund Managers. *SSRN Working Paper*.

Kerr, W. R., Nanda, R., & Rhodes-Kropf, M. (2014). Entrepreneurship as Experimentation. *Journal of Economic Perspectives*, *28*(3), 25–48.

Lerner, J. (1995). Venture Capitalists and the Oversight of Private Firms. *Journal of Finance*, *50*(1), 301–318.

Lerner, J., & Nanda, R. (2020). Venture Capital's Role in Financing Innovation: What We Know and How Much We Still Need to Learn. *Journal of Economic Perspectives*, *34*(3), 237–61.

Malmendier, U., & Tate, G. (2009). Superstar CEOs. *Quarterly Journal of Economics*, *124*(4), 1593–1638.

Nanda, R., Samila, S., & Sorenson, O. (2020). The persistent effect of initial success: Evidence from venture capital. *Journal of Financial Economics*, *137*(1), 231–248.

Oyer, P. (2008). The Making of an Investment Banker: Stock Market Shocks, Career Choice, and Lifetime Income. *Journal of Finance*, *63*(6), 2601–2628.

Ritter, J. R. (2026). IPO Data [Warrington College of Business, University of Florida, Gainesville].

Rosen, S. (1981). The Economics of Superstars. *American Economic Review*, *71*(5), 845–858.

Sørensen, M. (2007). How Smart Is Smart Money? A Two-Sided Matching Model of Venture Capital. *Journal of Finance*, *62*(6), 2725–2762.

Strebulaev, I. A., & Wang, A. (2021). Organizational Structure and Decision-Making in Corporate Venture Capital. *SSRN Working Paper*.

Topel, R. H., & Ward, M. P. (1992). Job Mobility and the Careers of Young Men. *Quarterly Journal of Economics*, *107*(2), 439–479.

Figure 1: Example Archived Webpages Over Time

Panel A: New Enterprise Associates 2005 Team Page



Panel B: New Enterprise Associates 2025 Team Page

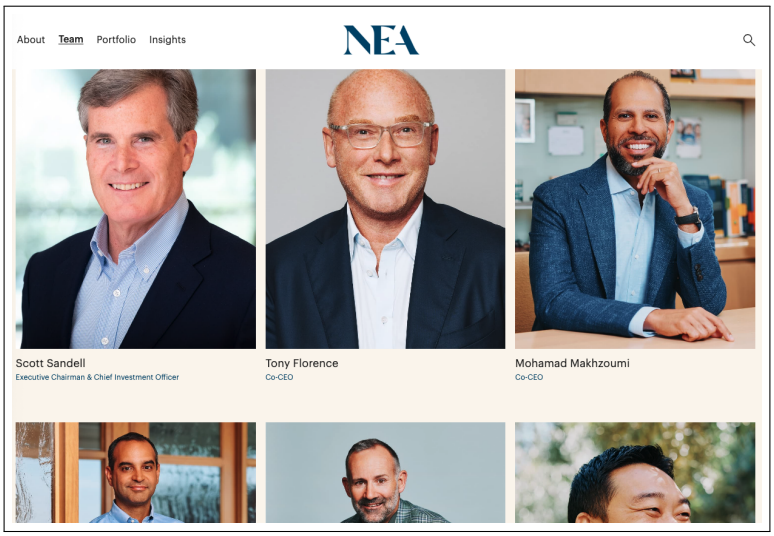


Figure 1: Displays partial snapshots of example webpages archived from the Wayback Machine used to construct the dataset of VC investment professionals. Panel A shows the 2005 team page for VC firm New Enterprise Associates (https://web.archive.org/web/20050626013845/http://www.nea.com/Partners/invops/). Panel B displays the 2025 team page for New Enterprise Associates (https://web.archive.org/web/20250629182903/https://www.nea.com/team).

Figure 2: Sources of VC Investment Level Outcomes

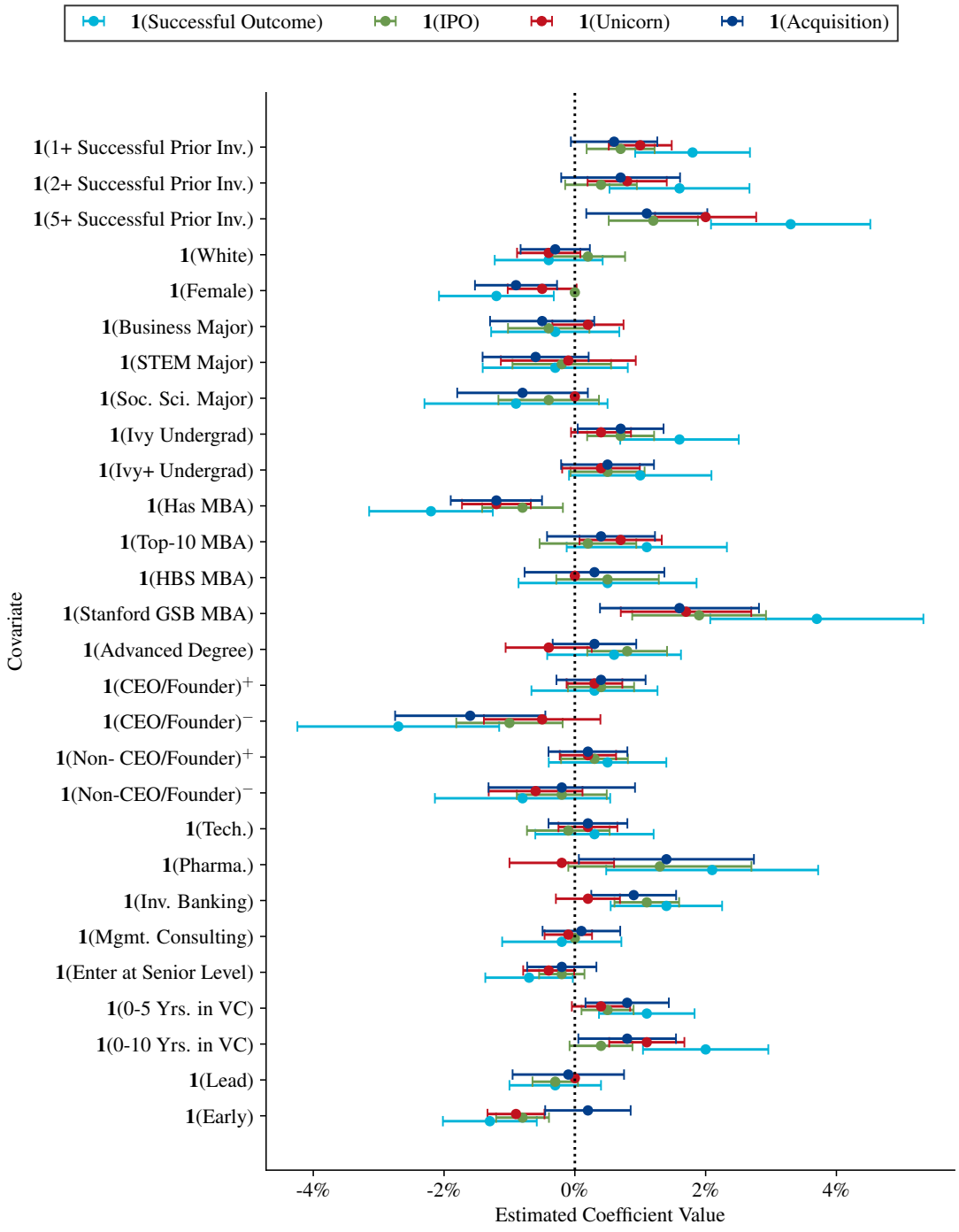


Figure 2: Plots coefficients from four separate regressions of indicators for the success of a VC deal on characteristics of the VC that made the deal. All specifications include fixed effects for: the year of the investment, the state of the target company, the industry of the target company, the age 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

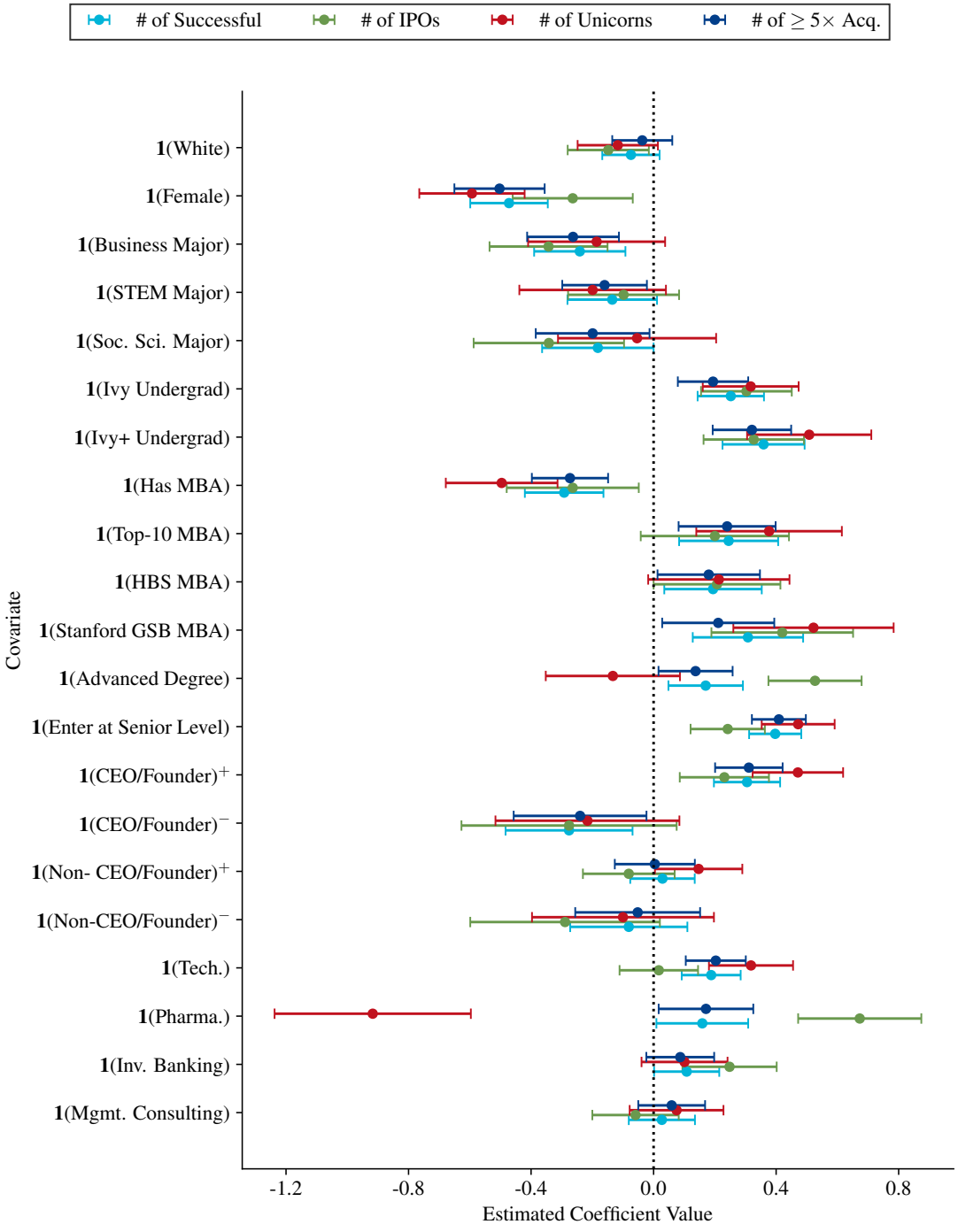


Figure 3: Plots coefficients from four separate Poisson regressions of the total number of successful investments that each individual VC in our sample has made. All specifications include fixed effects for the year the VC first was employed by an institutional U.S. VC firm. Standard errors are clustered 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

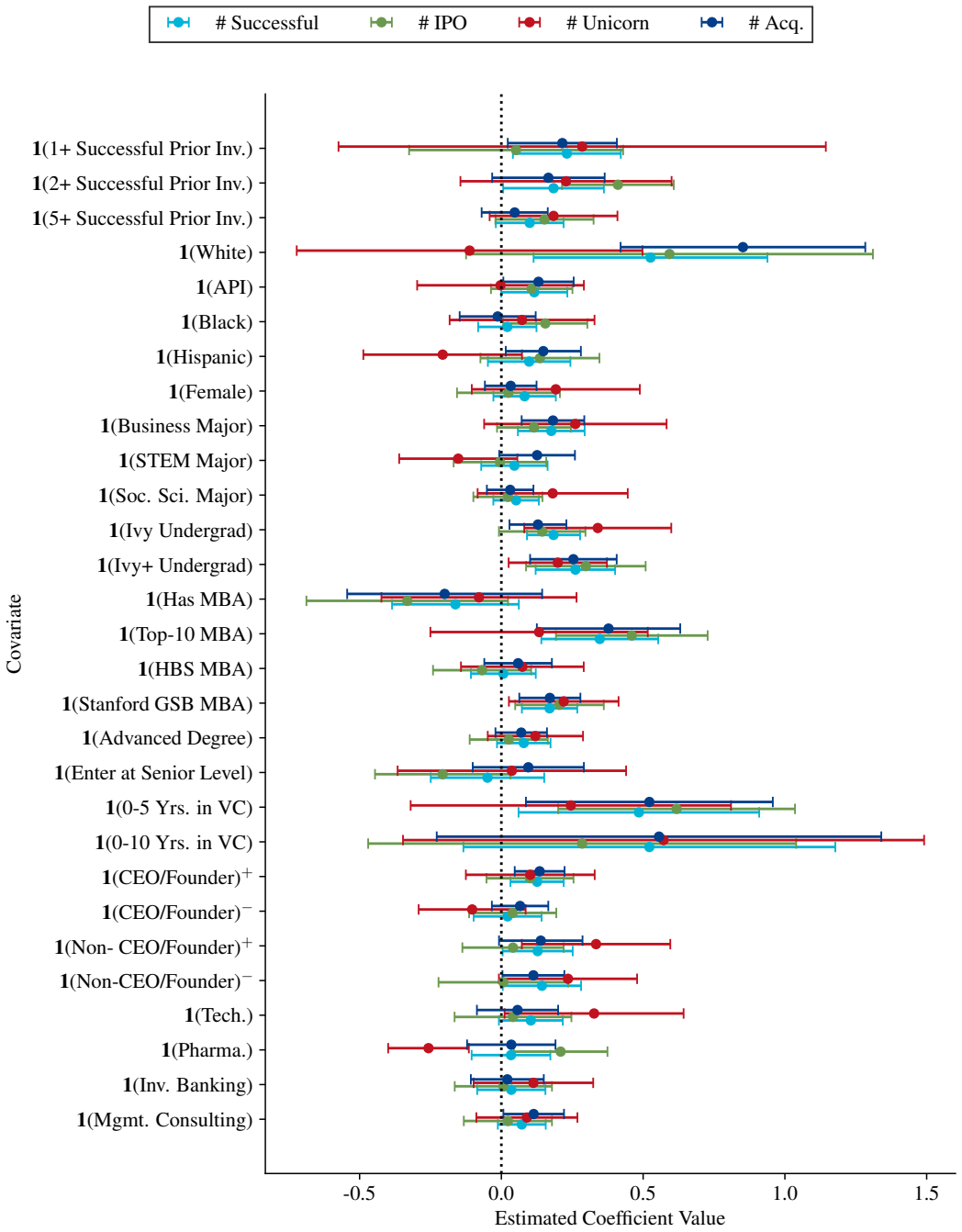


Figure 4: Plots coefficients from separate regressions of the returns of each fund on the characteristics of the professional most involved with the fund via our data. All specifications include controls for the log size of the fund and fixed effects for the vintage of the fund and the category and industry focus 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 2019 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: Concentration of VC Economic Value

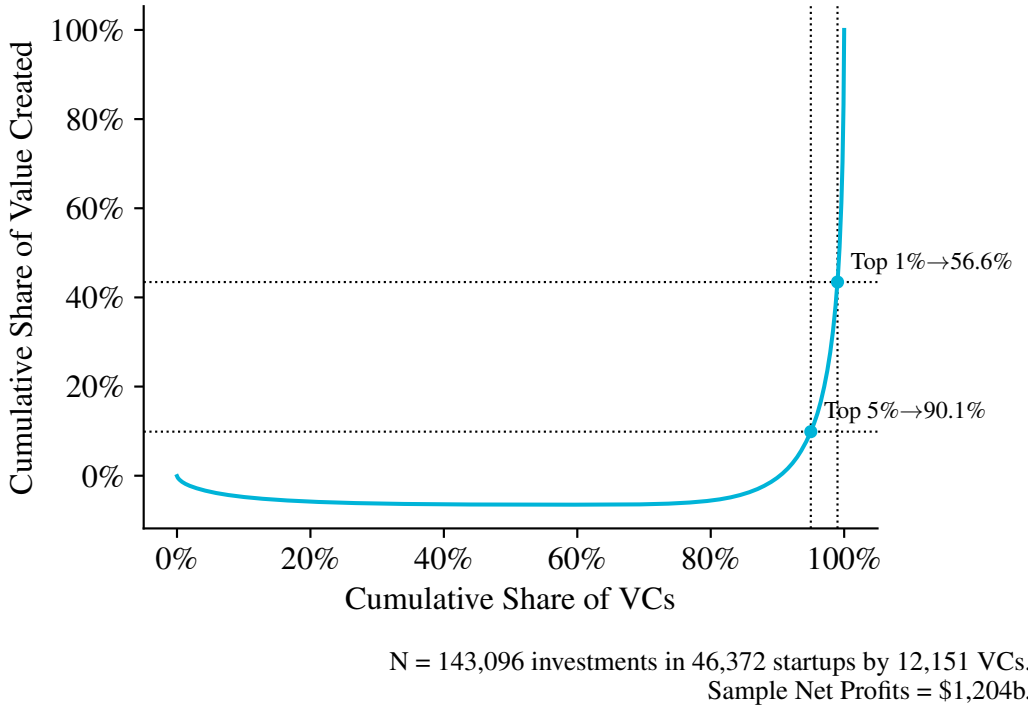


Figure 5: Plots the fraction of net profits generated by the bottom- X% of VCs in our sample. For instance, the plot shows that 1% of VCs accounted for about 57% of net profits. Net profits are calculated following Equation (1) and by assuming the cost is equal to the amount invested at the individual VC × Company × Round level. Net profits are in dollars of 2024 purchasing power and are then aggregated at the individual VC level across all individual investments.

Figure 6: Sources of Cumulative VC Economic Value

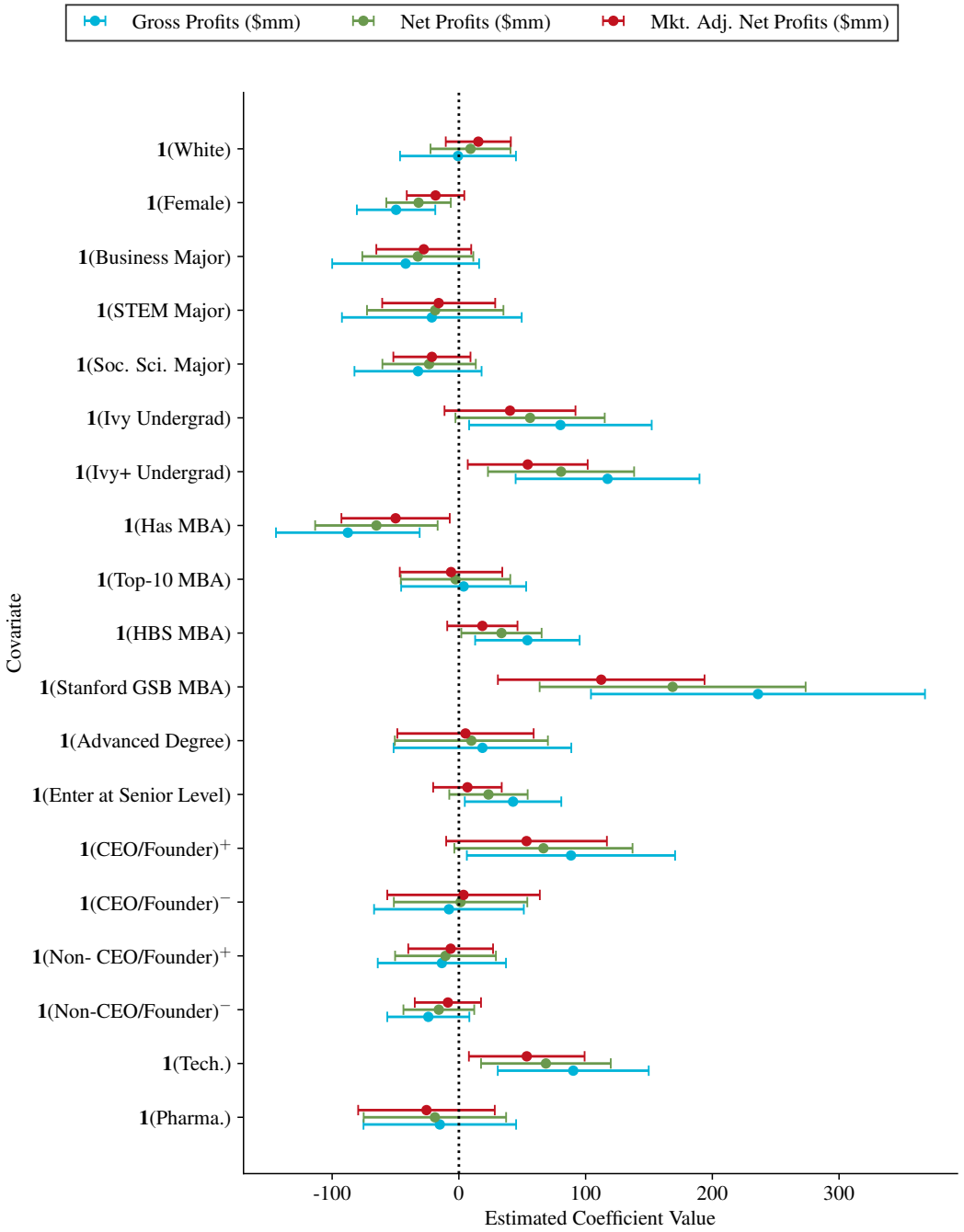
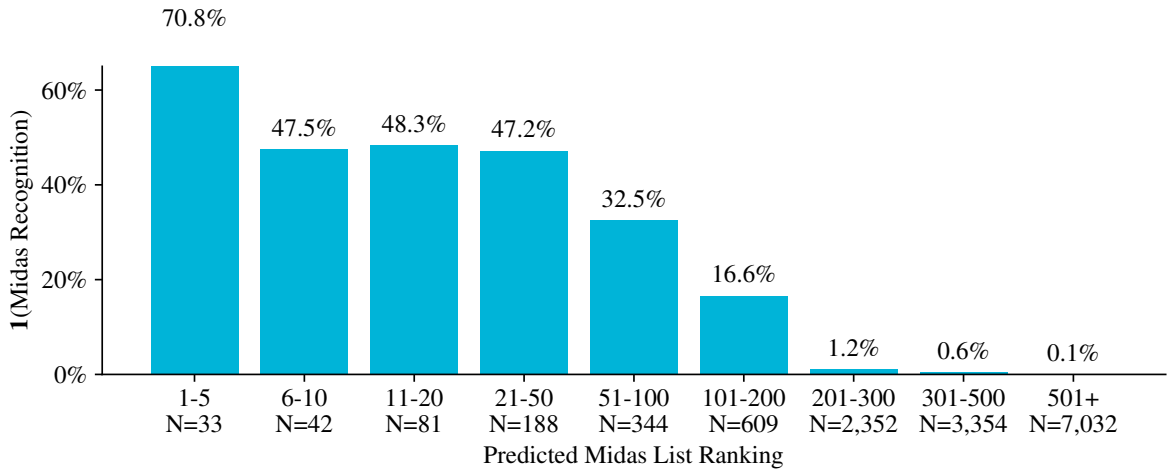


Figure 6: Plots coefficients from three separate OLS regressions of the lifetime profits of VCs' investments on their characteristics. Lifetime profits are calculated following Equation (1). Costs are calculated following Equation (2), which varies by outcome. All specifications include fixed effects for the year the VC first was employed by an institutional U.S. VC firm. Standard errors are clustered at the start year level. Horizontal bars display 95% confidence intervals. Table 9 displays the estimated coefficient values.

Figure 7: Midas List Predictions

Panel A: Inclusion on the Midas List by Predicted Rank



Panel B: Predicted Rank by Observed Midas Ranking

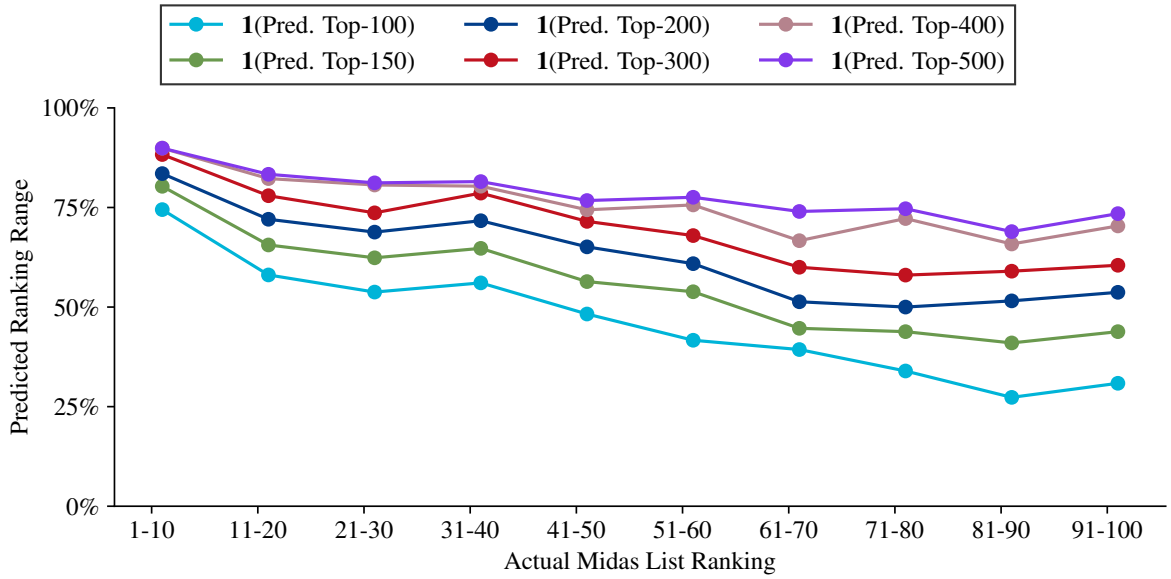


Figure 7: Panel A displays the likelihood for whether a VC professional is included on the Midas list in a given year based on the predicted likelihood that the VC professional will be included on the list for that year. The unit of observation is the VC professional × year. "N" refers to the number 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 8: Access to High Quality Startups Following Midas List Surprise Makes

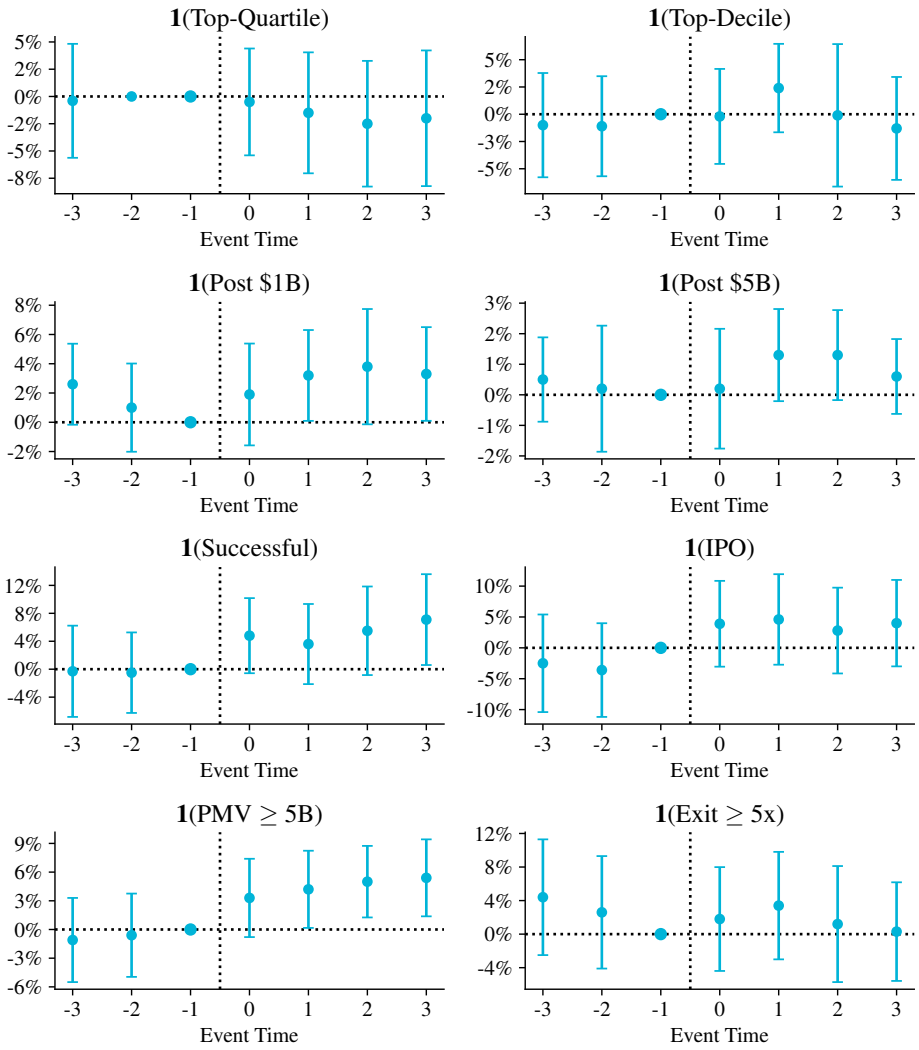


Figure 8: Plots dynamic stacked difference-in-differences estimates of the effect of Midas List recognition on individual VCs' investing activity each calendar year. The unit of observation is the individual VC×calendar year. Indicators denote whether a professional made an investment of a given type each year relative to the Midas List treatment event. Top-25p and Top-10p measure whether a company was in the top-quartile or decile of unique VCs it raised capital from as of the VC's investing year. Post variables are indicators for whether the VC invested in the startup after it had already achieved a high valuation. Indicators in remaining plots take values of one only if the VC invested before the company achieved a particular outcome. 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	w/ 1+ Inv.	0	1–2	3–5	6+
# Professionals	103,909					
# Investment Professionals	37,290	16,425	10,133	3,883	1,377	1,034
w/ Demographics	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
w/ Education	72.9%	86.0%	84.3%	86.8%	90.5%	92.4%
w/ Work Exp	72.5%	84.2%	83.4%	84.2%	87.1%	88.0%
Panel A: Demographics						
1(White)	69.7%	75.0%	73.7%	75.8%	78.9%	78.4%
1(Female)	23.0%	16.3%	19.9%	12.8%	8.3%	5.4%
Panel B: Pre-VC Education						
1(Ivy Undergrad)	16.4%	17.5%	15.4%	18.6%	21.6%	27.1%
1(Ivy+ Undergrad)	9.9%	10.3%	9.0%	10.6%	13.0%	17.1%
1(Business Major)	40.5%	36.5%	39.3%	34.4%	31.1%	25.4%
1(STEM Major)	35.7%	39.5%	35.8%	43.7%	44.2%	52.3%
1(Soc. Sci. Major)	10.8%	10.7%	11.3%	9.6%	11.2%	8.5%
1(Humanities/Arts Major)	9.0%	9.4%	9.6%	8.6%	9.8%	9.7%
1(Has MBA)	31.5%	38.0%	34.4%	41.2%	44.0%	49.6%
1(Top-10 MBA)	14.3%	20.4%	16.4%	23.5%	29.0%	36.9%
1(HBS MBA)	3.9%	5.9%	4.5%	6.5%	10.5%	12.5%
1(Stanford GSB MBA)	2.5%	3.9%	2.4%	5.0%	6.2%	11.8%
1(Advanced Degree)	10.4%	14.6%	13.3%	15.5%	17.9%	19.4%
Panel C: Pre-VC Experience						
1(CEO/Founder)$^{+}$	7.5%	13.4%	11.6%	14.1%	18.4%	22.1%
1(CEO/Founder)$^{-}$	3.0%	4.2%	4.8%	3.3%	3.6%	2.7%
1(Non- CEO/Founder)$^{+}$	12.3%	17.1%	17.4%	16.3%	16.2%	19.3%
1(Non-CEO/Founder)$^{-}$	4.8%	5.0%	5.9%	3.9%	3.3%	2.5%
1(Tech.)	28.6%	34.4%	33.4%	35.2%	36.3%	39.1%
1(Inv. Banking)	25.2%	23.3%	23.3%	23.2%	22.4%	24.5%
1(Mgmt. Consulting)	21.0%	21.3%	21.1%	20.7%	23.1%	22.3%
1(Pharma.)	7.1%	9.0%	7.9%	10.6%	10.4%	10.8%
1(Hedge Fund)	2.1%	2.0%	1.9%	2.1%	2.2%	2.5%
1(Private Equity)	7.1%	7.4%	7.0%	7.2%	9.3%	10.0%
1(Other Fin. Firm)	15.3%	15.6%	16.2%	15.8%	13.3%	12.2%
1(Govt.)	7.8%	8.1%	8.4%	8.3%	7.2%	6.4%
1(Law Firm)	3.1%	3.5%	3.6%	4.0%	2.6%	3.0%
1(Other)	36.7%	37.3%	40.5%	33.2%	32.9%	29.1%
Panel D: VC Experience						
1(Enter at Junior Level)	34.5%	16.3%	17.4%	14.8%	15.8%	10.5%
1(Enter at Middle Level)	15.8%	12.0%	12.4%	11.7%	10.4%	11.3%
1(Enter at Senior Level)	32.0%	40.3%	34.4%	45.5%	54.7%	62.9%
1([1,10) Yrs. in VC)	76.6%	69.3%	85.1%	60.0%	26.1%	6.6%
1([10,20) Yrs. in VC)	17.2%	23.2%	12.8%	32.9%	55.0%	45.6%
1(20+ Yrs. in VC)	6.2%	7.5%	2.1%	7.2%	18.8%	47.9%
1(Ever Midas List)	1.1%	2.4%	0.2%	0.9%	4.6%	26.6%
Avg. # of Successful Inv.	0.6	1.3	0.0	1.3	3.7	10.4

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. $^{+}$ denotes experience at a successful startup. $^{-}$ denotes experience at a startup that was not successful.

Table 2: Portfolio Company Characteristics by Outcome

	All	Successful	Not Successful
# Companies	68,010	7,991	61,603
w/ Founding Year	95.7%	97.1%	95.5%
w/ Industry	98.0%	99.2%	97.9%
w/ Country	98.0%	99.2%	97.9%
Panel A: Founding Years			
1(Pre-2000)	9.9%	21.7%	8.4%
1(2000-2009)	18.9%	34.0%	17.2%
1(2010-2019)	53.7%	43.0%	55.1%
1(2020+)	17.6%	1.2%	19.3%
Panel B: Company Industry			
1(Software)	43.6%	37.3%	44.5%
1(Commercial Services)	8.8%	6.6%	9.0%
1(Pharma/BioTech)	7.6%	15.5%	6.7%
1(Healthcare Devices)	4.1%	5.8%	3.8%
1(Media)	3.1%	2.5%	3.2%
Panel C: Company Country			
1(United States)	74.0%	76.1%	74.0%
1(United Kingdom)	4.3%	3.0%	4.5%
1(India)	2.6%	2.8%	2.5%
1(Canada)	2.6%	1.8%	2.7%
1(China)	2.4%	5.0%	2.0%
Panel D: Company State			
1(California)	29.1%	34.0%	28.9%
1(New York)	9.1%	7.3%	9.3%
1(Massachusetts)	5.9%	9.0%	5.6%
1(Texas)	3.8%	3.5%	3.8%
1(Washington)	2.6%	2.5%	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. IPOs include public listings via direct listings and SPACs. Characteristics of the companies are from PitchBook. "Not Successful" refers to companies that, as of our sample construction, have not yet been exited or had a liquidity event. Note that the Successful and Not Successful columns sum to more than the total because a company may appear in both: if some VCs invested prior to the company's successful outcome while others invested only after the company had already achieved a successful valuation, the former are credited with a successful investment and the latter are not, so the company contributes to both columns.

Table 3: Investment Characteristics by Outcome

	Outcome					
	All	IPO	Unicorn	Acq. ≥ 5× Entry	Successful	Not Successful
# Professionals × Companies	134,151	7,767	5,712	13,169	20,972	113,194
Panel A: Affiliation Type						
1(Board Seat)	48.9%	71.6%	52.4%	70.4%	66.4%	45.6%
1(Lead)	23.3%	17.6%	29.4%	21.7%	22.6%	23.4%
1(Early Stage)	61.4%	58.0%	60.7%	67.1%	62.1%	61.3%
Panel B: Investment Timing						
1(Pre-2000)	2.6%	16.9%	1.0%	7.8%	8.2%	1.6%
1(2001-2009)	17.2%	36.0%	7.0%	40.2%	30.6%	14.8%
1(2010-2019)	45.8%	43.7%	78.2%	50.1%	55.4%	44.0%
1(2020+)	34.4%	3.4%	13.8%	1.9%	5.9%	39.6%
Panel C: GP Prior Success						
1(Prev. Midas Recognition)	5.5%	7.5%	11.6%	7.9%	8.4%	4.9%
1(0 Prior Successful Inv.)	47.2%	36.5%	32.4%	38.6%	37.0%	49.1%
1(1+ Successful Prior Inv.)	52.8%	63.5%	67.6%	61.4%	63.0%	50.9%
1(2+ Successful Prior Inv.)	37.3%	45.4%	52.9%	43.9%	46.0%	35.7%
1(5+ Successful Prior Inv.)	18.0%	22.3%	29.5%	20.5%	22.8%	17.1%

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)	-0.834***	-0.718***	-0.275***	-0.302***	-0.178***	-0.288***
	(-151.03)	(-52.97)	(-31.85)	(-17.72)	(-24.15)	(-16.72)
1(White)	0.009**	0.012	0.025***	0.015	0.010	0.005
	(2.29)	(1.18)	(3.17)	(0.92)	(1.35)	(0.30)
1(Female)	-0.026***	-0.053***	-0.057***	-0.123***	-0.050***	-0.128***
	(-6.19)	(-4.37)	(-6.51)	(-5.65)	(-6.90)	(-5.98)
1(Business Major)	0.002	-0.014	-0.014	-0.040*	-0.009	-0.039
	(0.42)	(-1.18)	(-1.20)	(-1.81)	(-0.83)	(-1.55)
1(STEM Major)	0.006	0.006	-0.009	-0.021	-0.005	-0.021
	(1.12)	(0.49)	(-0.79)	(-0.98)	(-0.49)	(-0.88)
1(Soc. Sci. Major)	0.004	-0.016	-0.033**	-0.037	-0.009	-0.020
	(0.68)	(-1.15)	(-2.26)	(-1.35)	(-0.64)	(-0.65)
1(Ivy Undergrad)	0.007	-0.010	0.044***	0.029*	0.042***	0.082***
	(1.29)	(-0.98)	(4.46)	(1.68)	(4.51)	(4.33)
1(Ivy+ Undergrad)	0.023***	0.025*	0.020*	0.052***	0.047***	0.091***
	(3.45)	(1.91)	(1.68)	(2.66)	(4.15)	(4.12)
1(Has MBA)	0.024***	0.036***	0.057***	0.073***	0.028***	0.059***
	(4.33)	(3.13)	(5.29)	(3.94)	(2.70)	(2.93)
1(Top-10 MBA)	-0.000	-0.007	0.018	0.037	0.028**	0.030
	(-0.03)	(-0.48)	(1.30)	(1.62)	(2.07)	(1.19)
1(HBS MBA)	0.019*	0.021	0.030*	-0.004	0.037**	0.037
	(1.92)	(1.35)	(1.65)	(-0.15)	(2.00)	(1.25)
1(Stanford GSB MBA)	0.020*	0.017	0.042**	0.026	0.073***	0.081**
	(1.65)	(0.93)	(2.07)	(0.96)	(3.35)	(2.49)
1(Advanced Degree)	0.023***	0.043***	0.076***	0.103***	0.039***	0.064***
	(4.28)	(4.12)	(6.96)	(5.85)	(3.64)	(2.97)
1(CEO/Founder)$^{+}$	0.023***	0.040***	0.146***	0.149***	0.145***	0.170***
	(4.20)	(4.16)	(12.54)	(9.34)	(10.81)	(7.99)
1(CEO/Founder)$^{-}$	0.028***	0.062***	0.078***	0.136***	0.038**	0.149***
	(3.50)	(3.11)	(4.13)	(3.91)	(2.08)	(3.28)
1(Non-CEO/Founder)$^{+}$	0.039***	0.059***	0.074***	0.099***	0.051***	0.065***
	(7.08)	(5.18)	(7.37)	(5.99)	(5.17)	(3.27)
1(Non-CEO/Founder)$^{-}$	0.023***	0.046**	0.066***	0.057	0.040***	0.018
	(3.15)	(2.10)	(4.71)	(1.59)	(3.19)	(0.40)
1(Tech.)	0.020***	0.016*	0.073***	0.069***	0.058***	0.081***
	(4.42)	(1.90)	(8.08)	(4.65)	(6.52)	(4.58)
1(Pharma.)	0.002	0.001	0.065***	0.049**	0.018	0.053*
	(0.27)	(0.10)	(4.21)	(1.98)	(1.15)	(1.72)
1(Inv. Banking)	0.008*	0.005	0.022**	-0.003	0.014*	0.010
	(1.76)	(0.58)	(2.49)	(-0.21)	(1.70)	(0.56)
1(Mgmt. Consulting)	0.013***	0.015	0.032***	0.027*	0.026***	0.051***
	(2.72)	(1.48)	(3.57)	(1.66)	(3.08)	(2.80)
Sample	All	Pre-2011	All	Pre-2011	All	Pre-2011
Y-mean	0.626	0.776	0.514	0.702	0.292	0.509
Year Entered the VC Industry	x	x	x	x	x	x
Adj. R^2	0.818	0.686	0.290	0.205	0.251	0.175
N	14,420	4,050	14,420	4,050	14,420	4,050

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. $^{+}$ denotes experience at a successful startup. $^{-}$ denotes experience at a startup that was not successful. 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) ≥ 5× Acq.
1(1+ Successful Prior Inv.)	0.018***	0.007***	0.010***	0.006*
	(4.02)	(2.64)	(4.07)	(1.78)
1(2+ Successful Prior Inv.)	0.016***	0.004	0.008***	0.007
	(2.93)	(1.43)	(2.59)	(1.51)
1(5+ Successful Prior Inv.)	0.033***	0.012***	0.020***	0.011**
	(5.31)	(3.45)	(5.07)	(2.33)
1(White)	-0.004	0.002	-0.004	-0.003
	(-0.95)	(0.69)	(-1.62)	(-1.11)
1(Female)	-0.012***	-0.000	-0.005*	-0.009***
	(-2.68)	(-0.09)	(-1.86)	(-2.81)
1(Business Major)	-0.003	-0.004	0.002	-0.005
	(-0.60)	(-1.26)	(0.72)	(-1.23)
1(STEM Major)	-0.003	-0.002	-0.001	-0.006
	(-0.53)	(-0.52)	(-0.19)	(-1.45)
1(Soc. Sci. Major)	-0.009	-0.004	0.000	-0.008
	(-1.26)	(-1.02)	(0.12)	(-1.57)
1(Ivy Undergrad)	0.016***	0.007***	0.004*	0.007**
	(3.46)	(2.68)	(1.71)	(2.09)
1(Ivy+ Undergrad)	0.010*	0.005*	0.004	0.005
	(1.80)	(1.73)	(1.32)	(1.38)
1(Has MBA)	-0.022***	-0.008**	-0.012***	-0.012***
	(-4.56)	(-2.54)	(-4.47)	(-3.37)
1(Top-10 MBA)	0.011*	0.002	0.007**	0.004
	(1.76)	(0.53)	(2.18)	(0.95)
1(HBS MBA)	0.005	0.005	0.000	0.003
	(0.72)	(1.25)	(0.12)	(0.55)
1(Stanford GSB MBA)	0.037***	0.019***	0.017***	0.016**
	(4.45)	(3.64)	(3.34)	(2.58)
1(Advanced Degree)	0.006	0.008**	-0.004	0.003
	(1.15)	(2.57)	(-1.19)	(0.92)
1(CEO/Founder)$^{+}$	0.003	0.004	0.003	0.004
	(0.61)	(1.55)	(1.38)	(1.15)
1(CEO/Founder)$^{-}$	-0.027***	-0.010**	-0.005	-0.016***
	(-3.43)	(-2.41)	(-1.10)	(-2.73)
1(Non- CEO/Founder)$^{+}$	0.005	0.003	0.002	0.002
	(1.09)	(1.15)	(0.91)	(0.65)
1(Non-CEO/Founder)$^{-}$	-0.008	-0.002	-0.006	-0.002
	(-1.17)	(-0.57)	(-1.64)	(-0.35)
1(Tech.)	0.003	-0.001	0.002	0.002
	(0.65)	(-0.31)	(0.87)	(0.65)
1(Pharma.)	0.021**	0.013*	-0.002	0.014**
	(2.54)	(1.82)	(-0.49)	(2.05)
1(Inv. Banking)	0.014***	0.011***	0.002	0.009***
	(3.22)	(4.36)	(0.80)	(2.72)
1(Mgmt. Consulting)	-0.002	-0.000	-0.001	0.001
	(-0.43)	(-0.17)	(-0.54)	(0.33)
1(Enter at Senior Level)	-0.007**	-0.002	-0.004**	-0.002
	(-2.05)	(-1.13)	(-2.01)	(-0.74)
1(0-5 Yrs. in VC)	0.011***	0.005**	0.004*	0.008**
	(2.95)	(2.46)	(1.76)	(2.46)
1(0-10 Yrs. in VC)	0.020***	0.004	0.011***	0.008**
	(4.09)	(1.63)	(3.75)	(2.10)
Y-mean	0.142	0.044	0.042	0.090
FE	x	x	x	x
Controls	x	x	x	x
Adj. R^2	0.127	0.122	0.049	0.109
N	59,228	59,228	59,228	59,228

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. $^{+}$ denotes experience at a successful startup. $^{-}$ denotes experience at a startup that was not successful. Standard errors are clustered at the individual VC level. Fixed effects are for: investment years, the data source, and portfolio company location, industry, and age. Controls are indicators for lead investor positions and whether the investment was early-stage. *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) ≥ 5× Acq.
1(White)	-0.074	-0.148**	-0.117*	-0.037
	(-1.55)	(-2.19)	(-1.75)	(-0.74)
1(Female)	-0.472***	-0.264***	-0.593***	-0.503***
	(-7.31)	(-2.64)	(-6.76)	(-6.69)
1(Business Major)	-0.241***	-0.343***	-0.186	-0.263***
	(-3.17)	(-3.49)	(-1.63)	(-3.44)
1(STEM Major)	-0.135*	-0.098	-0.199	-0.160**
	(-1.81)	(-1.06)	(-1.63)	(-2.27)
1(Soc. Sci. Major)	-0.182**	-0.342***	-0.054	-0.199**
	(-1.96)	(-2.73)	(-0.41)	(-2.10)
1(Ivy Undergrad)	0.252***	0.303***	0.317***	0.194***
	(4.56)	(4.01)	(3.97)	(3.31)
1(Ivy+ Undergrad)	0.359***	0.327***	0.508***	0.321***
	(5.25)	(3.91)	(4.91)	(4.91)
1(Has MBA)	-0.292***	-0.264**	-0.496***	-0.273***
	(-4.46)	(-2.40)	(-5.33)	(-4.30)
1(Top-10 MBA)	0.245***	0.200	0.377***	0.240***
	(2.97)	(1.62)	(3.11)	(2.97)
1(HBS MBA)	0.194**	0.207*	0.213*	0.180**
	(2.39)	(1.96)	(1.81)	(2.11)
1(Stanford GSB MBA)	0.308***	0.420***	0.522***	0.211**
	(3.35)	(3.56)	(3.91)	(2.26)
1(Advanced Degree)	0.170***	0.527***	-0.133	0.137**
	(2.74)	(6.79)	(-1.19)	(2.22)
1(Enter at Senior Level)	0.397***	0.242***	0.472***	0.409***
	(9.14)	(3.91)	(7.77)	(9.10)
1(CEO/Founder)$^{+}$	0.305***	0.231***	0.471***	0.311***
	(5.53)	(3.11)	(6.25)	(5.53)
1(CEO/Founder)$^{-}$	-0.276***	-0.276	-0.216	-0.240**
	(-2.61)	(-1.54)	(-1.41)	(-2.17)
1(Non- CEO/Founder)$^{+}$	0.029	-0.081	0.147**	0.004
	(0.54)	(-1.06)	(2.02)	(0.06)
1(Non-CEO/Founder)$^{-}$	-0.081	-0.289*	-0.100	-0.052
	(-0.83)	(-1.83)	(-0.66)	(-0.50)
1(Tech.)	0.188***	0.017	0.318***	0.203***
	(3.83)	(0.26)	(4.54)	(4.06)
1(Pharma.)	0.159**	0.673***	-0.917***	0.171**
	(2.08)	(6.56)	(-5.61)	(2.17)
1(Inv. Banking)	0.108**	0.248***	0.101	0.087
	(1.99)	(3.16)	(1.41)	(1.54)
1(Mgmt. Consulting)	0.027	-0.059	0.075	0.059
	(0.49)	(-0.82)	(0.96)	(1.06)
Model	Poi	Poi	Poi	Poi
Y-mean	1.249	0.433	0.370	0.802
Y-Sd. Dev.	2.983	1.355	1.169	1.994
Year Entered the VC Industry	x	x	x	x
Pseudo R^2	0.311	0.303	0.176	0.343
N	9,034	8,654	9,029	8,882

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. $^{+}$ denotes experience at a successful startup. $^{-}$ denotes experience at a startup that was not successful. 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(1+ Successful Prior Inv.)	0.231**	0.052	0.285	0.215**	-0.041	0.197
	(2.38)	(0.27)	(0.65)	(2.19)	(-1.46)	(0.75)
1(2+ Successful Prior Inv.)	0.184**	0.411***	0.228	0.166	0.013	0.037
	(2.03)	(4.09)	(1.20)	(1.64)	(0.52)	(0.21)
1(5+ Successful Prior Inv.)	0.100	0.152*	0.184	0.047	0.029	0.590**
	(1.64)	(1.72)	(1.60)	(0.79)	(1.17)	(2.31)
1(White)	0.526**	0.593	-0.112	0.852***	-0.013	-0.209
	(2.50)	(1.62)	(-0.36)	(3.87)	(-0.39)	(-0.85)
1(API)	0.116*	0.107	-0.003	0.131**	0.004	-0.109
	(1.95)	(1.46)	(-0.02)	(2.07)	(0.26)	(-0.64)
1(Black)	0.021	0.155**	0.073	-0.013	-0.008	-0.052
	(0.40)	(2.05)	(0.56)	(-0.19)	(-0.35)	(-0.36)
1(Hispanic)	0.098	0.136	-0.207	0.148**	0.023	0.238
	(1.32)	(1.27)	(-1.45)	(2.19)	(0.96)	(1.09)
1(Female)	0.082	0.025	0.192	0.033	-0.023	-0.217
	(1.46)	(0.27)	(1.27)	(0.71)	(-1.19)	(-1.58)
1(Business Major)	0.176***	0.115*	0.261	0.182***	0.040**	0.215
	(2.93)	(1.73)	(1.59)	(3.23)	(2.49)	(1.67)
1(STEM Major)	0.046	-0.005	-0.152	0.126*	-0.012	-0.087
	(0.77)	(-0.06)	(-1.43)	(1.85)	(-0.44)	(-0.54)
1(Soc. Sci. Major)	0.052	0.023	0.181	0.031	-0.023	-0.276**
	(1.27)	(0.37)	(1.34)	(0.74)	(-1.50)	(-2.24)
1(Ivy Undergrad)	0.184***	0.144*	0.340**	0.129**	0.006	0.229
	(3.85)	(1.85)	(2.57)	(2.52)	(0.25)	(1.36)
1(Ivy+ Undergrad)	0.261***	0.298***	0.199**	0.254***	0.005	-0.076
	(3.65)	(2.77)	(2.25)	(3.26)	(0.26)	(-0.56)
1(Has MBA)	-0.162	-0.332*	-0.079	-0.200	-0.006	-0.025
	(-1.42)	(-1.83)	(-0.45)	(-1.14)	(-0.20)	(-0.07)
1(Top-10 MBA)	0.347***	0.460***	0.133	0.378***	0.020	-0.352
	(3.30)	(3.37)	(0.68)	(2.93)	(0.80)	(-0.94)
1(HBS MBA)	0.007	-0.068	0.074	0.059	0.012	-0.106
	(0.12)	(-0.77)	(0.67)	(0.97)	(0.61)	(-0.84)
1(Stanford GSB MBA)	0.170***	0.205**	0.220**	0.171***	0.018	0.084
	(3.41)	(2.57)	(2.23)	(3.11)	(0.82)	(0.73)
1(Advanced Degree)	0.079	0.026	0.120	0.070	0.033**	-0.040
	(1.64)	(0.37)	(1.40)	(1.51)	(2.26)	(-0.36)
1(Enter at Senior Level)	-0.049	-0.207*	0.037	0.095	-0.005	0.071
	(-0.48)	(-1.70)	(0.18)	(0.95)	(-0.17)	(0.28)
1(0-5 Yrs. in VC)	0.485**	0.618***	0.245	0.522**	0.025	0.153
	(2.24)	(2.90)	(0.85)	(2.35)	(0.89)	(0.60)
1(0-10 Yrs. in VC)	0.522	0.285	0.572	0.556	-0.069	-0.063
	(1.56)	(0.74)	(1.22)	(1.39)	(-1.49)	(-0.16)
1(CEO/Founder)$^+$	0.126***	0.101	0.102	0.135***	-0.008	-0.183
	(2.63)	(1.29)	(0.88)	(3.01)	(-0.38)	(-0.97)
1(CEO/Founder)$^-$	0.022	0.040	-0.103	0.066	-0.005	0.105
	(0.36)	(0.51)	(-1.07)	(1.30)	(-0.25)	(0.56)
1(Non- CEO/Founder)$^+$	0.128**	0.041	0.334**	0.139*	0.005	-0.003
	(2.03)	(0.45)	(2.50)	(1.85)	(0.28)	(-0.02)
1(Non-CEO/Founder)$^-$	0.143**	0.007	0.235*	0.113**	-0.046**	-0.435***
	(2.03)	(0.06)	(1.89)	(2.03)	(-2.69)	(-3.22)
1(Tech.)	0.104*	0.041	0.327**	0.057	-0.010	0.051
	(1.81)	(0.39)	(2.03)	(0.78)	(-0.48)	(0.21)
1(Pharma.)	0.034	0.209**	-0.257***	0.035	-0.026	-0.135
	(0.48)	(2.48)	(-3.54)	(0.44)	(-1.02)	(-0.76)
1(Inv. Banking)	0.035	0.007	0.113	0.021	0.005	0.183
	(0.57)	(0.08)	(1.05)	(0.32)	(0.28)	(1.20)
1(Mgmt. Consulting)	0.072*	0.023	0.090	0.114**	-0.019	-0.325*
	(1.67)	(0.29)	(0.99)	(2.09)	(-1.04)	(-1.78)
Model	Poi	Poi	Poi	Poi	OLS	OLS
Y-mean	4.189	1.740	0.782	2.952	0.145	2.083
FE	x	x	x	x	x	x
Industry FE	x	x	x	x	x	x
Pseudo R^2	0.446	0.391	0.473	0.405		
Adj. R^2					0.294	0.216
N	1,240	1,240	1,193	1,238	1,086	1,151

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. $^+$ denotes experience at a successful startup. $^-$ denotes experience at a startup that was not successful. 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, status, and industry focus 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: Distribution of VC Profits

Var.	Nobs.	Pct. > 0	Avg.	25p	50p	75p
Panel A. Person × Deal Level						
Deal Year	143,096		2016.1	2013	2017	2021
Profits.						
Invest Amnt. ($mm)	143,066		5.3	0.4	1.6	4.9
Gross Profits ($mm)	142,976		14.3	0.3	1.4	5.4
Net Profits ($mm)	142,976	32.3%	8.4	-1.3	-0.1	0.4
Mkt. Adj. Net Profits ($mm)	142,976	22.1%	4.1	-3.9	-0.8	-0.0
Panel B. Company Level						
# Deals	46,372		3.0	2	3	4
# VCs	46,372		3.9	2	3	5
Profits.						
Invest Amnt. ($mm)	46,372		16.2	0.8	3.6	13.5
Gross Profits ($mm)	46,372		44.1	0.5	2.3	11.2
Net Profits ($mm)	46,372	24.4%	26.0	-3.0	-0.5	0.0
Mkt. Adj. Net Profits ($mm)	46,372	14.9%	12.7	-9.2	-2.0	-0.2
Panel C. Person Level						
# Deals	12,151		11.8	2	5	13
# Early Stage	12,151		8.1	1	3	9
# Later Stage	12,151		3.7	0	1	4
# Companies	12,151		8.1	1	4	9
# Board	12,151		2.4	0	1	3
# Lead	12,151		2.6	0	1	3
Profits.						
Invest Amnt. ($mm)	12,151		62.0	2.3	12.0	50.7
Gross Profits ($mm)	12,151		168.3	1.8	11.2	63.7
Net Profits ($mm)	12,151	39.4%	99.1	-4.1	-0.3	7.4
Mkt. Adj. Net Profits ($mm)	12,151	20.6%	48.3	-22.8	-4.0	-0.2

Table 8: Tabulates the distribution of VC profits estimated following Equation (1). Investment costs are calculated following Equation (2).

Table 9: Cumulative Economic Value and VC Characteristics

	Lifetime:		
	(1) Gross Profits	(2) Net Profits	(3) Mkt. Adj. Net Profits
1(White)	-0.700	9.179	15.329
	(-0.03)	(0.57)	(1.17)
1(Female)	-49.560***	-31.807**	-18.415
	(-3.14)	(-2.45)	(-1.59)
1(Business Major)	-42.001	-32.405	-27.697
	(-1.42)	(-1.45)	(-1.45)
1(STEM Major)	-21.352	-18.675	-15.926
	(-0.59)	(-0.68)	(-0.70)
1(Soc. Sci. Major)	-32.243	-23.505	-21.276
	(-1.26)	(-1.25)	(-1.37)
1(Ivy Undergrad)	80.123**	56.192*	40.336
	(2.18)	(1.87)	(1.53)
1(Ivy+ Undergrad)	117.322***	80.616***	54.316**
	(3.17)	(2.74)	(2.25)
1(Has MBA)	-87.640***	-65.091**	-49.941**
	(-3.03)	(-2.64)	(-2.29)
1(Top-10 MBA)	3.774	-2.645	-6.192
	(0.15)	(-0.12)	(-0.30)
1(HBS MBA)	54.059**	33.614**	18.529
	(2.57)	(2.08)	(1.31)
1(Stanford GSB MBA)	236.020***	168.668***	112.318**
	(3.51)	(3.15)	(2.70)
1(Advanced Degree)	18.603	9.859	5.215
	(0.52)	(0.32)	(0.19)
1(Enter at Senior Level)	42.743**	23.349	6.762
	(2.20)	(1.48)	(0.49)
1(CEO/Founder)$^{+}$	88.460**	66.719*	53.389
	(2.11)	(1.86)	(1.65)
1(CEO/Founder)$^{-}$	-7.838	1.343	3.685
	(-0.26)	(0.05)	(0.12)
1(Non- CEO/Founder)$^{+}$	-13.422	-10.554	-6.486
	(-0.52)	(-0.52)	(-0.38)
1(Non-CEO/Founder)$^{-}$	-24.117	-15.822	-8.669
	(-1.46)	(-1.11)	(-0.65)
1(Tech.)	90.248***	68.670**	53.558**
	(2.97)	(2.63)	(2.30)
1(Pharma.)	-15.054	-18.924	-25.571
	(-0.49)	(-0.66)	(-0.93)
1(Inv. Banking)	49.331*	29.517	16.981
	(1.76)	(1.23)	(0.76)
1(Mgmt. Consulting)	-9.455	-12.233	-15.471
	(-0.55)	(-0.86)	(-1.28)
Y-mean	158.849	90.853	41.185
Year Entered the VC Industry	x	x	x
Adj. R^2	0.099	0.090	0.079
N	6,943	6,943	6,943

Table 9: Tabulates coefficients from regressions of lifetime profits for each VC. Lifetime profits are calculated following Equation (1). Costs are calculated following Equation (2), which varies by column. Profits are in millions. All specifications include fixed effects for the year the VC first was employed by an institutional U.S. VC firm. $^{+}$ denotes experience at a successful startup. $^{-}$ denotes experience at a startup that was not successful. Regression samples require that all characteristics are observed. Standard errors are clustered at the start year. *t*-stats are in parentheses and */**/*** respectively denote significance at the 10, 5, and 1 % levels.

Table 10: Midas List Recognition and Access to High-Quality Startups

	(1) **1**(Top-25p)	(2) **1**(Top-10p)	(3) **1**(Post $1B)	(4) **1**(Post $5B)	(5) **1**(Successful)	(6) **1**(PMV ≥ 5B)	(7) **1**(IPO)	(8) **1**(Exit ≥ 5x)
Panel A. Surprise Makes vs. Surprises Misses								
Surprise × Post	-0.013	0.008	0.018	0.005	0.055***	0.058***	0.048***	-0.005
	(-0.70)	(0.54)	(1.62)	(1.07)	(2.86)	(2.76)	(3.86)	(-0.25)
Y-mean	0.306	0.174	0.058	0.014	0.604	0.231	0.106	0.192
Adj. R^2	0.278	0.238	0.160	0.059	0.259	0.150	0.198	0.187
N	11,932	11,932	11,932	11,932	11,932	11,932	11,932	11,932
Panel B. Near Makes vs. Near Misses ± 5								
Surprise × Post	0.078	0.083	0.067	0.027	0.001	0.143***	0.116***	0.072*
	(1.21)	(1.30)	(1.14)	(0.48)	(0.02)	(3.31)	(2.69)	(1.95)
Y-mean	0.629	0.250	0.470	0.343	0.269	0.127	0.095	0.060
Adj. R^2	0.210	0.114	0.295	0.336	0.249	0.217	0.126	0.094
N	1,018	1,018	1,018	1,018	1,018	1,018	1,018	1,018
Panel C. Near Makes vs. Near Misses ± 10								
Surprise × Post	-0.013	0.036	0.092**	0.037	0.072	0.094***	0.110***	0.080***
	(-0.33)	(0.83)	(2.36)	(0.82)	(1.61)	(3.41)	(3.99)	(2.92)
Y-mean	0.217	0.175	0.263	0.294	0.277	0.239	0.155	0.142
Adj. R^2	0.270	0.247	0.211	0.098	0.209	0.244	0.172	0.177
N	2,191	2,191	2,191	2,191	2,191	2,191	2,191	2,191

Table 10: 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. Top-25p and Top-10p measure whether a company was in the top-quartile or decile of unique VCs it raised capital from as of the VC's investing year. Post variables are indicators for whether the VC invested in the startup after it had already achieved a high valuation. Columns 5-8 take values of one only if the VC invested before the company achieved a particular outcome. Panel A stacks 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. For Panels B and C, the treated groups include 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. *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

June 16, 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 websites, 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" post-money 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 crawlers. These web crawlers do not have a fixed pattern of deciding which websites they visit and how often they do so, but capture a site more frequently if the site 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 were 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 3,897 of the 4,402 firms comprising the institutional U.S. VC industry. 505 firms have websites we did not retrieve using our LLM track because we are unable to identify a historical website for the firm, the firm does not list professionals on its website, or the firm's website format does not allow for automatic parsing of the HTML.

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. 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 content-wise. 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.

In total, 2,032 firms are collected using only LLM, 1,865 firms are collected using both LLM and our manual track, and 61 incremental firms are recovered by our manual collections but not by our LLM track. Of these resulting 3,958 firms, 528 are further excluded from our final sample because the recovered data are insufficient for our research purposes, listing, for instance, only names of professionals but not enough information to determine the professionals' role with the firm, investing activity, or background. Table IA.B1 summarizes our resulting sample of VC firms by source. 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 about 95% of all U.S. VC funds in the 1996-2025 period (based on PitchBook data).

Table IA.B1: Average Firm Characteristics and Composition by Website Availability

	LLM Only	Manual Only	LLM & Manual	Collected LLM ∪ Manual	Collected w/ Web Data	Excluded
# Firms	2,032	61	1,865	3,958	3,430	972
1(Inactive)	26.0%	36.1%	9.0%	18.1%	16.6%	24.7%
# Unicorns	1	3	4	2.5	2.6	1.4
1(0 Unicorns)	56.7%	47.5%	31.2%	44.6%	42.2%	55.3%
1(1-5 Unicorns)	40.3%	44.3%	51.1%	45.4%	47.2%	39.4%
1(6-9 Unicorns)	1.7%	0.0%	8.5%	4.9%	5.1%	3.1%
1(10+ Unicorns)	1.3%	8.2%	9.2%	5.1%	5.5%	2.2%
1(0-1 VC Funds)	74.8%	88.5%	52.1%	64.3%	61.3%	87.4%
1(2-4 VC Funds)	22.2%	6.6%	31.6%	26.4%	28.6%	10.1%
1(5+ VC Funds)	3.0%	4.9%	16.2%	9.2%	10.1%	2.5%
$ VC Capital Raised	110.1	968.1	553.6	332.3	365.3	89.7
1($1B+ VC Capital Raised)	1.4%	4.9%	11.1%	6.0%	6.7%	1.2%

Table IA.B1: Tabulates average characteristics of U.S. VC firms based on how the firm's data are collected.

Table IA.B2 provides summary statistics for the resulting sample of 3,430 U.S. institutional VC firms. An average VC firm has about nine years of internet archival or live website presence, is associated with 30 professionals (not all of whom are investment professionals, as detailed below), reports 24 unique titles, and 52 unique biographies for its professionals.

Table IA.B2: Data Point Counts by Firm

	Nobs.	Avg.	25p	50p	75p
# Years	3,430	9.37	5	8	13
# Names	3,430	33.39	6	15	35
# People	3,430	29.7	5	13	30
# Titles	3,430	23.87	4	10	25
# Bios.	3,430	51.74	7	19	54
# Bios. $\geq$ 250 Chars.	3,430	46.78	5	16	48
# Bios. $\geq$ 500 Chars.	3,430	39.78	3	13	41

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

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 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 based on the largest connected graph of names.[1] In total, 80% of investment professionals are successfully mapped to at least one of these datasets.

Inclusion of Professionals from Other Datasets: We augment our main sample of U.S. VC professionals with professionals who are affiliated with our in-sample firms via either PitchBook or VentureSource. We collect about 103,000 individual people affiliated with VC firms in total. Figure IA.B1 reports counts of VC-affiliated professionals based on which data source they are

[1] Suppose "Blake J." at Sequoia is matched to PitchBook ID "PB-1" and website ID "W-2", while "Blake A. J." is matched to PitchBook ID "PB-1" and website ID "W-3." In this case, all IDs of "PB-1", "W-2", and "W-3" are mapped to the same "internal" ID that we use throughout since they are all connected via the common "PB-1" ID.

observed in. About 97,000 of these professionals are listed on historical or live VC firm websites, and 60,000 are not successfully matched to or observed in either PitchBook or VentureSource.

Figure IA.B1: Professional Counts by Source

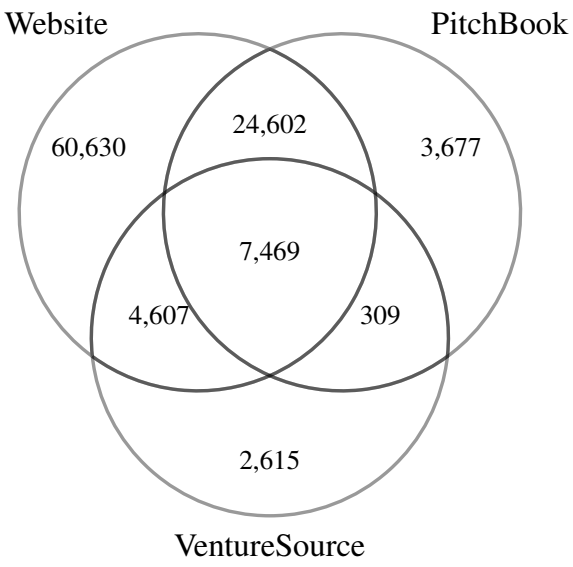


Figure IA.B1: Tabulates the count of professionals that appear in each data source. Circle sizes are the same for each source by construction.

Investment Teams: These 103,000 VC firm affiliated professionals can be broadly classified into full-time investment professionals (those working on sourcing, performing diligence on, negotiating, and managing investments) and non-investment professionals or those that do not work full-time. In addition, websites and commercial data 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 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 phrases. 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. We apply the same parsing rules for their reported titles for the professionals appended to our data that we view working at a VC firm in our sample only on PitchBook or VentureSource. However, we cannot view these professionals over time.

Our procedure identifies about 84,000 professionals with available information on their title for at least one year, meaning about 19,000 individuals are scraped from websites or recovered from commercial data without a title. These are generally professionals who are affiliated with the VC firm but are not formal employees, such as founders or CEOs of companies that the firm has invested in, and, therefore, do not have an official title. We have about 441,000 annual observations for these 84,000 professionals. About 37,000 of these people are classified as investment professionals. Table IA.B3 summarizes the top-25 most common titles among professionals across all observation years, such that the sum of all values in the table equals 100%.

Non-Investment Teams: The remaining 47,000 professionals listed on the website include the "non-investment" professionals. As some validation of our procedure, only about 6% of these 47,000 professionals are credited with having made at least one VC investment (discussed subsequently in Section IA.1.3). These 6% of professionals are almost always venture partners, operating partners, advisors, or CEOs/founders of portfolio companies listed on the VC firms' websites. By contrast, about 44% of our 37,000 investment professionals are credited with at least one investment. Additionally, 13,000 of the 37,000 professionals are observed for at least one year with a title that did not place them on the investment team. About 60,000 professionals are therefore observed outside of the investment team at least once. Several non-investment team titles are summarized in the right-most column of Table IA.B3.

Figure IA.B2 reports the fraction over time 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. Fairly consistently throughout our sample, about one out of every five VC firms lists a venture partner on its website; two of every five of the largest VC firms list a venture partner on its website. The prevalence of legal,

Table IA.B3: Frequency Distribution of The Most Common Titles

N=441,187	Investment Team 45.8%	Non-Investment Team 54.2%
Partner	7.5%	0.0%
Venture Partner	0.0%	4.7%
Managing Director	4.2%	0.0%
General Partner	4.1%	0.0%
Associate	3.0%	0.0%
Managing Partner	3.0%	0.0%
Principal	2.7%	0.0%
Advisor	0.0%	2.4%
Executive Assistant	0.0%	1.3%
Investor	1.2%	0.0%
Senior Associate	1.2%	0.0%
Analyst	1.1%	0.0%
Vice President	1.1%	0.0%
Advisory Board Member	0.0%	1.1%
Chief Financial Officer	0.0%	1.0%
Founding Partner	0.9%	0.0%
Operating Partner	0.0%	0.7%
Director	0.7%	0.0%
Founder	0.0%	0.6%
Controller	0.0%	0.6%
Senior Advisor	0.0%	0.5%
Alumni	0.0%	0.5%
Venture Advisor	0.0%	0.5%
Cofounder	0.4%	0.0%
Operations	0.0%	0.4%
Other	14.7%	40.0%

Table IA.B3: Tabulates the frequency of the top-25 most common titles observed among investment professionals. Percentages are reported as a fraction of all person-year observations.

compliance, operating, and investor relations positions has increased over time for all firms, and is significantly more pronounced among larger firms – those in the top-quartile for firm size by people (roughly at least 15 unique people listed on the website). 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.

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

Figure IA.B2: Fraction of Firms with Non-Investment Professionals

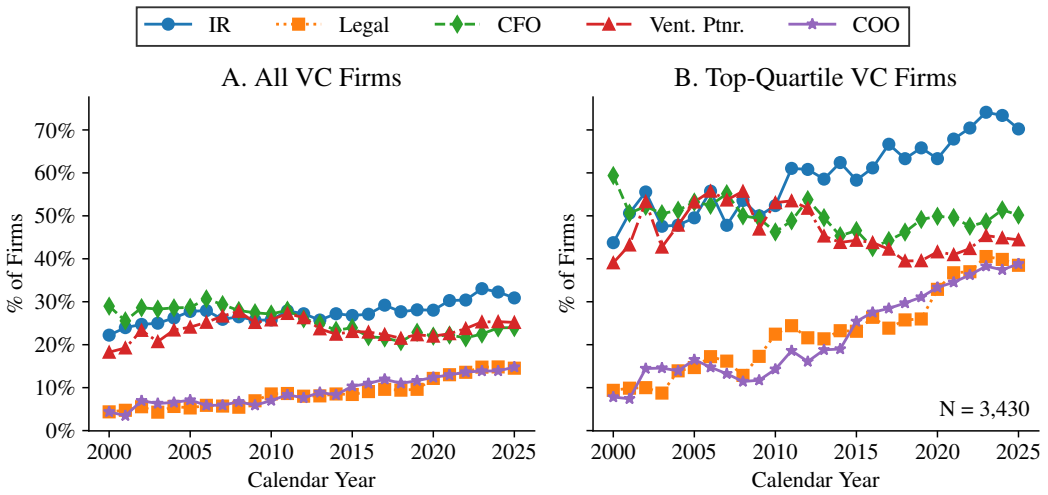


Figure IA.B2: Tabulates the fraction of VC firms with non-investment professionals assuming a particular role over time. Large VC firms are in the top-quartile of professionals on their website. "N" refers to the number of firms.

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.

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.B4 reports the fraction of person-year observations each seniority is observed and how often each of the top-25 most common titles corresponded to that seniority.

Table IA.B4: Frequency Distribution of The Most Common Titles by Seniority

N=441,187	Junior 9.5%	Middle 8.2%	Senior 28.6%
Partner	0.0%	1.0%	6.6%
Venture Partner	0.0%	0.0%	0.0%
Managing Director	0.0%	0.3%	3.9%
General Partner	0.0%	0.0%	4.1%
Associate	3.0%	0.0%	0.0%
Managing Partner	0.0%	0.0%	3.0%
Principal	0.0%	2.4%	0.3%
Advisor	0.0%	0.0%	0.0%
Executive Assistant	0.0%	0.0%	0.0%
Investor	1.1%	0.0%	0.0%
Senior Associate	1.1%	0.0%	0.0%
Analyst	1.1%	0.0%	0.0%
Vice President	0.0%	1.1%	0.0%
Advisory Board Member	0.0%	0.0%	0.0%
Chief Financial Officer	0.0%	0.0%	0.0%
Founding Partner	0.0%	0.0%	0.9%
Operating Partner	0.0%	0.0%	0.0%
Director	0.0%	0.5%	0.2%
Founder	0.0%	0.0%	0.0%
Controller	0.0%	0.0%	0.0%
Senior Advisor	0.0%	0.0%	0.0%
Alumni	0.0%	0.0%	0.0%
Venture Advisor	0.0%	0.0%	0.0%
Cofounder	0.0%	0.0%	0.4%
Operations	0.0%	0.0%	0.0%
Other	3.1%	2.9%	9.2%

Table IA.B4: Tabulates the frequency of the top-25 most common titles observed among investment professionals based on which seniority they are classified into. Percentages are reported as a fraction of all person-year observations.

Figure IA.B3 reports counts of investment professionals based on which seniority layers they were observed at. This figure only uses investment professionals recovered from archived websites since the investment team classifications for only PitchBook or VentureSource recovered investment professionals are static. Figure IA.B4 summarizes time trends in the seniority at which investment professionals entered the VC industry.

Employment Spells: For each professional, we attempt to recover which year they first worked at a firm in our sample and which year (if any) they last worked at a US VC firm in our

Figure IA.B3: Investment Professional Counts by Seniority

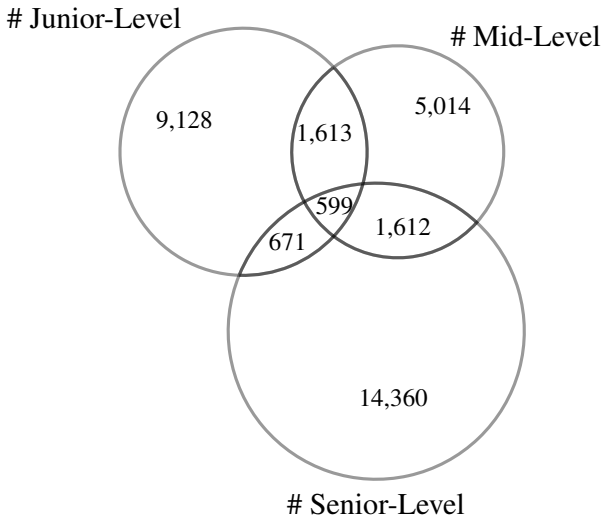


Figure IA.B3: Tabulates the count of investment professionals that appear in each seniority layer.

Figure IA.B4: Seniority Trends by Entry Cohort

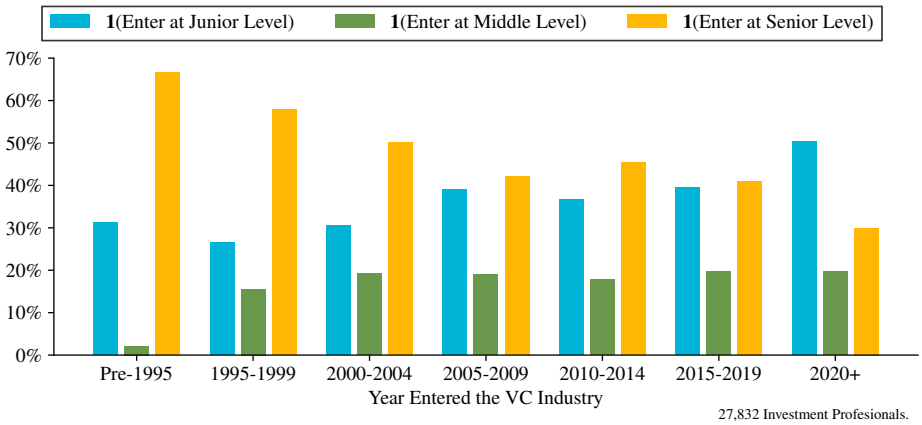


Figure IA.B4: Tabulates the fraction of investment professionals joining the industry at a given seniority.

sample. We recover start years by first extracting the year a professional is first observed on the website of a VC firm in our sample. We further supplement our website-retrieved start dates with information identifying when a professional joined the firm that can be parsed from biographies (e.g., "Scott Sandell joined NEA as an associate in 1996."). About 80% of website-derived start years are identical to the earliest start year recovered from LinkedIn, PitchBook, or VentureSource. Where they differ, start years on websites tend to be about one to two years later on websites compared to other datasets if the joining year is not mentioned in the biography as well. For these

cases, we calculate a professional's start year to be the earliest start year available in other datasets so long as it is on or after the year of the focal firm's founding.

We recover separation years by first assuming that a professional is still affiliated with a VC firm if they are listed on the firm's website as of our latest scrape. For the remaining professionals, we then calculate the last year they are observed on the website of a VC firm in our sample. About 75% of website-derived end years are identical to the latest exit year recovered from LinkedIn, PitchBook, or VentureSource. Where they differ, end years based on website presence tend to be about one to two years later compared to end years reported in other datasets. This combines to suggest that firms may not immediately update websites and the Wayback machine may not archive websites at a sufficiently high periodicity. In the case of such differences, we calculate a professional's end year to be the latest end year available in other datasets. Hence, our end year measure can be interpreted as capturing whether there is any evidence that a professional still is affiliated with a VC firm.

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.B5 summarizes trends in the number of years investment professionals have worked in the VC industry. 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

Figure IA.B5: Years Working in VC Over Time

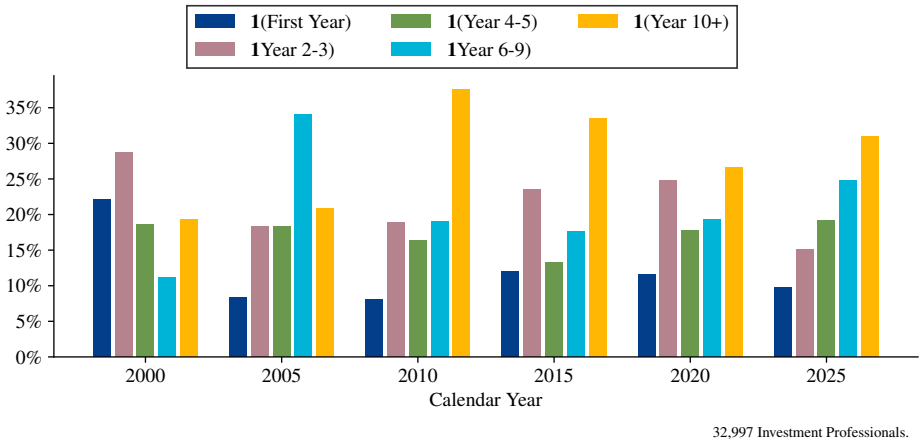


Figure IA.B5: Tabulates trends in the number of years investment professionals have worked in the VC industry for snapshots of six years. Gaps in employment are not counted.

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.B6 summarizes time trends in these demographics. White males comprise the majority of investment professionals and are omitted from this plot for scale.

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).

Figure IA.B6: Demographic Trends by Entry Cohort

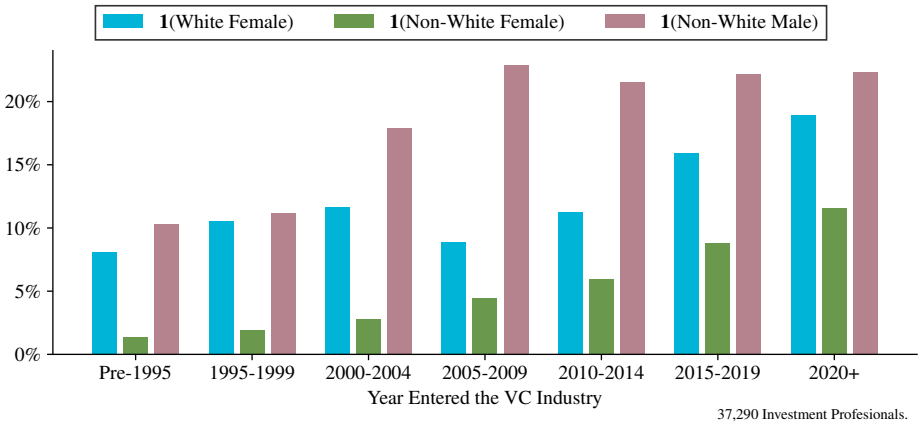


Figure IA.B6: Tabulates the fraction of investment professionals joining the industry of a given demographic.

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 2025 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.B7 summarizes trends in education by school and degree type.

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, Astronomy, Earth Sciences, Engineering);

2. Humanities & Arts (Philosophy, Literature, History, Languages, Religious Studies, Arts,

Figure IA.B7: Education Trends by Entry Cohort

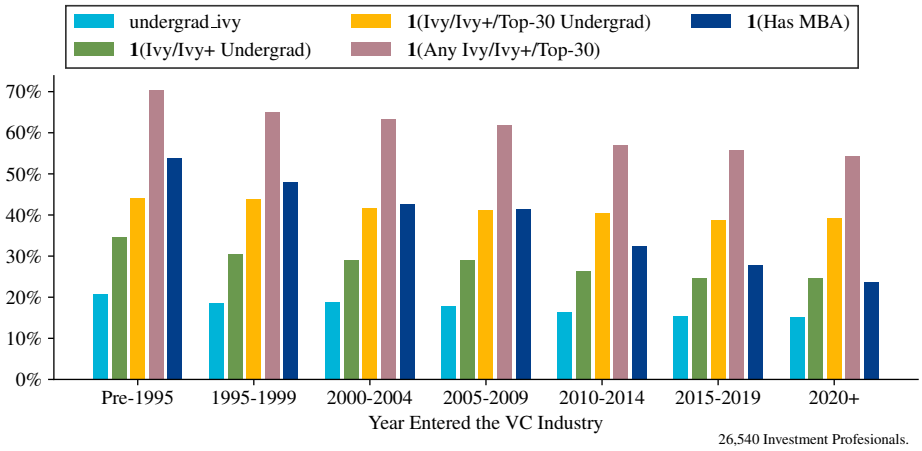


Figure IA.B7: Tabulates trends in education among investment professionals upon entering the VC industry.

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 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.B8 summarizes trends in fields of study.

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 de-

Figure IA.B8: Undergraduate Major Trends by Entry Cohort

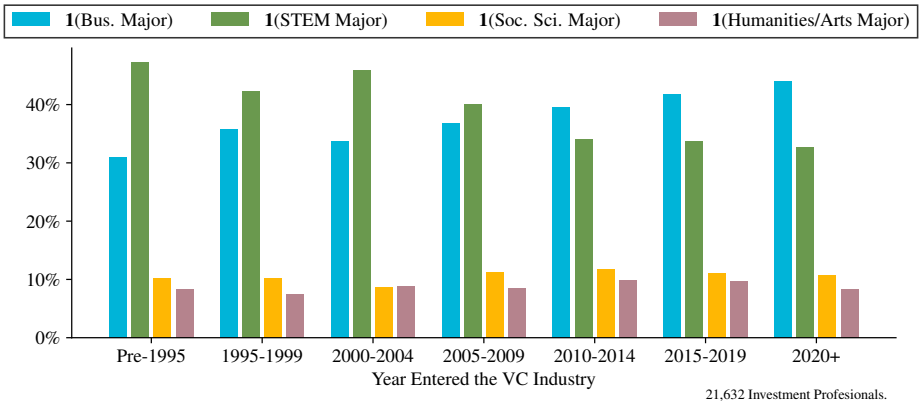


Figure IA.B8: Tabulates trends in undergraduate major types among investment professionals upon entering the VC industry.

grees that business schools may give (such as other master's degrees including MIT Sloan Master's 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 conditions are met:

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

2. Professional i began working at company k before it 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 is flagged as startup experience for this professional, assuming the other conditions are met. Figure IA.B9 summarizes time trends in pre-VC work experience.

Figure IA.B9: Work Experience Trends by Entry Cohort

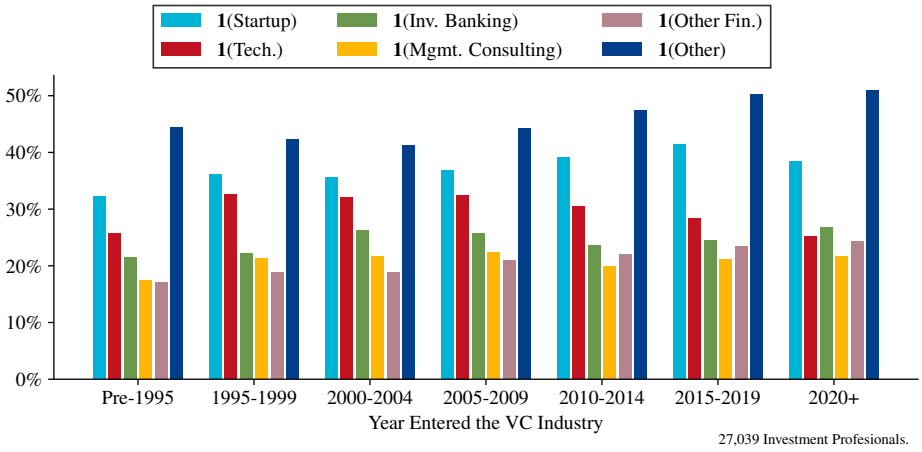


Figure IA.B9: Tabulates trends in pre-VC work experience among investment professionals. Numbers can exceed one for professionals with multiple pre-VC work experiences.

For startup experience, throughout our paper, we further use the extracted titles affiliated with each experience to classify professionals as a founder, a CEO, or a C-suite level executive ("CXO") at a startup company. We also partition startup experience based on whether the startup achieved what is plausibly a successful financial outcome for the individual or not. Successful startups went public, were acquired, or achieved a valuation of at least $1 billion after the professional

joined the company. Note that this "success" definition is less strict than that of our main sample which considers successful acquisitions to be only those where the startup was acquired for at least five-times the amount invested.

Table IA.B5 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 do so include Vineet Buch (BlueRun) who co-founded Ojos and Karient 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.

Table IA.B5: Frequency Distribution of Initial Investment Team Title by Startup Experience

		Entry-Seniority		
	# Professionals	Junior	Middle	Senior
All IPs	28,193	42.6%	19.2%	38.2%
Successful Startup CEO/Founder	1,677	14.7%	13.5%	71.9%
Successful Startup Other CXO	627	13.2%	18.7%	68.1%
Successful Startup Non-CXO/Founder	2,562	37.4%	23.3%	39.2%
Unsuccessful Startup CEO/Founder	737	23.1%	15.6%	61.3%
Unsuccessful Startup Other CXO	186	21.0%	22.0%	57.0%
Unsuccessful Startup Non-CXO/Founder	1,222	51.1%	20.3%	28.6%

Table IA.B5: Tabulates the frequency that investment professionals who previously worked at startup companies join the VC industry in each seniority group (junior, middle, or senior).

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.B10 summarizes time trends in post-VC work experience, which is calculated using LinkedIn profiles as these professionals are those that leave the sample.

Three main work experiences omitted from our main analysis include: working at a VC firm outside of our sample (e.g., a non-U.S. VC firm or a Corporate Venture Capital firm); working as an intern at a VC firm; and working at a VC firm in our sample but outside of the investment team. Figure IA.B11 summarizes the prevalence of each of these experiences based on when a

Figure IA.B10: Post-VC Work Experience Trends by Entry Cohort

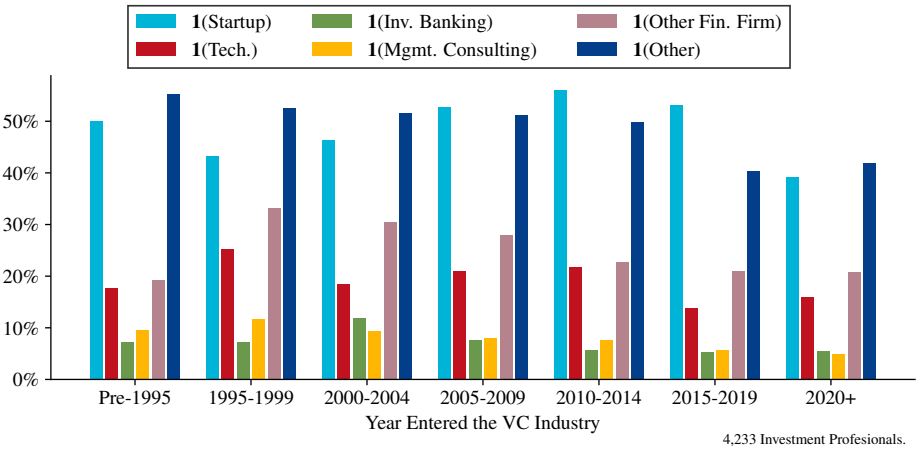


Figure IA.B10: Tabulates trends in post-VC work experience among investment professionals. Numbers can exceed one for professionals with multiple post-VC work experiences.

professional joined our sample. Intern experience at a top VC firm (Sequoia, Kleiner Perkins, Andreessen Horowitz, CRV, NEA, Founders Fund, Accel, General Catalyst, Index, Bessemer, or Lightspeed) is rare. About 6% of professionals worked at a VC firm outside of our sample. Fewer than 4% worked outside of the investment team (e.g., as a venture partner) before they joined the investment team.

Figure IA.B11: Additional Work Experience Trends by Entry Cohort

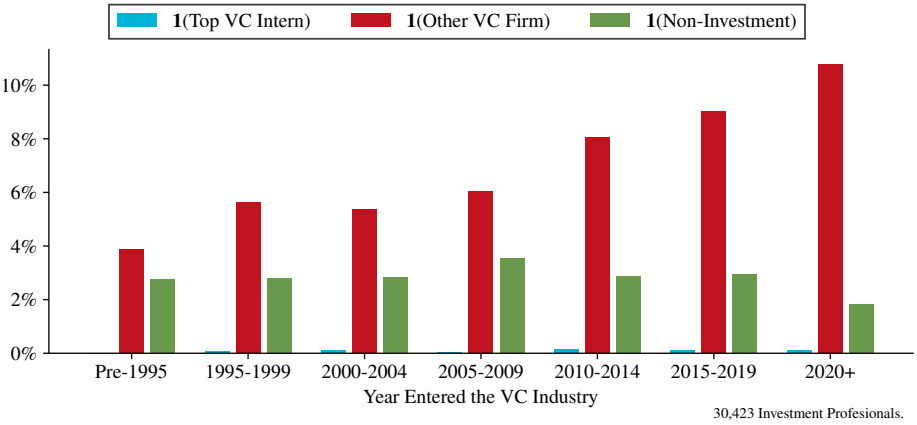


Figure IA.B11: Tabulates trends in work experience among investment professionals. Numbers can exceed one for professionals with multiple work experiences.

Comparisons of Professionals. Table IA.B6 reports several characteristics on the compo-

sition of professionals with deals based on the source from which they are retrieved and how this composition differs from that of the resulting full sample. Website data tend to add female and non-white VCs. They are also more likely to add VCs without advanced degrees and VCs that are earlier in their careers or have not worked at startups.

Table IA.B6: Statistics of Investment Professionals by Data Source

	Full Sample	Websites Only	PB+VS Only	All Overlap
# Investment Professionals	37,290	12,705	1,021	23,564
Panel A: Demographics				
1(White)	69.7%	-2.4%***	-2.2%	+1.4%***
1(Female)	23.0%	+5.2%***	-7.5%***	-2.3%***
Panel B: Pre-VC Education				
1(Ivy Undergrad)	16.4%	-1.9%***	+1.6%	+0.5%
1(Ivy+ Undergrad)	9.9%	+0.2%	-0.4%	+0.0%
1(Business Major)	40.5%	+2.6%***	+0.4%	-0.7%
1(STEM Major)	35.7%	-2.3%***	-0.6%	+0.6%
1(Has MBA)	31.5%	-8.2%***	-1.8%	+2.5%***
1(Top-10 MBA)	14.3%	-8.0%***	-1.5%	+4.4%***
1(HBS MBA)	3.9%	-2.2%***	-3.9%***	+1.4%***
1(Stanford GSB MBA)	2.5%	-1.5%***	-2.5%***	+0.9%***
1(Advanced Degree)	10.4%	-5.2%***	-10.4%***	+3.3%***
Panel C: Pre-VC Experience				
1(CEO/Founder)$^{+}$	7.5%	-5.0%***	-7.5%***	+3.0%***
1(CEO/Founder)$^{-}$	3.0%	-1.5%***	-3.0%***	+0.9%***
1(Non- CEO/Founder)$^{+}$	12.3%	-6.3%***	-12.3%***	+3.9%***
1(Non-CEO/Founder)$^{-}$	4.8%	-1.9%***	-4.8%***	+1.2%***
1(Tech.)	28.6%	-4.8%***	-4.0%**	+1.6%***
1(Pharma.)	7.1%	-1.4%***	-3.2%***	+0.5%**
1([1,10) Yrs. in VC)	76.6%	+15.9%***	-9.7%***	-9.2%***
1([10,20) Yrs. in VC)	17.2%	-11.0%***	+12.3%***	+6.2%***
1(20+ Yrs. in VC)	6.2%	-4.9%***	-2.6%***	+2.9%***

Table IA.B6: Tabulates the characteristics of investment professionals by different data sources. Columns report differences in means (and statistical significance thereof) compared to the main sample of investment professionals.

As an additional set of comparisons, Table IA.B7 reports how investment professional VCs differ on observables of interest from VCs that are not investment professionals. Investment professionals are more likely to have an undergraduate degree from an Ivy or Ivy+ school. They also are more likely to have an advanced degree or have founded a successful startup. An exception includes venture partners, who are more likely to have advanced degrees or successful startup experience.

Table IA.B7: Statistics For Professionals by Classification

	Main Sample	Venture Partners	Investor Relations	Internal Operations	All Other Non-IPs	Other Affiliates
# Professionals	37,290	12,451	1,472	9,439	24,858	18,399
Panel A: Demographics						
1(White)	69.7%	+4.9%***	+4.7%***	+4.9%***	-0.7%*	+3.4%***
1(Female)	23.0%	-3.4%***	+25.9%***	+35.4%***	+16.1%***	-3.0%***
Panel B: Pre-VC Education						
1(Ivy Undergrad)	16.4%	-2.8%***	-9.2%***	-10.7%***	-7.8%***	-2.5%***
1(Ivy+ Undergrad)	9.9%	-2.4%***	-6.1%***	-6.9%***	-4.6%***	-2.8%***
1(Business Major)	40.5%	-9.7%***	+4.1%**	+11.3%***	-4.8%***	+0.5%
1(STEM Major)	35.7%	+6.0%***	-21.5%***	-26.7%***	-6.2%***	+0.0%
1(Has MBA)	31.5%	-2.4%***	-9.4%***	-16.0%***	-11.2%***	-0.5%
1(Top-10 MBA)	14.3%	+0.1%	-5.6%***	-10.2%***	-5.5%***	+2.2%***
1(Advanced Degree)	10.4%	+24.6%***	-0.7%	+14.2%***	+12.0%***	+16.6%***
Panel C: Pre-VC Experience						
1(CEO/Founder)$^{+}$	7.5%	+4.8%***	-5.7%***	-6.3%***	-1.9%***	+3.0%***
1(CEO/Founder)$^{-}$	3.0%	+2.7%***	-1.6%***	-2.1%***	+0.2%	+2.8%***
1(Non- CEO/Founder)$^{+}$	12.3%	+8.9%***	-0.7%	+7.5%***	+7.1%***	+5.5%***
1(Non-CEO/Founder)$^{-}$	4.8%	+2.6%***	+4.2%***	+4.5%***	+5.1%***	+6.8%***
1(Tech.)	28.6%	+11.2%***	-6.7%***	-4.8%***	+1.9%***	-4.5%***
1(Inv. Banking)	25.2%	-11.9%***	+4.4%***	-12.6%***	-12.1%***	-2.5%***
1(Pharma.)	7.1%	+4.8%***	-3.4%***	-2.9%***	-0.8%***	-2.2%***
1(Hedge Fund)	2.1%	-0.5%***	+3.1%***	+0.6%***	-0.5%***	+0.5%*
1(Private Equity)	7.1%	-3.4%***	+3.8%***	+0.4%	-2.9%***	-0.8%*
1(Other Fin. Firm)	15.3%	-0.9%**	+8.0%***	+3.9%***	-0.7%*	+2.5%***
1(Govt.)	7.8%	+3.0%***	-0.1%	-1.2%***	+1.0%***	+0.2%
1(Law Firm)	3.1%	+0.1%	-1.1%**	+7.4%***	-0.8%***	+0.7%*
1(Other)	36.7%	+7.8%***	+3.3%**	+6.6%***	+9.8%***	+11.5%***

Table IA.B7: Tabulates the characteristics of investment professionals by different investment team classifications. Columns report differences in means (and statistical significance thereof) compared to the main sample of investment professionals.

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 any of the below are true:

1. They sat on the board of company c (according to PitchBook, VentureSource, or historical websites);

2. They led an investment in company c (according to PitchBook or historical websites);

3. They were actively involved in an investment 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. 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. The first column of Table IA.B8 denotes the number of investments recovered from websites after removing these service boards.

Table IA.B8: Investment Counts by Datasource

	Websites (Raw)	Websites	PitchBook	VentureSource	All
# VCs	18,646	9,850	+11,895	+1,883	16,425
# Investments	131,077	59,556	+70,464	+4,131	134,151
% w/ Deal Year	45.4%	100%	100%	100%	100%

Table IA.B8: Tabulates incremental investment counts by provenance.

Our main set of investments from websites is tabulated in the second column of Table IA.B8. This sample is the result of further applying our most impactful filter, which is to require that we recover the year the person first invested in the startup. Doing so is important to ensure

that the professional invested in the startup before any successful outcome. We recover these years by first requiring 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.

As a second step, we then 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. The average target company removes 0.3 people after 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. 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,[2] 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,*

[2] https://www.wsj.com/articles/airbnb-raises-1-5-billion-in-one-of-largest-private-placements-1435363506

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). . . .

Our final sample of investments then includes professionals and their deals covered in PitchBook or VentureSource but not successfully recovered from website data. Figure IA.B12 reports the unique and overlapping investment counts based on their provenance.

Figure IA.B12: Investments by Provenance

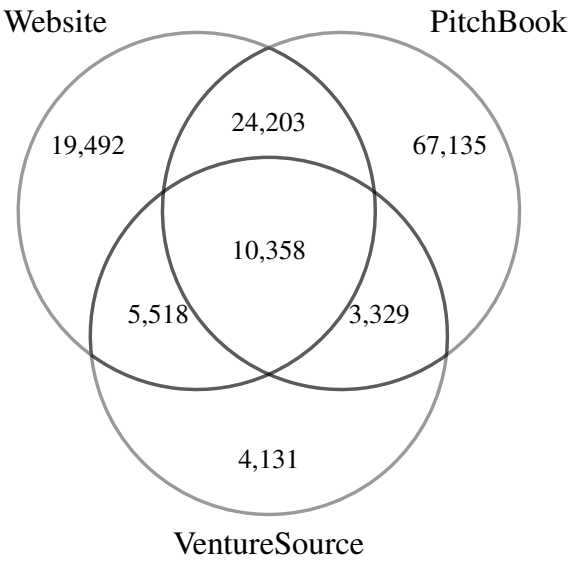


Figure IA.B12: Tabulates the count of investments by datasource. Circles are of equal size by construction.

Table IA.B9 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 about 4,000 more professionals in our data.

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

Table IA.B9: Companies Per Person and People Per Company

	Nobs.	Avg.	25p	50p	75p
Panel A: Counts Per Person					
# Deals (All Combined)	16,425	8.17	1	4	9
# Boards	16,425	3.99	0	1	5
# Early	16,425	5.02	1	2	5
# Leads	16,425	6.82	1	3	8
Deals by Source:					
# Deals PB	16,425	6.39	1	2	7
# Deals VS	16,425	1.42	0	0	0
# Deals Website	16,425	3.63	0	1	4
Panel B: Counts Per Company					
# People (All Combined)	68,010	1.97	1	1	2
# People w/ Board	68,010	0.96	0	1	1
# People w/ Early	68,010	1.21	0	1	2
# People w/ Leads	68,010	1.65	1	1	2
Affiliations by Source:					
# People from PB	68,010	1.54	1	1	2
# People from VS	68,010	0.34	0	0	0
# People from Websites	68,010	0.88	0	0	1

Table IA.B9: 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.

sale value that was more than five times the amount invested (stricter than the two-times multiple used by 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 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 investment 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.

IA.2 Calculating the Economic Value of VC Investments

This section discusses the data inputs to our calculations for the economic value of individual VC investments. The main equation of interest is Equation (1), reproduced below:

$$\text{Gross Investment Value}_{i,c,d,T} = \left(\frac{K_{i,c,d}}{V_{c,d}} \left[\prod_{j=d+1}^{N} \left(1 - \frac{K_{c,j}}{V_{c,j}} \right) \right] \times V_{c,T} \right).$$

$K_{i,c,d}$ denotes the dollar value invested in round d, and $V_{c,d}$ denotes the post-money valuation of company c during round d. Throughout, we report dollar values inflation adjusted to 2024 purchasing power. Jackson and Strebulaev (2026) present a similar discussion in constructing rankings of venture investors based on the net profits of their investments.

1. **Ownership Estimation:** A key input is the investor's ownership of the company for each round as of time T: $\pi_{i,c,d,T}$. To approximate the ownership of that VC on the fully-diluted basis we take the amount any VC invested in that round. Suppose that VC_1 invested 50% of Round A of \$50 million at \$200 million PMV. VC_2 invested 50% of Round B of \$500 million at a \$5 billion valuation. VC_1 invested 10% of Round B as well. VC_1's ownership is

therefore $50\% \times 50/200 = 12.5\%$ after Round A. Round B dilutes Round A at 0.9. Therefore, after round B, VC_1's ownership percentage is $0.9 \times 12.5\% + 10\% \times 500/5000 = 12.25\%$. VC_2 owns $50\% \times 500/5000 = 5\%$. In practice, the amount invested by a specific investor in a given round is often missing. We impute missing amounts according to the following algorithm:

(a) If the investor is a lead investor, they are assumed to contribute the same fraction of the round as other lead investors at the same stage of development. For instance, if the lead investors in Series A tend to contribute 50% of Series A rounds, the lead investor of a $100 Series A with a missing investment amount is estimated to have contributed $50 to the round.

(b) If the investor is not a lead investor, they are assumed to evenly split any residual round amount after accounting for the lead investor and known investment amounts evenly.

(c) *Pro-rata:* To account for pro-rata, we assume any previous investors contribute their pro-rata so long as doing so does not exceed the round amount after accounting for other known investment amounts and as long as we are able to confirm that they participated in the round. All other new investors then evenly split the residual.

2. **Round-specific ownership approximation:** More generally, even if we can observe all investment amounts, we typically don't know the exact fully-diluted ownership of investors in one equity round, because of additional shares issued to common stockholders, e.g., through an employee stock option pool. This does not matter within one round, but makes the comparison of relative ownership in between rounds less precise.

(a) *Data from S-1 Filings:* For companies that went public in the U.S., we supplement our ownership estimates with data collected from S-1 filings. Specifically, we collect all beneficial owners – entities owning at least 5% – and use their reported ownership values as of the IPO. If the estimated ownership exceeds 7.5%, but the investor is not listed as a 5%+ beneficial owner, their ownership is reduced to 4.5%. For 5%+ beneficial owners, the estimated ownership is adjusted by the ratio of the ownership from the S-1 filing to the estimated ownership. For example, if the ownership at the

IPO equals 20%, and the estimated ownership is 18%, the fully diluted ownership from each round the VC invested in is adjusted by 1.11 (= 20%/18%). In the present implementation, we use S-1 data for the about 600 most highly valued VC-backed IPOs.

3. **Missing information:** If we miss any information about equity rounds, we impute that information based on average values known about similarly situated companies.

   (a) *Missing Post Money Valuations:* Imputations are mostly needed for missing post money valuations, where we use the round amount and the average round ownership percentages to impute missing PMVs (generally for early seed rounds). For instance, if Series A investors, on average, own 20% of the company after Series A, then another company's \$100 Series A with a missing PMV would have an imputed PMV of \$100/20% = \$500. We further impose a monotonicity check on PMVs across the rounds for the imputation to be valid.

   (b) *Additional Missing Values:* If round amounts or pre-money valuations are otherwise missing, we linearly interpolate values across rounds within the same company based on the time elapsed since the previous rounds and subject to the identity pre-money valuation+ round investment amount = PMV.

Table IA.B10 summarizes our resulting sample of deals after applying these data adjustments based on the year of the round.

Comparison with Company Success Outcome Measures. The main results in our paper (using the full set of recovered affiliations) 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 value that was more than five times the amount invested. Table IA.B11 presents regressions of our net profits measures on each of these possible outcomes, as well as the condensed indicator for whether the company achieved any of outcomes (a) - (c). Net profits are aggregated at the person-company level and are calculated assuming investment costs equal the amount invested or instead the amount invested adjusted assuming a market beta of one.

Table IA.B10: Investment-Level Summary Statistics

	All	Pre-2000	01-10	11-20	2021+
# Deals	85,596	2,059	13,280	43,076	27,181
Panel A: Stage					
Seed/Angel	23%	3%	5%	26%	30%
Series A	29%	25%	33%	29%	26%
Series B	17%	18%	23%	16%	15%
Series C+	31%	55%	39%	29%	29%
Panel B: Round Statistics ($ mm)					
Pre-Money	197	120	65	155	348
Round Size	33	32	22	28	48
Post-Money	230	152	87	183	396
Invest/Round	25%	28%	27%	25%	24%
Panel C: Investment Outcomes					
1(Exited)	32%	76%	69%	35%	3%
1(IPO)	6%	21%	11%	8%	1%
1(M&A)	25%	56%	59%	27%	2%
1(Expired)	32%	23%	29%	41%	20%
1(Active)	36%	0%	2%	25%	77%

Table IA.B10: Tabulates average statistics for investments in our sample with person-company-round level granularity by the year of the round.

Successful outcomes, on average, have net profits that are about $75 million higher compared to affiliations that do not have a successful outcome. The regression sample mean is about $12 million, implying a large differential. IPO exits generate the highest net profits. Unicorn investments generate the second most, even though we mechanically deflate the reported post-money valuations to account for overvaluation, following results presented in Gornall and Strebulaev (2020). High-value M&A exits translate to about $10 million more in net profits.

Table IA.B11: Success Measures and Net Profits

	Net Profits		Mkt. Adj. Net Profits	
	(1)	(2)	(3)	(4)
1(Successful Outcome)	75.447***		65.974***	
	(17.45)		(15.77)	
1(IPO)		141.411***		132.077***
		(13.88)		(13.20)
1(Unicorn)		55.285***		37.042***
		(9.46)		(6.59)
1(Acquisition)		40.155***		39.469***
		(10.28)		(10.28)
Y-mean	12.208	12.208	5.948	5.948
Invest Year FE	x	x	x	x
Adj. R^2	0.022	0.041	0.017	0.036
N	99,238	99,238	99,238	99,238

Table IA.B11: Tabulates the correlation between the net profits of a given person-company investment and indicators for whether the company achieved a successful outcome. Standard errors are clustered at the individual VC level. *t*-stats are in parentheses. */**/*** respectively denote significance in the difference in sample means at the 10, 5, and 1% percent levels.

Internet Appendix References

Baker, A., Larcker, D. F., & Wang, C. C. (2022). How Much Should we Trust Staggered Difference-In-Difference Estimates? *Journal of Financial Economics*, *144*(2), 370–395.

Eskandar, W., & Murray, B. (2019). Retrieving and Archiving Information from Websites. https://kit.exposingtheinvisible.org/en/web-archive.html

Ewens, M., & Rhodes-Kropf, M. (2015). Is a VC Partnership Greater Than the Sum of Its Partners? *Journal of Finance*, *70*(3), 1081–1113.

Gornall, W., & Strebulaev, I. A. (2020). Squaring Venture Capital Valuations with Reality. *Journal of Financial Economics*, *135*(1), 120–143.

Jackson, B. (2025). How do Barbarians Get to the Gates? Private Equity Careers, Styles, and Returns. *SSRN Working Paper*.

Jackson, B., & Strebulaev, I. A. (2026). Ranking Venture Investors. *Working Paper*.

Strebulaev, I. A., & Wang, A. (2021). Organizational Structure and Decision-Making in Corporate Venture Capital. *SSRN Working Paper*.

IA.3 Additional Figures and Tables

Figure IA1: Composition of Midas Recognition Over Time

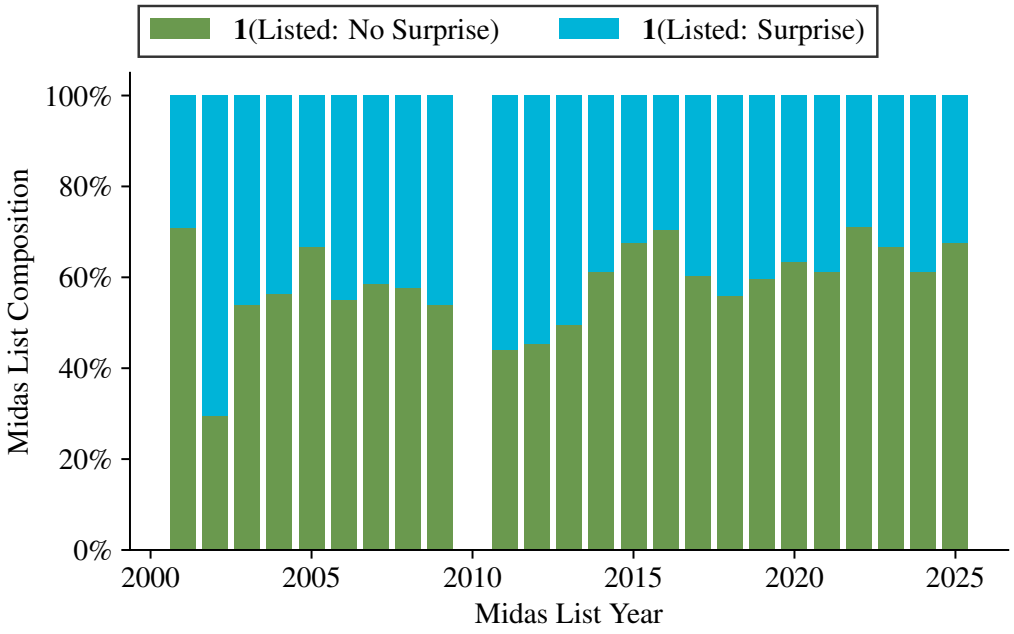


Figure IA1: Plots the composition of the Midas List each year based on whether the listed VC professional was predicted to be in the list versus whether they were not. A VC professional is said to be predicted to be included in the Midas list in year t if their estimated coefficients over the rolling 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 Near Makes Versus Nears Misses

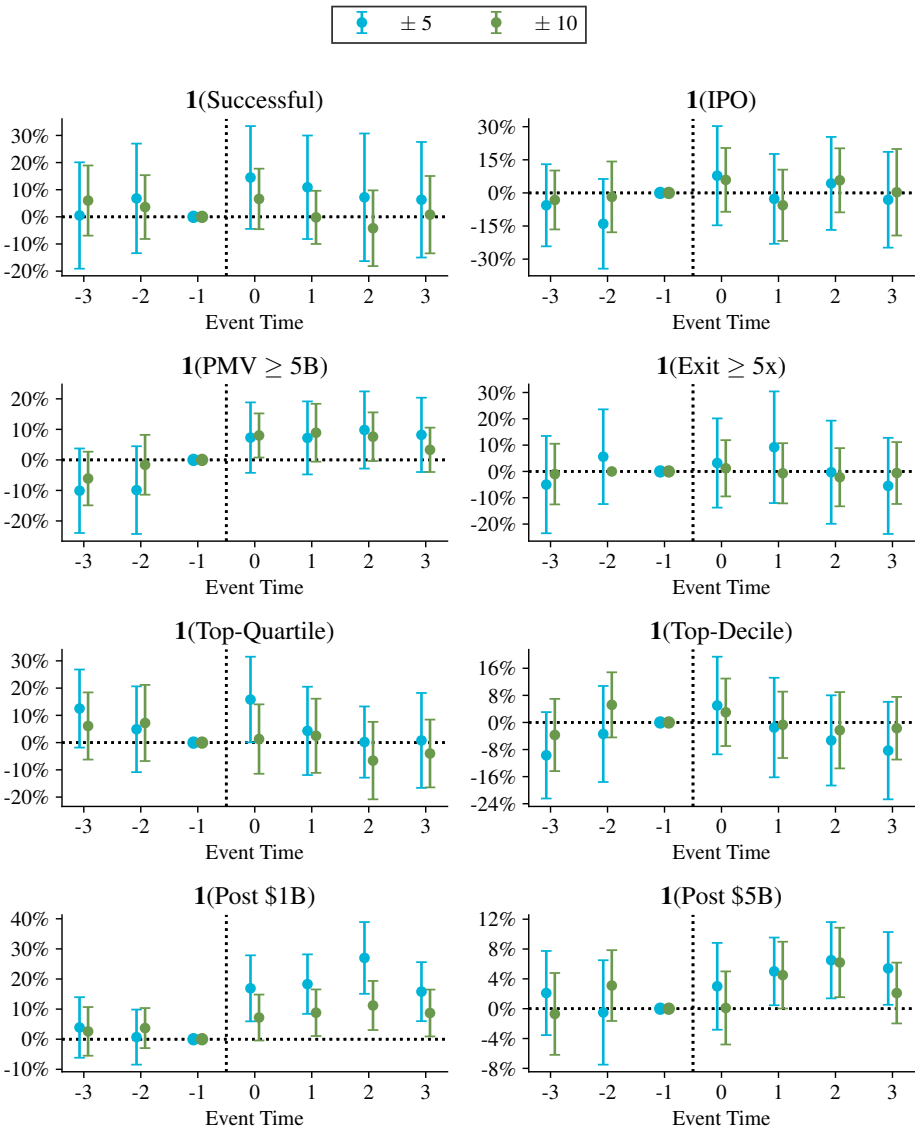


Figure IA2: Plots dynamic stacked difference-in-differences estimates of the effect of Midas List recognition on individual VCs' investing activity each calendar year. The unit of observation is the individual VC×calendar year. Indicators denote whether a professional made an investment of a given type 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 and Outcome

	Outcome					
	All	IPO	Unicorn	Acq. ≥ 5× Entry	Successful	Not Successful
# Professionals × Companies	134,151	7,767	5,712	13,169	20,972	113,194
1(Only PB/VS)	55.6%	28.1%	46.2%	33.2%	35.9%	59.3%
1(Only Websites)	14.5%	22.6%	14.0%	17.5%	17.7%	13.9%
1(Websites & PB/VS)	29.9%	49.3%	39.8%	49.3%	46.4%	26.8%
1(PitchBook Deal)	70.1%	46.1%	75.1%	56.5%	58.7%	72.2%
1(PitchBook Board)	32.2%	38.8%	42.6%	42.0%	41.0%	30.6%
1(VentureSource Board)	17.4%	41.9%	18.3%	40.4%	34.9%	14.2%
1(Website Deal)	22.0%	45.3%	35.5%	41.0%	39.3%	18.8%
1(Website Board)	31.0%	48.9%	32.9%	47.0%	44.0%	28.6%

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 Web	PB/VS - Web
# Professionals × Companies	134,151	40,079	74,595	19,492	
Panel A: Investment Outcomes					
1(Successful Outcome)	15.6%	24.3%	10.1%	19.1%	-9.0%***
1(IPO)	5.8%	9.5%	2.9%	9.0%	-6.1%***
1(Unicorn)	4.3%	5.7%	3.5%	4.1%	-0.6%***
1(Acquisition)	9.8%	16.2%	5.9%	11.8%	-6.0%***
Panel B: Investment Relationships					
1(Early Stage)	61.4%	61.4%	62.5%	57.6%	4.8%***
1(Board Seat)	48.9%	93.0%	27.5%	40.1%	-12.6%***
Panel C: Investment Timing & Characteristics					
1(Pre-2000)	2.6%	4.4%	1.2%	4.2%	-2.9%***
1(2001-2009)	17.2%	26.6%	8.8%	30.3%	-21.5%***
1(2010-2019)	45.8%	46.5%	47.7%	36.9%	10.8%***
1(2020+)	34.4%	22.5%	42.2%	28.7%	13.5%***
1(California)	35.2%	37.1%	33.9%	35.9%	-1.9%***
1(New York)	9.8%	8.1%	11.0%	8.6%	2.4%***
1(Massachusetts)	7.0%	9.7%	5.1%	8.7%	-3.6%***
1(Software)	44.4%	40.7%	47.5%	40.3%	7.2%***
1(Cmcl. Services)	8.2%	7.6%	8.5%	8.0%	0.6%**
1(Pharma/BioTech)	8.5%	12.5%	5.9%	10.4%	-4.5%***

Table IA2: Tabulates characteristics 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: Investment Counts Per VC

	Nobs.	Avg.	25p	50p	75p
# Investments	16,425	8.17	1	4	9
# Successful	16,425	1.28	0	0	1
# IPO	16,425	0.47	0	0	0
# Acq.	16,425	0.8	0	0	1
# Unicorn	16,425	0.35	0	0	0
# Board Seats	16,425	3.99	0	1	5
# Lead Relations	16,425	1.9	0	0	2
# Early Stage	16,425	5.02	1	2	5

Table IA3: Tabulates the number of investments and the nature of these investments for each VC with at least one investment in our sample.

Table IA4: Most Common Schools Among VC Professionals

By # of Successful Involvements:

Panel A. Undergraduate Schools

Rank	Any (N = 13,326)	0 Successes (N = 7,978)	1-2 Successes (N = 3,209)	3-5 Successes (N = 1,213)	6+ Successes (N = 926)
1	Stanford (4.8%)	Stanford (3.9%)	Stanford (4.8%)	Stanford (6.5%)	Stanford (9.5%)
2	Harvard (4.2%)	Harvard (3.5%)	Harvard (4.4%)	Harvard (5.3%)	Harvard (7.3%)
3	UPenn (3.2%)	UPenn (3.1%)	UC-Berkeley (3.2%)	UPenn (4.4%)	Dartmouth (4.6%)
4	UC-Berkeley (2.9%)	UC-Berkeley (2.5%)	UPenn (3.0%)	UC-Berkeley (4.1%)	Princeton (4.0%)
5	Yale (2.1%)	Yale (1.9%)	Yale (2.5%)	Princeton (3.5%)	MIT (3.6%)
6	Princeton (2.0%)	Cornell (1.8%)	Princeton (2.2%)	Duke (2.4%)	UC-Berkeley (3.5%)
7	MIT (1.9%)	UMichigan (1.7%)	MIT (2.2%)	MIT (2.4%)	UPenn (3.1%)
8	Cornell (1.9%)	MIT (1.6%)	Dartmouth (1.9%)	Cornell (2.4%)	Yale (2.5%)
9	UMichigan (1.7%)	Princeton (1.5%)	Duke (1.8%)	UMichigan (2.1%)	Cornell (2.4%)
10	Dartmouth (1.7%)	Duke (1.4%)	Cornell (1.8%)	Yale (2.0%)	Brown (1.6%)
11	Duke (1.6%)	Dartmouth (1.3%)	UMichigan (1.7%)	Brown (1.6%)	Duke (1.5%)
12	Brown (1.3%)	Columbia (1.2%)	Brown (1.5%)	BYU (1.6%)	Northwestern (1.4%)
13	Columbia (1.2%)	UVA (1.1%)	Columbia (1.3%)	Dartmouth (1.4%)	UVA (1.3%)
14	UVA (1.1%)	Georgetown (1.1%)	UT-Austin (1.1%)	UVA (1.3%)	UMichigan (1.3%)
15	Georgetown (1.1%)	Brown (1.1%)	UIUC (1.0%)	Columbia (1.2%)	Columbia (1.1%)
16	UT-Austin (0.9%)	UT-Austin (1.0%)	Georgetown (1.0%)	UCLA (1.1%)	Boston College (1.0%)
17	Northwestern (0.9%)	NYU (1.0%)	UVA (1.0%)	Tufts (1.0%)	UCLA (1.0%)
18	UIUC (0.9%)	UIUC (1.0%)	UCLA (0.9%)	Northwestern (0.9%)	Johns Hopkins (0.9%)
19	UCLA (0.9%)	Univ. South. Cal. (0.9%)	Northwestern (0.9%)	Georgetown (0.8%)	Georgetown (0.9%)
20	NYU (0.8%)	Northwestern (0.9%)	Tufts (0.8%)	Amherst (0.7%)	UIUC (0.8%)

Panel B. MBA Schools

Rank	Any (N = 5,089)	0 Successes (N = 2,761)	1-2 Successes (N = 1,329)	3-5 Successes (N = 539)	6+ Successes (N = 460)
1	HBS (19.2%)	HBS (16.4%)	HBS (18.9%)	HBS (26.9%)	HBS (28.0%)
2	Stanford GSB (12.7%)	Stanford GSB (8.8%)	Stanford GSB (14.6%)	Stanford GSB (16.0%)	Stanford GSB (26.5%)
3	UPenn (9.1%)	UPenn (7.9%)	UPenn (11.4%)	UPenn (10.9%)	UPenn (7.6%)
4	Columbia (5.1%)	Columbia (5.4%)	UChicago Booth (5.2%)	Columbia (5.2%)	Columbia (4.3%)
5	UChicago Booth (4.7%)	UChicago Booth (4.8%)	Kellogg (4.7%)	Kellogg (5.2%)	Kellogg (4.1%)
6	Kellogg (4.7%)	Kellogg (4.7%)	Columbia (4.4%)	UChicago Booth (3.5%)	UChicago Booth (3.9%)
7	MIT Sloan (2.9%)	MIT Sloan (3.4%)	MIT Sloan (2.6%)	UC-Berkeley (2.4%)	Dartmouth Tuck (3.0%)
8	UC-Berkeley (2.4%)	UC-Berkeley (2.6%)	UCLA (2.3%)	MIT Sloan (1.9%)	MIT Sloan (2.0%)
9	UCLA (2.0%)	NYU Stern (2.0%)	UC-Berkeley (2.1%)	UCLA (1.9%)	UMichigan Ross (1.7%)
10	Dartmouth Tuck (1.8%)	UCLA (1.9%)	UMichigan Ross (1.7%)	INSEAD (1.7%)	UC-Berkeley (1.7%)
11	UMichigan Ross (1.7%)	INSEAD (1.8%)	Dartmouth Tuck (1.7%)	UMichigan Ross (1.5%)	UCLA (1.3%)
12	NYU Stern (1.7%)	Dartmouth Tuck (1.8%)	NYU Stern (1.4%)	NYU Stern (1.3%)	NYU Stern (1.1%)
13	INSEAD (1.5%)	UMichigan Ross (1.8%)	Johnson (1.2%)	Dartmouth Tuck (1.3%)	Duke Fuqua (0.7%)
14	Johnson (1.2%)	Johnson (1.4%)	INSEAD (1.1%)	Yale SOM (1.3%)	Johnson (0.7%)
15	UVA Darden (1.2%)	UVA Darden (1.4%)	UVA Darden (1.1%)	Boston (1.3%)	McCombs (0.7%)
16	Duke Fuqua (1.2%)	Duke Fuqua (1.3%)	Duke Fuqua (1.1%)	Duke Fuqua (0.9%)	Northeastern (0.7%)
17	Yale SOM (1.0%)	McCombs (1.1%)	Yale SOM (1.1%)	UVA Darden (0.7%)	Yale SOM (0.4%)
18	McCombs (0.9%)	Yale SOM (1.0%)	UNC (1.1%)	UNC (0.7%)	IIT-Ahmedabad (0.4%)
19	UNC (0.7%)	Babson (0.9%)	Santa Clara (0.8%)	McCombs (0.6%)	Santa Clara (0.4%)
20	Babson (0.7%)	WashU in St. Louis (0.7%)	USC Marshall (0.8%)	IIM Bangalore (0.6%)	UVA Darden (0.4%)

Table IA4: 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 IA5: Most Common Prior Employers of VC Professionals

Rank	# of Successful Involvements				
	Any (N = 14,529)	0 Successes (N = 8,995)	1-2 Successes (N = 3,391)	3-5 Successes (N = 1,219)	6+ Successes (N = 924)
1	McKinsey (4.0%)	McKinsey (3.5%)	McKinsey (4.1%)	McKinsey (5.3%)	McKinsey (6.8%)
2	Goldman Sachs (3.1%)	Goldman Sachs (3.2%)	Morgan Stanley (3.1%)	IBM (3.1%)	Goldman Sachs (4.2%)
3	Morgan Stanley (2.8%)	Morgan Stanley (2.5%)	Goldman Sachs (2.8%)	Morgan Stanley (2.8%)	Bain & Co. (3.7%)
4	Google (2.1%)	Google (2.3%)	Booz & Company (2.2%)	Bain & Co. (2.8%)	Morgan Stanley (3.7%)
5	Booz & Company (2.1%)	Merrill Lynch (2.0%)	IBM (2.2%)	Microsoft (2.7%)	IBM (3.0%)
6	Microsoft (2.0%)	Booz & Company (2.0%)	Microsoft (2.1%)	Booz & Company (2.6%)	BCG (2.7%)
7	IBM (2.0%)	Hambrect & Quist (1.9%)	Google (2.1%)	Goldman Sachs (2.6%)	Microsoft (2.2%)
8	Merrill Lynch (1.9%)	Microsoft (1.9%)	Merrill Lynch (1.9%)	Cisco Systems (2.1%)	HP (2.1%)
9	Hambrect & Quist (1.8%)	IBM (1.6%)	BCG (1.9%)	Oracle (1.7%)	Apple (1.9%)
10	BCG (1.7%)	Deloitte (1.6%)	Credit Suisse (1.7%)	Google (1.7%)	Alex. Brown & Sons (1.8%)
11	Bain & Co. (1.7%)	BCG (1.5%)	Deloitte (1.7%)	BCG (1.7%)	Verizon Media (1.8%)
12	Deloitte (1.5%)	Bain & Co. (1.5%)	Citi (1.6%)	Hambrect & Quist (1.6%)	Cisco Systems (1.7%)
13	Credit Suisse (1.4%)	Citi (1.4%)	Accenture (1.5%)	Credit Suisse (1.6%)	Hewlett Packard (1.7%)
14	Accenture (1.3%)	Credit Suisse (1.3%)	Hambrect & Quist (1.5%)	Merrill Lynch (1.6%)	Hambrect & Quist (1.7%)
15	Citi (1.3%)	Accenture (1.3%)	Oracle (1.5%)	Apple (1.5%)	AT&T (1.7%)
16	Oracle (1.1%)	UBS (1.1%)	Bain & Co. (1.4%)	Lehman Brothers (1.5%)	Sun Microsystems (1.7%)
17	Verizon (1.1%)	Meta (1.0%)	Cisco Systems (1.3%)	HP (1.4%)	Booz & Company (1.7%)
18	UBS (1.0%)	Verizon Media (0.9%)	Verizon (1.2%)	AT&T (1.3%)	Robertson Stephens (1.7%)
19	Cisco Systems (1.0%)	Oracle (0.9%)	Apple (1.2%)	Deloitte (1.3%)	Accenture (1.6%)
20	HP (1.0%)	EY (0.8%)	Intel (1.1%)	Intel (1.2%)	SGI (1.6%)

Table IA5: Tabulates top prior employers 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. For example, 4.0% indicates that 4.0% of all professionals worked at McKinsey. 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 IA6: Portfolio Company Characteristics Over Time

	Investment Year						
	All	Pre-2000	2001-2005	2006-2010	2011-2015	2016-2020	2021+
# Companies	68,010	2,079	4,710	7,365	14,952	22,810	24,575
Panel A: Outcomes							
1(Successful Outcome)	11.8%	50.1%	27.5%	24.3%	18.4%	10.6%	1.3%
1(IPO)	4.3%	37.0%	11.3%	9.2%	6.1%	2.5%	0.3%
1(Unicorn)	2.8%	1.6%	1.0%	2.3%	5.0%	5.4%	0.8%
1(Acquisition)	7.7%	32.0%	22.9%	19.7%	12.2%	4.5%	0.2%
Panel B: Involvement Types							
1(Early Stage)	67.9%	74.7%	60.1%	61.6%	68.6%	62.4%	58.6%
1(Board Seat)	53.8%	90.6%	90.5%	82.3%	59.4%	50.1%	33.5%
Panel C: Company Industry							
1(Software)	43.8%	31.0%	34.0%	33.6%	44.4%	44.2%	49.7%
1(Commercial Services)	8.7%	9.7%	9.2%	11.2%	9.9%	7.3%	7.5%
1(Pharma/BioTech)	7.7%	9.9%	11.7%	10.3%	6.3%	8.1%	7.0%
1(Healthcare Devices)	4.1%	7.3%	7.4%	7.6%	4.3%	4.0%	2.6%
1(Media)	3.1%	2.4%	2.1%	4.9%	4.8%	2.7%	1.9%
Panel D: Company Country							
1(United States)	74.1%	95.0%	90.4%	83.6%	78.3%	72.9%	69.6%
1(United Kingdom)	4.4%	1.2%	2.0%	2.7%	3.3%	4.6%	5.3%
1(India)	2.6%	0.1%	0.4%	2.5%	2.6%	2.7%	2.8%
1(Canada)	2.6%	0.4%	1.5%	1.6%	2.3%	2.8%	3.0%
1(China)	2.3%	0.3%	0.8%	2.9%	2.8%	2.6%	1.6%
Panel E: Company State							
1(California)	29.2%	41.2%	38.1%	35.0%	33.4%	29.1%	26.5%
1(New York)	9.1%	3.1%	3.1%	6.9%	9.6%	10.3%	10.6%
1(Massachusetts)	5.9%	12.9%	11.2%	8.4%	5.9%	5.5%	4.7%
1(Texas)	3.8%	6.2%	5.4%	4.6%	3.6%	3.4%	3.6%
1(Washington)	2.6%	4.3%	3.6%	3.2%	2.6%	2.4%	2.3%

Table IA6: 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. In Panel B, we report what percentage of person-company relationships for an average company are either early stage or board seats. Characteristics of the companies are from PitchBook.

Table IA7: Junior VC Career Outcomes and VC Characteristics

	1(Senior Level)		**1**(≥ 1 Deal)		**1**(≥ 5 Deals)	
	(1)	(2)	(3)	(4)	(5)	(6)
1(Start Analyst)	-0.035***	-0.058**	-0.070***	-0.090***	-0.035***	-0.066**
	(-4.20)	(-2.14)	(-5.84)	(-2.76)	(-4.55)	(-2.44)
1(Start Sr. Asso.)	0.022	0.025	0.053***	0.030	0.032**	0.032
	(1.60)	(0.56)	(3.04)	(0.63)	(2.38)	(0.71)
1(White)	0.014*	0.022	0.030***	0.047	0.005	0.029
	(1.81)	(0.85)	(2.78)	(1.60)	(0.63)	(1.11)
1(Female)	-0.039***	-0.109***	-0.050***	-0.138***	-0.039***	-0.106***
	(-5.20)	(-4.04)	(-4.58)	(-4.03)	(-5.48)	(-3.98)
1(Business Major)	0.012	-0.037	-0.013	-0.104**	-0.013	-0.073
	(0.99)	(-0.83)	(-0.75)	(-2.04)	(-1.07)	(-1.61)
1(STEM Major)	0.009	0.014	-0.013	-0.063	-0.011	-0.027
	(0.67)	(0.31)	(-0.72)	(-1.21)	(-0.84)	(-0.58)
1(Soc. Sci. Major)	-0.001	-0.067	-0.040*	-0.084	-0.009	-0.051
	(-0.03)	(-1.21)	(-1.78)	(-1.24)	(-0.54)	(-0.86)
1(Ivy Undergrad)	0.007	-0.027	0.029**	-0.010	0.018*	0.011
	(0.67)	(-0.94)	(2.01)	(-0.29)	(1.66)	(0.38)
1(Ivy+ Undergrad)	0.051***	0.073*	0.028	0.102**	0.026*	0.072*
	(3.49)	(1.95)	(1.58)	(2.44)	(1.92)	(1.89)
1(Has MBA)	0.049***	0.074**	0.060***	0.079**	0.025**	0.052*
	(3.64)	(2.30)	(3.46)	(2.18)	(1.97)	(1.66)
1(Top-10 MBA)	-0.012	-0.004	-0.003	0.041	0.028*	0.050
	(-0.70)	(-0.12)	(-0.14)	(0.97)	(1.70)	(1.41)
1(HBS MBA)	0.083***	0.067	0.129***	0.057	0.090***	0.083
	(2.72)	(1.25)	(3.70)	(0.97)	(2.93)	(1.47)
1(Stanford GSB MBA)	0.094**	0.100	0.125***	0.085	0.098**	0.032
	(2.50)	(1.38)	(3.01)	(1.14)	(2.55)	(0.44)
1(Advanced Degree)	0.049***	0.129***	0.100***	0.175***	0.046***	0.131***
	(3.20)	(2.67)	(5.20)	(3.60)	(3.17)	(2.74)
1(CEO/Founder)$^{+}$	0.163***	0.243***	0.287***	0.350***	0.190***	0.248***
	(4.55)	(3.64)	(8.12)	(6.91)	(5.30)	(3.77)
1(CEO/Founder)$^{-}$	0.071**	0.367***	0.121***	0.196	0.041	0.257**
	(2.20)	(3.13)	(2.97)	(1.49)	(1.42)	(2.06)
1(Non- CEO/Founder)$^{+}$	0.078***	0.169***	0.110***	0.176***	0.056***	0.103***
	(5.23)	(4.38)	(6.31)	(4.66)	(3.99)	(2.73)
1(Non-CEO/Founder)$^{-}$	0.037***	0.125*	0.044**	-0.003	0.031**	0.030
	(2.64)	(1.66)	(2.34)	(-0.03)	(2.37)	(0.39)
1(Tech.)	0.054***	0.047	0.075***	0.077**	0.048***	0.073**
	(4.11)	(1.32)	(4.68)	(2.03)	(3.86)	(2.07)
1(Pharma.)	0.013	0.011	0.050*	-0.011	0.007	-0.030
	(0.63)	(0.16)	(1.81)	(-0.16)	(0.36)	(-0.46)
1(Inv. Banking)	0.012	0.046	0.039***	0.020	0.019**	0.045
	(1.31)	(1.60)	(3.12)	(0.62)	(2.10)	(1.59)
1(Mgmt. Consulting)	0.028***	0.045	0.051***	0.045	0.027***	0.049
	(2.62)	(1.42)	(3.74)	(1.30)	(2.80)	(1.56)
Sample	All	Pre-2011	All	Pre-2011	All	Pre-2011
Y-mean	0.121	0.250	0.271	0.434	0.113	0.253
Year Entered the VC Industry	x	x	x	x	x	x
Adj. R^2	0.138	0.124	0.172	0.136	0.160	0.122
N	6,134	1,207	6,134	1,207	6,134	1,207

Table IA7: 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 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 IA8: Heterogeneity: Investment Outcomes and VC Characteristics

	1(Successful Outcome)					
	(1)	(2)	(3)	(4)	(5)	(6)
Sample	Board	No Board	Early Stage	Later Stage	Lead	Not-Lead
1(1+ Successful Prior Inv.)	0.017**	0.019***	0.015***	0.020***	0.022***	0.016***
	(2.54)	(3.36)	(2.67)	(2.97)	(2.58)	(3.22)
1(2+ Successful Prior Inv.)	0.029***	0.002	0.016**	0.016*	0.012	0.018***
	(3.72)	(0.22)	(2.40)	(1.94)	(1.27)	(2.89)
1(5+ Successful Prior Inv.)	0.048***	0.025***	0.033***	0.035***	0.049***	0.026***
	(5.45)	(3.15)	(4.65)	(3.83)	(5.05)	(3.57)
1(White)	-0.013**	0.002	-0.005	-0.003	-0.014*	-0.001
	(-2.17)	(0.45)	(-1.01)	(-0.46)	(-1.89)	(-0.24)
1(Female)	-0.012*	-0.013**	-0.014**	-0.011	-0.016**	-0.009*
	(-1.72)	(-2.48)	(-2.55)	(-1.64)	(-2.08)	(-1.84)
1(Business Major)	-0.010	0.001	-0.003	-0.005	-0.010	-0.001
	(-1.20)	(0.15)	(-0.46)	(-0.55)	(-1.06)	(-0.24)
1(STEM Major)	-0.006	-0.002	0.002	-0.010	-0.004	-0.003
	(-0.82)	(-0.25)	(0.24)	(-1.16)	(-0.38)	(-0.52)
1(Soc. Sci. Major)	-0.017*	-0.004	-0.003	-0.016	-0.006	-0.010
	(-1.65)	(-0.48)	(-0.33)	(-1.63)	(-0.50)	(-1.32)
1(Ivy Undergrad)	0.021***	0.008	0.012**	0.020***	0.018**	0.015***
	(3.22)	(1.62)	(2.34)	(3.01)	(2.21)	(2.93)
1(Ivy+ Undergrad)	0.021***	0.000	0.011*	0.008	0.018*	0.008
	(2.72)	(0.03)	(1.74)	(1.03)	(1.88)	(1.27)
1(Has MBA)	-0.022***	-0.021***	-0.023***	-0.019***	-0.017*	-0.024***
	(-3.22)	(-3.41)	(-3.99)	(-2.70)	(-1.88)	(-4.37)
1(Top-10 MBA)	0.006	0.014*	0.011	0.010	-0.000	0.015**
	(0.66)	(1.74)	(1.41)	(1.14)	(-0.03)	(2.12)
1(HBS MBA)	0.014	-0.002	0.005	0.006	0.026**	-0.002
	(1.36)	(-0.26)	(0.58)	(0.58)	(2.10)	(-0.23)
1(Stanford GSB MBA)	0.044***	0.028**	0.039***	0.030**	0.059***	0.027***
	(3.85)	(2.56)	(3.90)	(2.43)	(4.43)	(2.78)
1(Advanced Degree)	0.009	0.002	0.008	0.004	0.004	0.007
	(1.23)	(0.22)	(1.26)	(0.57)	(0.42)	(1.22)
1(CEO/Founder)$^{+}$	0.003	0.003	0.001	0.004	-0.011	0.007
	(0.51)	(0.64)	(0.29)	(0.57)	(-1.40)	(1.44)
1(CEO/Founder)$^{-}$	-0.033***	-0.019*	-0.034***	-0.019	-0.028**	-0.027***
	(-3.06)	(-1.76)	(-3.94)	(-1.61)	(-1.99)	(-3.00)
1(Non- CEO/Founder)$^{+}$	0.007	0.002	0.001	0.011*	0.002	0.005
	(1.18)	(0.44)	(0.19)	(1.72)	(0.28)	(1.09)
1(Non-CEO/Founder)$^{-}$	-0.006	-0.010	-0.008	-0.006	-0.024**	-0.003
	(-0.56)	(-1.24)	(-0.97)	(-0.61)	(-2.26)	(-0.42)
1(Tech.)	0.002	0.004	0.004	-0.001	-0.001	0.003
	(0.34)	(0.79)	(0.90)	(-0.14)	(-0.08)	(0.73)
1(Pharma.)	0.031***	-0.013	0.022*	0.019*	0.035**	0.017*
	(2.96)	(-1.09)	(1.90)	(1.69)	(2.11)	(1.73)
1(Inv. Banking)	0.024***	0.002	0.009*	0.021***	0.020***	0.011**
	(4.02)	(0.47)	(1.70)	(3.28)	(2.62)	(2.26)
1(Mgmt. Consulting)	-0.001	-0.003	-0.006	0.005	-0.010	0.001
	(-0.18)	(-0.65)	(-1.18)	(0.74)	(-1.35)	(0.26)
1(Enter at Senior Level)	-0.019***	0.005	-0.002	-0.013**	-0.011*	-0.006
	(-3.68)	(1.12)	(-0.42)	(-2.48)	(-1.79)	(-1.64)
1(0-5 Yrs. in VC)	0.026***	0.000	0.010**	0.013**	0.023***	0.008*
	(4.20)	(0.03)	(1.98)	(2.24)	(3.14)	(1.80)
1(0-10 Yrs. in VC)	0.020***	0.020***	0.025***	0.013*	0.023***	0.019***
	(2.88)	(3.44)	(4.30)	(1.95)	(2.97)	(3.39)
Y-mean	0.185	0.100	0.139	0.146	0.138	0.143
FE	x	x	x	x	x	x
Controls	x	x	x	x	x	x
Adj. R^2	0.117	0.121	0.138	0.125	0.132	0.127
N	29,057	30,105	35,058	24,115	14,913	44,238

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. Fixed effects are for: investment years, the data source, and portfolio company location, industry, and age. Controls are indicators for lead investor positions and whether the investment was early. 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 in Differing Sub-Samples

	1(Successful Outcome)	
	(1)	(2)
Sample	≤ 5 Affiliated VCs	Career VCs
1(1+ Successful Prior Inv.)	0.012***	0.018***
	(2.73)	(3.71)
1(2+ Successful Prior Inv.)	0.009	0.016***
	(1.58)	(2.80)
1(5+ Successful Prior Inv.)	0.021***	0.034***
	(3.38)	(5.14)
1(White)	-0.002	-0.003
	(-0.54)	(-0.57)
1(Female)	-0.008**	-0.013***
	(-2.03)	(-2.62)
1(Business Major)	-0.001	-0.006
	(-0.28)	(-0.88)
1(STEM Major)	0.002	-0.005
	(0.36)	(-0.72)
1(Soc. Sci. Major)	-0.006	-0.009
	(-1.10)	(-1.14)
1(Ivy Undergrad)	0.015***	0.016***
	(3.51)	(3.25)
1(Ivy+ Undergrad)	0.004	0.011*
	(0.81)	(1.79)
1(Has MBA)	-0.015***	-0.022***
	(-3.22)	(-4.11)
1(Top-10 MBA)	0.008	0.010
	(1.40)	(1.48)
1(HBS MBA)	-0.004	0.007
	(-0.57)	(0.90)
1(Stanford GSB MBA)	0.023***	0.034***
	(2.89)	(3.95)
1(Advanced Degree)	0.004	0.009
	(0.83)	(1.63)
1(CEO/Founder)$^{+}$	-0.004	0.000
	(-0.94)	(0.02)
1(CEO/Founder)$^{-}$	-0.025***	-0.027***
	(-3.77)	(-3.08)
1(Non- CEO/Founder)$^{+}$	0.001	0.003
	(0.14)	(0.59)
1(Non-CEO/Founder)$^{-}$	-0.010	-0.007
	(-1.61)	(-0.95)
1(Tech.)	-0.000	0.003
	(-0.04)	(0.79)
1(Pharma.)	0.028***	0.021**
	(2.98)	(2.26)
1(Inv. Banking)	0.008**	0.016***
	(2.06)	(3.31)
1(Mgmt. Consulting)	-0.002	-0.002
	(-0.59)	(-0.49)
1(Enter at Senior Level)	-0.003	-0.007*
	(-0.87)	(-1.87)
1(0-5 Yrs. in VC)	0.003	0.011**
	(0.74)	(2.50)
1(0-10 Yrs. in VC)	0.012***	0.021***
	(2.75)	(4.05)
Y-mean	0.102	0.147
FE	x	x
Controls	x	x
Adj. R^2	0.117	0.127
N	45,777	52,214

Table IA9: Tabulates coefficients from regressions of indicators of investment success on characteristics of the VC investment professionals within different subsamples (denoted in column headers). Fixed effects are for: investment years, the data source, and portfolio company location, industry, and age. Controls are indicators for lead investor positions and whether the investment was early. 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: 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.)	0.018***	0.020***	0.020***
	(4.02)	(5.41)	(5.42)
1(2+ Successful Prior Inv.)	0.016***	0.018***	0.018***
	(2.93)	(3.78)	(3.83)
1(5+ Successful Prior Inv.)	0.033***	0.033***	0.034***
	(5.31)	(5.78)	(5.92)
1(White)	-0.004	-0.005	-0.005
	(-0.95)	(-1.47)	(-1.40)
1(Female)	-0.012***	-0.013***	-0.013***
	(-2.68)	(-3.37)	(-3.29)
1(Business Major)	-0.003	-0.010**	0.005
	(-0.60)	(-2.46)	(1.46)
1(STEM Major)	-0.003	-0.008**	0.007**
	(-0.53)	(-1.99)	(1.99)
1(Soc. Sci. Major)	-0.009	-0.014**	0.004
	(-1.26)	(-2.54)	(1.19)
1(Ivy Undergrad)	0.016***	0.012***	0.009**
	(3.46)	(2.94)	(2.46)
1(Ivy+ Undergrad)	0.010*	0.010*	0.006
	(1.80)	(1.95)	(1.39)
1(Has MBA)	-0.022***	-0.021***	-0.024***
	(-4.56)	(-4.66)	(-5.87)
1(Top-10 MBA)	0.011*	0.013**	0.016***
	(1.76)	(2.25)	(2.92)
1(HBS MBA)	0.005	0.002	0.003
	(0.72)	(0.33)	(0.41)
1(Stanford GSB MBA)	0.037***	0.036***	0.036***
	(4.45)	(4.62)	(4.74)
1(Advanced Degree)	0.006	0.003	0.002
	(1.15)	(0.55)	(0.42)
1(CEO/Founder)$^{+}$	0.003	0.003	0.004
	(0.61)	(0.93)	(1.16)
1(CEO/Founder)$^{-}$	-0.027***	-0.015**	-0.015**
	(-3.43)	(-2.20)	(-2.17)
1(Non-CEO/Founder)$^{+}$	0.005	0.004	0.005
	(1.09)	(1.02)	(1.18)
1(Non-CEO/Founder)$^{-}$	-0.008	-0.009	-0.009
	(-1.17)	(-1.41)	(-1.41)
1(Tech.)	0.003	-0.005	-0.007**
	(0.65)	(-1.43)	(-2.11)
1(Pharma.)	0.021**	0.008	0.001
	(2.54)	(1.03)	(0.26)
1(Inv. Banking)	0.014***	0.016***	0.013***
	(3.22)	(4.02)	(3.59)
1(Mgmt. Consulting)	-0.002	-0.004	-0.006
	(-0.43)	(-0.93)	(-1.62)
1(Enter at Senior Level)	-0.007**	-0.007**	-0.007**
	(-2.05)	(-2.29)	(-2.31)
1(0-5 Yrs. in VC)	0.011***	0.014***	0.014***
	(2.95)	(4.33)	(4.43)
1(0-10 Yrs. in VC)	0.020***	0.021***	0.021***
	(4.09)	(5.03)	(5.08)
Y-mean	0.142	0.147	0.147
FE	x	x	x
Controls	x	x	x
Adj. R^2	0.127	0.131	0.131
N	59,228	81,888	81,888

Table IA10: 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. Fixed effects are for: investment years, the data source, and portfolio company location, industry, and age. Controls are indicators for lead investor positions and whether the investment was early. 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 IA11: Robustness: Cumulative Investment Success and VC Characteristics: Extended Sample

	Cumulative # of:			
	(1) Successful	(2) IPOs	(3) Unicorns	(4) ≥ 5× Acq.
1(White)	-0.008	-0.084	-0.057	0.031
	(-0.15)	(-1.22)	(-0.84)	(0.58)
1(Female)	-0.641***	-0.429***	-0.748***	-0.678***
	(-9.21)	(-4.08)	(-8.30)	(-8.40)
1(Business Major)	-0.261***	-0.366***	-0.208*	-0.286***
	(-3.31)	(-3.60)	(-1.81)	(-3.58)
1(STEM Major)	-0.148*	-0.097	-0.227*	-0.170**
	(-1.93)	(-1.02)	(-1.84)	(-2.32)
1(Soc. Sci. Major)	-0.178*	-0.332***	-0.065	-0.190*
	(-1.85)	(-2.58)	(-0.48)	(-1.93)
1(Ivy Undergrad)	0.294***	0.341***	0.365***	0.236***
	(5.09)	(4.42)	(4.45)	(3.86)
1(Ivy+ Undergrad)	0.384***	0.356***	0.520***	0.351***
	(5.46)	(4.18)	(5.00)	(5.17)
1(Has MBA)	-0.155**	-0.133	-0.334***	-0.140**
	(-2.40)	(-1.25)	(-3.81)	(-2.20)
1(Top-10 MBA)	0.205**	0.153	0.312***	0.205**
	(2.51)	(1.30)	(2.71)	(2.53)
1(HBS MBA)	0.238***	0.271**	0.259**	0.221**
	(2.75)	(2.47)	(2.12)	(2.43)
1(Stanford GSB MBA)	0.371***	0.511***	0.564***	0.278***
	(3.86)	(4.19)	(4.11)	(2.85)
1(Advanced Degree)	0.308***	0.675***	-0.006	0.275***
	(4.83)	(8.49)	(-0.06)	(4.28)
1(Enter at Senior Level)	0.610***	0.444***	0.692***	0.622***
	(13.12)	(6.79)	(10.75)	(12.88)
1(CEO/Founder)$^{+}$	0.520***	0.438***	0.705***	0.518***
	(9.02)	(5.68)	(9.11)	(8.79)
1(CEO/Founder)$^{-}$	-0.074	-0.078	-0.009	-0.042
	(-0.65)	(-0.40)	(-0.06)	(-0.36)
1(Non- CEO/Founder)$^{+}$	0.155***	0.051	0.276***	0.124**
	(2.75)	(0.65)	(3.71)	(2.12)
1(Non-CEO/Founder)$^{-}$	0.013	-0.193	0.004	0.040
	(0.13)	(-1.18)	(0.03)	(0.35)
1(Tech.)	0.308***	0.120*	0.461***	0.318***
	(5.95)	(1.72)	(6.34)	(5.97)
1(Pharma.)	0.276***	0.792***	-0.794***	0.281***
	(3.42)	(7.43)	(-4.77)	(3.39)
1(Inv. Banking)	0.078	0.210**	0.080	0.053
	(1.33)	(2.50)	(1.08)	(0.88)
1(Mgmt. Consulting)	0.049	-0.031	0.092	0.079
	(0.86)	(-0.42)	(1.15)	(1.36)
Model	Poi	Poi	Poi	Poi
Y-mean	0.677	0.246	0.200	0.452
Year Entered the VC Industry	x	x	x	x
Pseudo R^2	0.365	0.342	0.233	0.382
N	16,684	15,240	16,679	15,775

Table IA11: 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. $^{+}$ denotes experience at a successful startup. $^{-}$ denotes experience at a startup that was not successful. 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 IA12: Robustness: Fund Returns Within Small Teams

	# Successful			IRR		
	(1)	(2)	(3)	(4)	(5)	(6)
Sample	Baseline	≤ 5 VCs	≤ 5 Senior	Baseline	≤ 5 VCs	≤ 5 Senior
1(1+ Successful Prior Inv.)	0.231**	0.115	0.258**	-0.041	-0.024	-0.004
	(2.38)	(0.78)	(2.01)	(-1.46)	(-0.78)	(-0.11)
1(2+ Successful Prior Inv.)	0.184**	0.136	0.022	0.013	0.015	-0.027
	(2.03)	(1.31)	(0.25)	(0.52)	(0.46)	(-0.77)
1(5+ Successful Prior Inv.)	0.100	0.064	0.007	0.029	0.008	-0.017
	(1.64)	(0.72)	(0.06)	(1.17)	(0.32)	(-0.90)
Model	Poi	Poi	Poi	OLS	OLS	OLS
Y-mean	4.189	1.807	2.291	0.145	0.156	0.141
FE	x	x	x	x	x	x
Industry FE	x	x	x	x	x	x
Pseudo R^2	0.446	0.317	0.362			
Adj. R^2				0.294	0.315	0.330
N	1,240	648	508	1,086	550	432

Table IA12: 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. The characteristics from Table 7 are included in the estimation, but omitted from the display; results are summarized based just on the prior investing success of the affiliated VCs. 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, status, and industry focus of the fund in PitchBook. Regression samples require that all characteristics are observed. The baseline 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. Other samples have either 5 or fewer VCs that have led a deal for the fund or five or fewer senior-level VCs affiliated with the sponsor within the two years before or after the fund's vintage. 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 IA13: Robustness: Fund Returns With Different Aggregations

	# Successful			IRR		
	(1)	(2)	(3)	(4)	(5)	(6)
Average of:	Baseline	Senior	Inv. Team	Baseline	Senior	Inv. Team
1(1+ Successful Prior Inv.)	0.230**	0.001	0.055	-0.042	-0.051	0.023
	(2.34)	(0.01)	(0.34)	(-1.48)	(-0.89)	(0.32)
1(2+ Successful Prior Inv.)	0.187**	0.604***	0.363*	0.013	0.085	0.041
	(2.11)	(3.71)	(1.81)	(0.53)	(1.14)	(0.53)
1(5+ Successful Prior Inv.)	0.092	0.306**	0.552***	0.028	0.031	0.049
	(1.49)	(2.25)	(2.66)	(1.14)	(0.56)	(0.73)
Model	Poi	Poi	Poi	OLS	OLS	OLS
Y-mean	4.189	4.049	3.983	0.145	0.131	0.130
FE	x	x	x	x	x	x
Industry FE	x	x	x	x	x	x
Pseudo R^2	0.448	0.414	0.411			
Adj. R^2				0.293	0.285	0.274
N	1,240	1,155	1,189	1,086	1,020	1,050

Table IA13: The baseline specification 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. Other specifications present regressions on the average of all investment professionals (or senior investors) employed by the sponsor in the two years surrounding the fund's vintage. The characteristics from Table 7 are included in the estimation, but omitted from the display; results are summarized based just on the prior investing success of the affiliated VCs. 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, status, and industry focus 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 IA14: Robustness: Fund Returns and Team Diversity

	Senior Team			Investment Team		
	(1) # Succ.	(2) IRR	(3) TVPI	(4) # Succ.	(5) IRR	(6) TVPI
Diversity (Demographics)	0.195*	-0.073*	-0.770*	0.078	-0.082	-0.757**
	(1.83)	(-1.78)	(-1.95)	(0.48)	(-1.62)	(-2.06)
Diversity (Edu. Tier)	0.496***	0.047	0.674	0.533***	0.080*	0.784**
	(3.01)	(1.01)	(1.55)	(3.75)	(1.75)	(2.26)
Diversity (Edu. Field)	-0.245**	-0.074	-0.738	-0.136	-0.102	-0.848*
	(-2.35)	(-1.30)	(-1.55)	(-0.93)	(-1.44)	(-2.02)
Diversity (Exp. Bg.)	0.657***	0.036	0.681*	0.781***	0.060	0.809
	(3.94)	(0.74)	(1.82)	(3.39)	(0.70)	(1.47)
Model	Poi	OLS	OLS	Poi	OLS	OLS
Y-mean	4.077	0.131	1.976	4.029	0.131	1.984
FE	x	x	x	x	x	x
Industry FE	x	x	x	x	x	x
Pseudo R^2	0.383			0.382		
Adj. R^2		0.266	0.213		0.269	0.210
N	1,174	1,039	1,094	1,193	1,054	1,111

Table IA14: Tabulates coefficients from regressions of the returns of VC funds on diversity indices constructed from the characteristics of investment professionals affiliated with the fund. "Senior Team" restricts to senior-level investment professionals employed by the fund sponsor in the two years surrounding the fund's vintage; "Investment Team" uses all investment professionals credited with deploying capital for the fund. Diversity measures are Blau's index (= $1 - \sum p_i^2$, where p_i is the share of team members from category i). We consider four different categories: demographics (white-male, non-white male, white female, non-white female), education tier (ivy-league and ivy-plus), undergraduate major (STEM, business, social sciences, and other), and experience background (prior startup CEO/founder, prior startup non CEO/founder, technology, banking, or consulting experience). 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, status, and industry focus 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 IA15: Robustness: Fund Returns With Few Deals

	# Successful			IRR		
	(1)	(2)	(3)	(4)	(5)	(6)
Sample	Baseline	≤ 10 Deals	≤ 5 Deals	Baseline	≤ 10 Deals	≤ 5 Deals
1(1+ Successful Prior Inv.)	0.231**	0.079	-0.156	-0.041	-0.019	0.003
	(2.38)	(0.42)	(-0.55)	(-1.46)	(-0.46)	(0.05)
1(2+ Successful Prior Inv.)	0.184**	0.054	0.296	0.013	-0.032	-0.007
	(2.03)	(0.43)	(1.37)	(0.52)	(-0.78)	(-0.12)
1(5+ Successful Prior Inv.)	0.100	0.197**	0.246**	0.029	0.059	0.078
	(1.64)	(2.21)	(1.99)	(1.17)	(1.45)	(1.53)
Model	Poi	Poi	Poi	OLS	OLS	OLS
Y-mean	4.189	1.252	0.803	0.145	0.168	0.157
FE	x	x	x	x	x	x
Industry FE	x	x	x	x	x	x
Pseudo R^2	0.446	0.239	0.259			
Adj. R^2				0.294	0.336	0.359
N	1,240	527	289	1,086	449	246

Table IA15: 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. The characteristics from Table 7 are included in the estimation, but omitted from the display; results are summarized based just on the prior investing success of the affiliated VCs. 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, status, and industry focus of the fund in PitchBook. Regression samples require that all characteristics are observed. The baseline 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. Other samples have no more than 5 or 10 deals from which results are estimated. 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 IA16: Distribution of VC Profits by Deal Type

Var.	Nobs.	Pct. > 0	Avg.	25p	50p	75p
Panel A. Lead Investors						
Invest Amnt. ($mm)	55,593		9.3	1.6	4.1	9.8
Gross Profits ($mm)	55,562		24.1	1.1	3.5	11.4
Net Profits ($mm)	55,562	33.2%	13.8	-2.9	-0.6	1.3
Mkt. Adj. Net Profits ($mm)	55,562	22.0%	6.4	-8.4	-2.4	-0.1
Panel B. Board Investors						
Invest Amnt. ($mm)	57,429		6.9	0.9	2.7	7.1
Gross Profits ($mm)	57,412		23.8	0.6	2.6	9.8
Net Profits ($mm)	57,412	38.4%	16.1	-1.8	-0.1	1.9
Mkt. Adj. Net Profits ($mm)	57,412	26.3%	9.8	-6.2	-1.4	0.1
Panel C. Early Stage						
Invest Amnt. ($mm)	98,489		3.9	0.3	1.3	4.1
Gross Profits ($mm)	98,433		13.0	0.3	1.2	4.8
Net Profits ($mm)	98,433	34.1%	8.4	-1.0	-0.1	0.5
Mkt. Adj. Net Profits ($mm)	98,433	23.1%	4.9	-3.2	-0.6	-0.0
Panel D. Later Stage						
Invest Amnt. ($mm)	44,577		8.3	0.6	2.5	7.3
Gross Profits ($mm)	44,543		17.2	0.3	1.7	7.3
Net Profits ($mm)	44,543	28.3%	8.5	-2.1	-0.3	0.2
Mkt. Adj. Net Profits ($mm)	44,543	19.8%	2.3	-5.9	-1.2	-0.1

Table IA16: Tabulates the distribution of VC profits estimated following Equation (1) by deal type. Panel A restricts to deals where the VC is identified as the lead investor. Panel B restricts to deals where the VC holds a board seat. Panels C and D restrict to early-stage (Seed/Angel and Series A) and later-stage (Series B and above) deals, respectively.

Table IA17: 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 IA17: Tabulates our collections and coverage of the historical Midas List produced by Forbes.

Table IA18: 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 IA18: Tabulates the types of professionals included 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 IA19: 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 IA19: Tabulates quotes on the described methodology for constructing the Midas List by year.

Table IA20: Robustness: Midas List Recognition and Access to High-Quality Startups: Counts

	(1) # Top-Quartile	(2) # Top-Decile	(3) # Post $1B	(4) # Successful	(5) # PMV ≥ 5B	(6) # IPO	(7) # Exit ≥ 5x
Panel A. Surprise Makes vs. Surprises Misses							
Surprise × Post	0.110	0.187*	0.268	0.126**	0.505***	0.225**	0.081
	(1.37)	(1.65)	(1.19)	(2.21)	(3.42)	(1.99)	(0.77)
Y-mean	0.792	0.530	0.295	1.441	0.344	0.418	0.419
Pseudo R^2	0.367	0.361	0.192	0.310	0.247	0.221	0.201
N	8,726	6,596	2,852	11,515	4,854	9,229	7,204
Panel B. Near Makes vs. Near Misses ± 5							
Surprise × Post	0.444	0.367	5.387***	0.186	1.441***	-0.076	-0.103
	(1.53)	(0.90)	(3.93)	(1.15)	(3.21)	(-0.24)	(-0.28)
Y-mean	0.936	0.740	0.589	1.490	0.540	0.620	0.547
Pseudo R^2	0.411	0.462	0.374	0.290	0.229	0.283	0.233
N	580	381	124	947	289	652	488
Panel C. Near Makes vs. Near Misses ± 10							
Surprise × Post	0.373**	0.649***	1.181***	0.129	1.003***	0.103	-0.064
	(2.09)	(2.62)	(2.75)	(1.07)	(3.74)	(0.49)	(-0.30)
Y-mean	0.746	0.551	0.443	1.419	0.439	0.490	0.472
Pseudo R^2	0.360	0.396	0.258	0.281	0.252	0.277	0.233
N	1,532	1,122	451	2,123	859	1,632	1,194

Table IA20: 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. Top-25p and Top-10p measure whether a company was in the top-quartile or decile of unique VCs it raised capital from as of the VC's investing year. Post variables are indicators for whether the VC invested in the startup after it had already achieved a high valuation. There is not enough variation in the Post-$5billion from the main specifications to be estimated via Poisson regressions. Columns 4-7 count the number of times the VC invested before the company achieved a particular outcome. Panel A stacks 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. For Panels B and C, the treated groups include 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 are Poisson regressions and 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. *t*-stats are in parentheses and */**/*** respectively denote significance at the 10, 5, and 1 % levels.

Table IA21: Midas List Recognition and Investment Success: Economic Value

	(1) Invest Amnt.	(2) Gross Profits	(3) Net Profits	(4) Mkt. Adj. Net Profits
Panel A. Surprise Makes Versus Surprise Misses				
Surprise × Post	5.944**	61.733**	56.321**	52.763**
	(2.31)	(2.52)	(2.44)	(2.39)
Y-mean	14.679	73.642	54.605	38.598
Adj. R^2	0.133	0.086	0.072	0.055
N	11,960	11,960	11,960	11,960
Panel B. Near Makes vs. Near Misses ± 5				
Surprise × Post	13.113***	221.944*	213.382*	198.062*
	(2.78)	(1.85)	(1.80)	(1.72)
Y-mean	14.827	97.325	78.326	59.664
Adj. R^2	0.313	0.103	0.085	0.067
N	997	997	997	997
Panel C. Near Makes vs. Near Misses ± 10				
Surprise × Post	5.987	75.839**	70.903**	64.805*
	(1.48)	(2.21)	(2.07)	(1.89)
Y-mean	15.398	78.487	58.385	40.286
Adj. R^2	0.234	0.104	0.084	0.062
N	2,230	2,230	2,230	2,230

Table IA21: Tabulates stacked difference-in-differences estimates of the effect of Midas List recognition on the economic value of individual VCs' investing activity each year. Profits and dollar amounts are reported in millions. 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. In Panel A, 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. In Panel B, 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 "±10" includes professionals ranked 91–100 and the ten 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. *t*-stats are in parentheses and */**/*** respectively denote significance at the 10, 5, and 1 % levels.