Alumni Networks in Venture Capital Financing

Jon A. Garfinkel
Erik J. Mayer
Ilya A. Strebulaev
Emmanuel Yimfor

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Abstract

One-third of deals in the venture capital market involve a founder and investor from the same university. Venture capitalists are more likely to invest in, and place larger bets on, startups with founders from their alma mater. These deals are also more likely to lead to IPOs post-funding. Tests using VC partner turnover confirm a direct link between education ties and funding likelihood. Taken together, our results suggest that university connections facilitate improved deal-making and outcomes, rather than diverting funds toward lower-quality startups.

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⋆ Jon A. Garfinkel, University of Iowa Tippie College of Business, jon-garfinkel@uiowa.edu;
Erik J. Mayer, University of Wisconsin-Madison, erik.mayer@wisc.edu;
Ilya A. Strebulaev, Stanford University GSB and NBER, istrebulaev@stanford.edu;
Emmanuel Yimfor, Columbia University, eay2121@columbia.edu.

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I. Introduction

Venture capital (VC) funding is considered the lifeblood of entrepreneurial endeavors. VC-backed startups account for an outsized share of innovation and almost half of all U.S. IPOs.[1] However, the venture capital market is characterized by severe information asymmetry, and many startup founders struggle to obtain financing. In this paper, we study the effects of professional networks created by university attendance on the venture capital market.

We start by documenting the striking fact that one in three deals in the venture capital market involve a startup founder and a VC partner with a shared alma mater. We show that this is driven by venture capital investors tilting their portfolios toward startups from their alma mater, rather than by factors such as co-location or top schools' tendency to produce both entrepreneurs and VC investors. We then conduct several cross-sectional analyses and examine ex post outcomes to shed light on whether the tilt in portfolios reflects an information advantage, or alternatively, investors' favoritism toward startups from their alma mater. Our findings throughout demonstrate that alumni networks are a major force shaping venture capital investment and the U.S. entrepreneurial landscape.

Historically, empirical examination of the influence of education networks on early-stage financing has been impeded by two main factors: data limitations and identification challenges. We circumvent the traditional data limitations by using expansive new data from PitchBook on startup founders and VC partners, including their education backgrounds.[2] We supplement these

1 See for example, Kaplan and Lerner (2010), Gornall and Strebulaev (2021), and The National Venture Capital Association (2020).

2 PitchBook provides the most comprehensive data available on entrepreneurial financing. We discuss the advantages of PitchBook relative to Crunchbase and VentureXpert in Appendix A.

data with measures of education quality based on standardized test scores and early-career pay of alumni. Combined, our data allow us to credibly identify shared university alumni status between founders and investors, while controlling for school quality. Throughout the paper, we take several approaches to mitigate identification concerns as we examine the effect of alumni connections on the extensive margin of deal selection, on the intensive margin of deal size, and on post-funding startup outcomes. We utilize carefully constructed proxies for the set of startups that VCs consider, as well as plausibly exogenous departures of VC partners from their investment firms to isolate the effect of alumni networks.

Our first set of tests examines the extensive margin of venture capital investment (i.e., deal selection). Because investors see many more deals than they take, we start by establishing a proxy for the set of deals that VCs consider. We utilize the broad coverage of PitchBook data, as well as the fact that VCs tend to consider deals from certain industries and geographies (Gompers, Gornall, Kaplan, and Strebulaev (2020)), to construct VCs' consideration sets. Specifically, we define a VC's consideration set (i.e., set of counterfactual investments) as any deals that occurred in the same state-industry-year-deal stage as one of the VC's actual deals. We contend that these counterfactual startup investments were the most likely to have been considered by the focal VC, given the VC's investment patterns, and the fact that other investors deemed these startups worthy of funding.

Our first extensive margin test is then a simple linear probability model examining whether a VC investor's choice between the focal deal and counterfactuals is influenced by the presence or absence of a shared alma mater with founders. We find that it is: the effect of same-alma-mater is to raise deal likelihood by 0.22 percentage points, which corresponds to roughly 10% relative to the 2% average probability of investment in this panel. While this estimate in itself is not necessarily a causal effect, the cross-sectional variation in the estimated effect is much more consistent with an explanation rooted in human connections, compared to explanations based on omitted variables. Specifically, the effects of alumni connections on investment are stronger when the public signal of founder quality is weaker (when founders attended less prestigious universities), when there is overlap in the years the investor and founder attended the same university, and when founders and investors attended the same school within the university (especially the same MBA program).

Next, we implement an identification strategy based on VC partner hiring and departure events in order to further isolate the effect of alumni connections on venture capital investment. We test whether VC firms increase (decrease) their investment in startups from a newly hired (departed) partner's alma mater. To conduct these tests, we match treated VC firms (experiencing a hiring or departure) to control VC firms that are in the same state and have similar investment patterns. We then employ a stacked difference-in-differences design around partner hiring/departure events. Intuitively, these tests compare treated VC firms' likelihood of investing in startups from a certain partner's alma mater to their likelihood of investing in startups from other universities, all relative to how similar control VC firms are investing. We find strong evidence that alumni networks matter: VCs' likelihood of investing in startups from a departing partner's alma mater decreases by 2.8 percentage points post-departure, which represents 68% of the mean in this setting. This reduction in investment persists for at least three years post-departure, suggesting that the knowledge and relationships that partners bring from their alma mater networks are not fully transferred to remaining partners. This finding is consistent with Ewens and Rhodes-Kropf (2015) who document that partner human capital is more important than VC firm organizational capital for explaining VC performance.

The identifying assumption this approach makes is that partner departures are uncorrelated with time-series variation in the number of startups from the partner's alma mater that merit investment by the VC firm. While prior work suggests that many partner departures are driven by idiosyncratic factors (Ivashina and Lerner (2019)), one might still be concerned that departures could be correlated with omitted variables. For example, departing partners and founders from their alma mater could share unobserved characteristics such as insights acquired during their time at university that influence both departures and investments. We take two steps to help mitigate such concerns. First, we document parallel investment trends between treated and control VC firms prior to departures. Second, we study a subsample where the departures are more likely to be idiosyncratic to the partner and hence exogenous in our setting. To do so, we hand-collect information on each VC partner departure and classify them as either exogenous (cases where the partner died, retired, or left the VC industry) versus endogenous (cases where the partner moved within the VC industry).[3] We confirm that our results hold in the exogenous subsample (and the endogenous one), helping to mitigate concerns about omitted variables.

Our final extensive margin analysis takes advantage of the broad coverage of PitchBook data, which includes even startups that do not receive VC funding. With this broad sample of startups, we run a linear probability model where the dependent variable is an indicator for whether the startup gains funding within its first two years. We explain this probability with the proportion of deals in the focal startup's sector and year of founding that were funded by VCs that attended the same university as the focal startup's founder. We find strong evidence of a positive relationship between VC partners from an alma mater being active in a sector, and startup

[3] We also implement a stricter definition, where only deaths and retirements are classified as exogenous.

founders from that alma mater obtaining funding. We further document that this relationship weakened slightly during the Covid-19 Pandemic when there was a reduction in networking events and in-person interactions between university alumni. Overall, this series of results provides strong evidence that alumni networks play a significant role in shaping the extensive margin of venture capital investment.

Our second set of tests studies whether alumni networks influence the intensive margin of investment, in terms of the quantity of funding raised in VC deals. Access to sufficient funding is critical for early-stage startups' success, and here too we find that alumni networks matter. When an investor and founder share an alma mater, the investment amount is 18% larger on average. Moreover, the cross-sectional variation in the effect helps mitigate omitted variable concerns: alumni connections have the largest effect on funding when the investor and founder attended their shared alma mater at the same time and studied at the same school within the university. These results hold while controlling for a rich set of startup characteristics and conducting the analysis at various levels, some of which even allow the inclusion of founder-university level fixed effects. The robust positive effect of alumni connections on funding amounts throughout the analysis provides evidence that connections play a critical role in startups' fundraising success.

Although our results up to this point document a positive effect of alumni network connections on funding likelihood and amount, the efficiency of such relationships is still unclear. If alumni networks help resolve information asymmetry between investors and founders, then connections may improve investment decisions. On the other hand, if the investment patterns we document are driven by favoritism or homophily (a "taste" for founders from the same alma mater), then investment outcomes may be worse.[4] Our third set of tests explores this tension by examining whether connected investments perform better or worse than non-connected investments.

We start by testing for differences in connected versus non-connected startups' performance within a given investor's portfolio. We measure startups' performance based on whether they conduct an IPO post-funding (e.g., Hochberg, Ljungqvist, and Lu (2007), Gompers, Mukharlyamov, and Xuan (2016), and Farre-Mensa, Hegde, and Ljungqvist (2020)). We find strong evidence that connected startups outperform their non-connected counterparts: they are 2.6 percentage points (over 40% of the mean) more likely to IPO post-funding. These results hold even while controlling for investor fixed effects and a large set of startup characteristics.

The superior performance of connected investments points toward a mechanism grounded in information advantages rather than favoritism. Yet, such advantages could manifest through either superior ex ante deal selection or through superior ex post monitoring or advising of startups. We delve into this question by examining the performance of connected investments where the relevant VC partner departs the venture capital firm post-investment (when monitoring would take place). We do not find any significant reduction in performance in such cases compared to cases where the connected partner remains in place. Together, our findings provide evidence that alumni connections help venture capital investors make more informed decisions during the deal selection process.

Our final set of results illustrates the potential distributional consequences of differential

[4] Another possibility is that the information and favoritism effects could cancel each other out, leading to no significant effect of connections on performance, as Kuhnen (2009) finds in the context of connections between mutual fund directors and advisory firms.

access to alumni networks. First, we provide a striking fact: the percentage of deals involving a same-alma-mater investor is over twice as high when the founders are from universities that consider family legacy in admissions. This pattern holds even after conditioning on university academic quality and deal characteristics. Then, we document that legacy schools have fewer students who come from underrepresented minority groups, who are first-generation college students, or who come from families of lower socioeconomic status. Hence, even absent favoritism in VC investment, differential access to valuable alumni networks is an important factor affecting equality of opportunity in entrepreneurship.

Our paper makes several important contributions to the literature. We first add to studies on the determinants of VC financing.[5] A common thread running through this literature is that resolving information frictions is paramount (see Da Rin, Hellmann, and Puri (2013) for a review). Bernstein, Korteweg, and Laws (2017) provide evidence that information about founding teams is perhaps the most important factor in attracting VC investors. However, the ways in which specific founder attributes influence VC investors' decision-making remain unclear. We offer the first thorough exploration of how founders' college alma mater, and their access to alumni networks, influence venture capital financing.[6]

We also contribute to the literature on the effects of education networks in financial markets more broadly. Studies show that school connections improve the performance of mutual fund managers' investments (Cohen, Frazzini, and Malloy (2008)), sell-side analysts' stock

[5] See for example, Tian (2011) for geographic proximity, Ewens, Nanda, and Rhodes-Kropf (2018) for technological shocks, Townsend (2015) for financial shocks, Hellmann and Puri (2015) for product market strategies, Calder-Wang and Gompers (2021) for gender diversity, Denes, Howell, Mezzanotti, Wang, and Xu (2023) for tax credits, and Bottazzi, Da Rin, and Hellmann (2016) for trust.

[6] We note that roughly one year after this paper was posted publicly, two subsequent papers were posted that provide overlapping findings using various samples. See Koenig (2022) for evidence using data from Crunchbase and Huang (2023) for evidence from a subset of PitchBook data.

recommendations (Cohen, Frazzini, and Malloy (2010)), and banks' loans (Engelberg, Gao, and Parsons (2012)). Connections also influence firms' internal capital markets (Duchin and Sosyura (2013)). However, the influence of education networks on VC investments is neither well-understood nor easily predicted, for several reasons. First, the most related study in the VC literature, which examines connections between investors in a VC syndicate (rather than between founders and investors), shows that these connections lead to worse decision-making and hurt VC investors' performance (Gompers et al. (2016)). Second, given the difficulty of obtaining early-stage funding and its importance for startup outcomes (Kerr, Lerner, and Schoar (2014)), VC investors may be more likely to derive private utility from investing in companies from their alma mater than in other settings such as the stock market. Indeed, any favoritism exhibited toward connected startups could outweigh informational advantages and lead to worse performance and distortions in the allocation of capital. We contribute to this literature by providing the first direct evidence that alumni networks affect the extensive and intensive margins of VC investment, and that ultimately, alumni-connected investments outperform non-connected ones. Our findings show that alumni networks play a major role in shaping venture capital investment and access to entrepreneurship in the United States.

II. Data and Methodology

A. Sample Construction

We construct our main sample using data from PitchBook and the Department of Education's College Scorecard. PitchBook is the industry-standard for data on VC-backed companies (see, e.g., Retterath and Braun (2020), Brown, Kenyon, and Robinson (2020), Gompers, Gornall, Kaplan, and Strebulaev (2021), and Ewens, Gorbenko, and Korteweg (2022)).

The College Scorecard data include information on the characteristics of U.S. institutions of higher education, such as enrollment, location, and average scholastic assessment test (SAT) score of students admitted.[7]

We restrict our tests to strictly VC rounds of financing. These are defined (in PitchBook) as "early-stage VC," "later-stage VC," or "Seed Round." We also restrict our investor types to PitchBook labels of "Venture Capital," "PE/Buyout," "Growth/Expansion," "Corporate Venture Capital," "Family Office," "Other Private Equity," or "Not-For-Profit Venture Capital." Our primary unit of observation for the analysis is at the startup-investor-deal level, where a deal is a round of financing for the startup, and investors are lead investors (which PitchBook defines as the investor(s) making the largest investment in the round – 85% of deals have a single lead). When appropriate, in later analyses, we collapse the data and run tests at less granular levels, such as the deal level.

From PitchBook, we also collect information on the founding team and on partners working for the lead investor. We identify founding team members by keeping company employees with the following titles: Founders, CEO (Chief Executive Officer), CFO (Chief Financial Officer), CTO (Chief Technology Officer), CMO (Chief Marketing Officer), COO (Chief Operating Officer), President, and Owner. We only keep people with these titles who started working for the company before the year the funding round was closed and were still working for the company in the year the round was closed. When employment start and end dates are absent from PitchBook data, we supplement this information using LinkedIn. We call this set

[7] The College Scorecard data can be found at: https://data.ed.gov/dataset/college-scorecard-all-data-files-through-6-2020/resources

of individuals "founding team" or "founders," although this can include people who joined the company in the early years after its founding.

We collect extensive data on the education history of founders, the funding rounds, and whether the company exited via an initial public offering (IPO) or an acquisition as of June 2021. We then collect information on the education history of the partners working for the lead investor in each funding round.[8] Because our data on the quality of education institutions is for U.S. colleges and universities, we focus on deals involving U.S.-based startups and investors.

There is no common identifier between College Scorecard and PitchBook. Therefore, we perform a fuzzy name match, which we hand check, between the university attended by the founders and investors in PitchBook and the university name in the College Scorecard database. We match the 485 largest U.S. universities in the PitchBook data to College Scorecard. This results in our sample covering over 90 percent of all the deals in PitchBook (for which we have data on the education history of founders and at least one partner employed by the lead investor at the time of the deal). Hence, our final sample comprises the set of deals in PitchBook from 2000 to 2020 where either the founders of the portfolio company or the partners working for the lead venture capital firm attended one of the 485 largest U.S. universities.

B. Summary Statistics

Table 1 presents descriptive statistics of our sample at five different levels: startups, founders, investors, deals, and universities.[9] The startup-level statistics parallel those documented

[8] We identify partners by keeping employees with the following titles: Partners, Senior Partners, CEO, Founder, and Managing Director. We only consider partners that started working for the investment firm before the deal year and were still working there during the deal year. When employment start and end dates are absent from PitchBook data, we supplement this information using LinkedIn. We further restrict the set of partners to those that were affiliated with the specific fund within the investment firm that led the deal.

[9] Internet Appendix Table A.1 provides variable definitions.

in extant work. The average startup in our sample has 1.63 rounds, skewed early with nearly two-thirds being seed rounds instead of later rounds. They raise an average of $26 million in cumulative funding across all their recorded equity deals. The companies also average 2.33 founders. Finally, VC-backed startups in our sample average a 6% IPO exit rate and a 26% M&A exit rate. See Ewens and Marx (2018) and Puri and Zarutskie (2012) for similar statistics on exits by VC-backed companies.[10]

Moving to founder-level statistics, we see that the average founder attended 1.46 higher educational institutions and founded 1.05 startups. Our investor-level statistics show that the average VC firm had around 7 unique lead partners tied to deals, was founded around 2005, and had an average and median AUM of $2.9 billion and $215 million, respectively.

At the deal-level, we provide summary statistics for all deals in our sample, as well as for the first deal for a startup. Since we focus some of our analysis on first deals (see Appendix Table A.2), it is reassuring that the number of lead investors, partners at lead investors, and founders, are all similar across the two groups. Moreover, as expected, both the amount raised and the post-money valuations are higher on average across all deals than for first deals.

Finally, our university-level statistics show that there is wide variation across schools in the number of lead investors and founders they produce. The statistics also document significant variation in university admission rates, SAT scores, and enrollment size. Hence, we control for this variation in our empirical specifications and use fixed effects where possible.

[Insert Table 1 Here.]

[10] To mitigate the concern of counting acquisitions that generate modest returns as successes, our statistic on acquisitions only counts an exit as an acquisition if we observe the sale price and if the sale price is at least twice the total investment amount in the company. See Yimfor and Garfinkel (2023) for support of the 2x filter.

C. Descriptive Evidence of Alumni Networks' Importance

We start by providing simple descriptive evidence on the importance of alumni networks in venture capital financing. We first examine the prevalence of entrepreneurs and founders from each of the top 20 U.S. universities and tabulate the investor-founder pairing rates at each school. We then document that the same alma mater match rates between investors and founders far exceed random matching when we examine all universities in the data.

Table 2 presents statistics on the entrepreneurs and venture capital partners in our sample from the top 20 universities (according to U.S. News 2021 rankings of the best U.S. bachelor's degree-granting institutions). Columns 1, 2, and 3 present the rank, name, and recent data (2019) on the mean SAT score of accepted freshmen at these universities. Columns 4 and 5 present the number of founders per 1,000 students enrolled at the university and the number of startups founded by alumni of the university. Columns 6, 7, and 8 present the number of investors per 1,000 students from each school, the number of deals, and the percentage of deals that are connected.

From Table 2, we see that the same alma mater match rate is high: VC partners with degrees from top universities tend to invest in startups from their alma mater 20-40% of the time. Nevertheless, there is also substantial variation in the number of deals involving startups and investors from the same alma mater, even among schools of similar prestige. While 45% of the deals with investors from Harvard involve at least one founder from Harvard, only 20% of the deals with investors from MIT also involve a founder from MIT.

[Insert Table 2 Here.]

Next, we show that the high rate of matching between founders and investors from the same alma mater holds across the full set of universities in the data. Figure 1 presents a scatter plot of the chances that deals involve an investor from the founders' (same) alma mater against the proportion of all investors that are from the founders' alma maters. The solid line represents the 45-degree line, which we would expect the data points to cluster along if founder-investor matching were random. Instead, the figure shows that founders are much more likely to pair with investors from their same alma mater. This result holds for highly-selective universities with average SAT scores over 1400, and appears even slightly stronger for universities with lower average SAT scores.

[Insert Figure 1 Here.]

III. Empirical Results

A. Alumni Networks and the Extensive Margin of VC Investment

In this section, we test whether alumni network connections influence deal selection, i.e., the extensive margin of venture capital funding. We start by examining whether investors tilt their portfolios toward startups from their alma mater, by comparing their actual investments to counterfactual investments they may have considered. We then explore cross-sectional variation in the effects. Finally, we use two separate event-based identification strategies to further isolate the effect of alumni connections on funding decisions. Our first approach studies changes in investment around VC partner hiring and departure events. Our second approach examines the effect of founders' potential ties to VC partners on their receipt of VC funding, and how this changed during the Covid-19 pandemic (which limited interactions between university alumni).

1. Investors' School Ties and Deal Selection

Our first test examines whether investors tilt their portfolios toward startups from their alma mater. This type of analysis is typically challenging because researchers only observe actual investments, and do not directly observe the full set of startups that investors considered. To circumvent this issue, we use data on PitchBook deals consummated in the same industry, state, year, and stage as a focal investment, but with a different investor, as stand-ins for the counterfactual investments the focal investor could have made.

We first construct the dataset containing both actual investments and investors' potential/considered deals, then we compute connection measures for both the actual and potential deals. For example, in 2010, True Ventures (a venture capital firm) led a seed round for Duo Security, a Michigan-based startup operating in the Information Technology sector. To create the data for this extensive margin test, we need a set of counterfactuals comprised of other Michigan-based startups operating in the Information Technology sector that also received seed financing in 2010, but whose deals True Ventures did not lead. These were GamerSaloon and Local Orbit. So we view the general partners at True Ventures as deciding between investing in Duo Security or these other two companies. Consequently, in our test data, True Ventures will get three observations (one actual and two counterfactual). We then test whether True Ventures' decision to invest in Duo instead of GamerSaloon or Local Orbit is influenced by the absence or presence of alumni ties between the partners at True Ventures and the founding teams at Duo, GamerSaloon, and Local Orbit (respectively).

Our extensive margin test is then a linear probability model explaining whether the deal is actually done, with the key independent variable being *Same Alma Mater*, an indicator equal to one if any of the VC partners share an alma mater with any of the founders. From VCs' perspective, the test evaluates whether they tilt their portfolios toward startups from their alma mater, relative to similar startups they could have invested in. Before formally implementing this test, we first provide graphical evidence that actual deals are more likely to exhibit connections than counterfactuals, then we provide summary statistics for the actual versus counterfactual deals and discuss the controls we will use.

Figure 2 presents binned scatter plots of the fraction of deals that include alumni investors, against the average SAT score of founders' alma maters (Panel A) and against the average size of founders' alma maters (Panel B). The plots document the relationship for both the actual deals and for the counterfactual deals. The results show that real deals are much more likely to include an alumni investor than counterfactual deals, and that this holds throughout the distribution of founder university quality and size.[11]

[Insert Figure 2 Here.]

Table 3 columns 1-4 present summary statistics for actual deals. A unit of observation in this table is a startup–lead investor–deal pairing. Because 85% of deals have a single lead investor, this dataset is similar to a deal-level dataset. The first row of column 1 shows that 37 percent of deals feature a *Same Alma Mater* connection. Further statistics in column 1 show that 14% of the sample (or roughly a third of the alumni connections) had a founder and investor at the same university overlap for at least one year. It is also common for alumni connections to be within the same school (for example, Columbia Business School rather than Columbia

[11] We note that these binned scatter plots are based on data collapsed to the deal level, whereas our more formal regression analysis is conducted at the more granular startup–lead investor–deal level as discussed below.

University), and to occur within MBA programs. We explore the incremental effects of these tighter connections in our tests.

[Insert Table 3 Here.]

Table 3 also reports firm and deal characteristics that are well-known determinants of early-stage financing and serve as controls in our tests. (See, e.g., Bengtsson and Hsu (2010), Tian (2011), Howell (2017), and Ewens and Townsend (2020))

Mean SAT Score is the average SAT score of entering freshmen at the university attended by the founder of the portfolio company (averaged for companies with multiple founders), in the year preceding the investment.

University Size is the class size of graduating students from the founders' alma mater in the year preceding the deal.

Young Firm is an indicator for the firm being formed less than five years prior to the deal date. By design, our sample is largely composed of young firms (72%).

Distance is the average distance (in miles) between the portfolio company and the lead investor location. Several studies document the importance of distance in early-stage financing (e.g., Sorenson and Stuart (2001), Chen, Gompers, Kovner, and Lerner (2010), Tian (2011)).

Seed Round indicates the deal is the first recorded venture capital funding round for the company in PitchBook.

Past Funding Relationship is an indicator for an investor having already invested in the company in an earlier round.

Past Industry Experience is an indicator for when the lead investor in the deal has previously invested in a portfolio company in the same industry sector. PitchBook classifies industries into seven main sectors comprising: Business Products and Services, Consumer Products and Services, Energy, Financial Services, Healthcare, Information Technology, and Materials and Resources.

Past Affiliation captures how often the lead investor in the current round has collaborated with other lead investors that previously funded the startup (see Appendix C for construction details). Crucially, past affiliation captures whether there is an established relationship between the new and former investors in a startup.

Columns 1-4 present statistics for the full sample, the sample of connected (same alma mater) deals, the sample of unconnected deals, and the difference between connected and unconnected deals. The statistics show that connected deals tend to come from slightly higher SAT score schools and are closer to investors geographically. Columns 5-8 present a similar set of summary statistics for the counterfactual deals. Comparing the sample averages in column 1 to those in column 5 shows that the actual deals are similar to the counterfactual deals on each dimension, except in terms of *Past Funding Relationship* and *Past Affiliation* (which is largely by construction given the persistence in VC-startup relationships). Overall, these statistics provide support for using this set of startups as the counterfactual investments VCs may have considered.

At this point, we implement our extensive margin test for the effect of alumni network connections on deal selection. Table 4 presents the results. Column 1 shows that a shared alma mater between investor and founder increases the likelihood of investment by 0.22 percentage points. Given the mean probability of investment of 2.03%, a shared alma mater corresponds to an approximately 10% higher likelihood of an investor deciding to fund a startup.

The regression controls for startup firm and deal characteristics, as well as investor-state-year-industry fixed effects. These high-dimensional fixed effects control for many potential confounders at both the investor and startup firm level. For instance, the fixed effects control for factors such as investor size, location, and specialization, as well as startup firms' state-year-industry. Importantly, the fixed effects ensure that our tests only draw inference from within investors considering similar investment opportunities.

[Insert Table 4 Here.]

Next, we examine cross-sectional variation in the effect of alumni network connections on investment. In the specification in column 2, we interact *Same Alma Mater* with *Mean SAT Score*. The coefficient on the interaction term is negative, showing that when SAT scores of the founder's university are higher, alumni connections with investors matter less. A one standard deviation increase in the average SAT score of founders' alma mater decreases the effect of *Same Alma Mater* on the likelihood of investment by 0.08 percentage points. Assuming university academic quality provides a public signal about founder or startup quality, the smaller effect of alumni connections when the public signal is strong, implies partial substitution. Put differently, the finding that connections matter less when founders have strong public signals of their quality, suggests that alumni connections' effect likely stems from their ability to resolve information asymmetries about founder quality.

Columns 3-5 present tests that examine the effects of tighter measures of alumni connections between founders and VC investors. Column 3 shows that the effect of connections nearly doubles when there is time overlap between when the investor and founder attended the same university. Columns 4 and 5 show that the results are largely driven by cases where founders and investors attended the same school within the university, or cases where both graduated with an MBA from the same university, respectively. Importantly, this cross-sectional variation in the effect of alumni connections on investment lines up with an explanation rooted in human connections, but it does not line up with explanations based on omitted variables such as founder/investor quality.

We report the results of several additional tests in the Internet Appendix Table A.2, which documents even stronger effects of alumni connections if we restrict the sample to first deals only, where there is greater information asymmetry about founders and startups. We also document that the results are robust to using measures of school quality based on graduated students' incomes rather than incoming students' SAT scores (Table A.3), or to using continuous measures of alumni connections based on the fraction of founder-investor pairs that attended the same university rather than an indicator variable (see Table A.4, and Appendix B for details on variable construction). Finally, we document that our main finding that alumni connections facilitate VC investment is not limited to the (already extensive) PitchBook universe. In Internet Appendix D, we discuss how we replicate our main result from Table 4 using a sample of startups constructed from LinkedIn data (see Table A.5).

Overall, the results thus far provide evidence that alumni networks influence the extensive margin of VC investment. The cross-sectional variation in the effect also suggests a mechanism rooted in human connections, rather than an omitted variable explanation. We now turn to two event-based identification strategies to further pin down the alumni network effects documented above.

2. Evidence from VC Partner Moves

Our first identification strategy exploits VC partner hiring and departure events in order to isolate the effect of alumni networks on VC investment. We test whether VC firms increase (decrease) their investment in startups from a newly hired (departed) partner's alma mater. The identifying assumption is that partner arrivals and/or departures are uncorrelated with time-series variation in the number of viable startups seeking funding from their alma mater. Existing research supports this notion by highlighting that partner moves are typically driven by idiosyncratic factors and partners' career concerns (Ivashina and Lerner (2019)).

To conduct our tests, we build an investor-alma mater-year panel covering 2000 to 2020, where each investor-year has observations for all 485 universities in our sample. The dependent variable is an indicator (multiplied by 100) for whether the VC firm invested in a startup from the given university that year.[12] We then construct independent variables to implement difference-in-differences tests around partner hiring and departure events. *Treated* equals one if a partner from the VC-alma mater pair is hired (departs) the VC firm during the sample. *Post* equals one after the hiring (departure) event. The interaction term, *Treated X Post*, is the key object of interest.

We employ a stacked difference-in-differences design following Cengiz, Dube, Lindner, and Zipperer (2019) to address potential biases from treatment effect heterogeneity in staggered adoption settings. Recent econometric work has demonstrated that standard two-way fixed effects estimators can produce biased estimates when treatment timing varies across units and treatment effects are heterogeneous (Goodman-Bacon (2021) and Baker, Larcker, and Wang (2022)). The stacked approach circumvents these issues by constructing separate datasets for each treatment cohort and their corresponding controls, ensuring that treated units are never compared to already-treated units that could contaminate the estimated treatment effects.

[12] For startups with founders from several universities, a deal counts toward each unique affiliation of the founding team.

In our implementation, we exploit variation in the timing of partner hiring and departure events across VC firms. For each partner movement event, we construct a cohort-specific dataset containing the treated VC firm and a carefully selected set of control firms. The control firm selection follows a multi-step matching procedure informed by the institutional features of venture capital markets documented in Gompers et al. (2020). First, we identify all VC firms operating in the same state as the treated firm, recognizing that venture capital markets exhibit strong geographic clustering. Second, we restrict to firms investing in similar deal stages (e.g., seed, Series A, or later-stage), as investment strategies and evaluation criteria differ markedly across the venture lifecycle. Third, we require control firms to have made their first investment in the same year as the treated firm, ensuring similar organizational maturity and market entry conditions.

Within this set of potential controls, we further refine the match by selecting firms with the most similar cumulative deal count in the year prior to treatment. This step is crucial because firm size and investment frequency strongly predict future investment patterns. The matching procedure thus ensures that control firms represent credible counterfactuals; they operate in similar geographic markets, pursue comparable investment strategies, entered the market under similar conditions, and exhibit similar levels of investment activity. To prevent contamination from overlapping treatment effects, we exclude from the control group any firms that experience their own partner movement within three years on either side of the focal event.

After constructing these cohort-specific datasets, we stack them and estimate:

$$Y_{ifct} = \beta \cdot \text{Treated}_{ic} \times \text{Post}_{ct} + \alpha_{ifc} + \lambda_{tc} + \varepsilon_{ifct} \tag{1}$$

where Y_{ifct} indicates whether investor i made an investment in a founder from university f in year t within event-cohort c. The coefficient β captures the change in investment probability following partner movements. We include investor-by-university-by-cohort fixed effects (α_{ifc}) to absorb time-invariant differences in investment propensities across investor-university pairs within each cohort. Note that the α_{ifc} subsumes the treatment dummy. Year-by-cohort fixed effects, λ_{tc}, control for cohort-specific time trends.

Table 5 presents the results. Column 1 examines the effect of partner hiring on investment patterns. Following the arrival of a new partner, VC firms increase their investments in startups founded by alumni from that partner's alma mater by 7.2 percentage points. Panel A of Figure 3 presents event-study estimates for each year from -3 to +3 surrounding the partner hiring event. The pre-period exhibits an upward trend, with investments in founders from the given universities already increasing before the partner hire. This pattern suggests that firms may hire partners that graduated from universities where they are already developing stronger investment relationships. While the subsequent increase in investment indicates an effect of the partner addition, the pre-existing positive trend implies that some portion of the 7.2 percentage point estimate may reflect the continuation of organic relationship development rather than the direct effect of the hiring event.

[Insert Table 5 and Figure 3 Here.]

Columns 2–6 of Table 5 analyze departure events. Column 2 shows that when a partner departs, the VC firm's likelihood of investment in their alma mater's founders decreases by 2.8 percentage points. This effect is economically important, representing a decrease of 68% relative to the average likelihood of investment (which is reported in the bottom row of Table 5). Panel B of Figure 3 presents event-study estimates for partner departures. In contrast to the hiring analysis, there is no discernible pre-trend in alma mater investments at treated versus control VC firms leading up to partner departures, providing support for the parallel trends assumption. The decline following departure persists over time, with investments remaining lower even three years after the partner's exit. This pattern indicates that the knowledge and relationships that partners bring from their alma mater networks are not fully transferred to remaining partners, resulting in a persistent loss of deal flow from those universities. We view this result as consistent with Ewens and Rhodes-Kropf (2015) who find that partner human capital is several times more important than VC firm organizational capital for explaining VC performance.

Although the parallel trends leading up to partner departures are encouraging, it is important to acknowledge that departures are not randomly assigned, and to address any related concerns. The remaining tests in Table 5 work to address two potential concerns with the difference-in-differences framework. First, we address the possibility of violations of the Stable Unit Treatment Value Assumption (SUTVA) that could arise from departing partners going to work for other VC firms, such as those in the control group. Second, we address concerns about partner departures potentially being correlated with omitted variables. For example, departing partners and their alma mater's founders might share unobserved characteristics such as family legacies or insights acquired during their time at university that influence both departures and investments. To help mitigate such concerns, we study two subsamples where the departures are more likely to be idiosyncratic to the partner and hence are more likely to be exogenous in our setting.

Column 3 addresses potential SUTVA violations by excluding from the control group any VC firms that hired a departing partner from another firm. This adjustment ensures that our control firms are not themselves experiencing positive treatment effects from receiving experienced partners. The results remain virtually unchanged (-2.4pp), indicating that SUTVA violations do not drive our findings.

Next, we classify VC partner departures based on the reason for exit. We start with every partner at the lead investor firms from Table 4, recording when they were last involved in a deal for the firm either as a lead partner or board member on a startup board following an investment. Since first involvement dates do not necessarily correspond to hiring dates, we match partners to their LinkedIn profiles (using URLs provided by PitchBook) and track their complete employment history at these firms. We capture both their earliest start date and latest end date, with the latter determined as the maximum of either the LinkedIn end date or their last involvement with a portfolio company according to PitchBook. When LinkedIn data has gaps, we supplement our search using the Wayback Machine to examine archived firm websites for missing dates. We identify departures as instances where a partner's end year occurred before 2020 (our sample period end). For these 1,297 partner departures, we manually research each exit's circumstances through LinkedIn, firm websites, and news articles to determine where partners went after leaving. This allows us to classify departures into six categories: two "exogenous" categories where partners left VC entirely (retirement/death or moving to non-VC industries), and four "endogenous" categories where they remained in venture capital (founding their own fund, promotion at another firm, demotion at another firm, or lateral move).[13] When LinkedIn shows no subsequent position or our searches yield no results, we search for press releases about

[13] We categorize across-firm moves within the VC industry as promotions, demotions, or lateral moves based on the following standard hierarchy of job titles: Managing Partner/Managing Director/Founder > Partner > Principal > Associate > Analyst.

retirements or deaths within two years of departure. Table 5 Panel B presents the breakdown by type for the 1,007 departure events we are able to classify and include in the analysis.

In Column 4 of Table 5 Panel A, we restrict the analysis to the exogenous departure events. The effect increases slightly in magnitude to -3.7 percentage points, suggesting that endogenous selection into departure, if anything, attenuates our estimates. Column 5 further restricts the analysis to deaths and retirements, perhaps representing the cleanest (albeit small) sample of exogenous departures. Here we observe an even stronger effect of partner departures of -7.9 percentage points. Finally, in Column 6 we examine the set of endogenous departures—cases where partners started their own VC firm or moved to other VC firms through promotions, demotions, or lateral transfers. The effect (-2.5pp) is similar to our baseline estimate. Overall, the tests in Table 5 provide consistent evidence that alumni network connections influence VC investment.

3. Evidence Including Unfunded Startups, as well as a Covid-19 Pandemic Effect

Our next set of tests estimates the effect of founders' alumni networks on their overall access to VC funding, and how this effect varies in the cross-section and time series. These tests use the entire PitchBook database of startups (even those not receiving funding), and are conducted at the startup level. We examine whether having many VC partners from the founders' alma maters being active in the startup sector (i.e., a strong alumni network), increases the startup's chances of receiving funding. We also implement a second identification strategy that uses the Covid-19 Pandemic as a negative shock to the strength of alumni networks due to the reduction in in-person interactions between university alumni.

Our analysis proceeds as follows. We first recognize that most startups need their first round of funding within two years of founding, or else they run out of "friends-and-family" funding. Thus, we set the dependent variable equal to 100 if they receive funding in the year of or the year following founding; zero otherwise. Then we construct a measure of potential alumni-connected VC investors who might provide capital to the focal startup. We create a variable, *P(Partners in Sector)*, that equals the proportion of deals in the focal startup's industry sector – during the year of focal startup founding – that were led by partners from the focal founder's alma mater.[14] This variable still recognizes that VC investors tend to specialize in a sector, but can now be constructed to measure potential alumni connections even for startups not receiving funding. Given the preceding results, we expect this variable to have a positive effect on startups' likelihood of receiving VC funding.

Table 6 presents our regression results. Column 1 shows that the likelihood that a startup receives VC funding is indeed increasing in *P(Partners in Sector)*. Although these tests include state-year-industry fixed effects, the correlation documented here may still reflect difficult-to-observe differences in startup quality that correlate with founders' alma maters (i.e., alumni networks). Therefore, we control directly for school quality using *Mean SAT Score*. Columns 2 and 3 show that while school quality correlates with VC funding, the alumni networks effect is distinct from both school quality and school size effects, and remains large. We also note that the results in column 4, where we interact *P(Partners in Sector)* with *Mean SAT Score*, show that alumni networks have the largest impact on access to VC funding for founders from schools with lower SAT Scores. This finding is consistent with earlier tests conducted from the investors' perspective.

[14] If there is more than one founder, we average *P(Partners in Sector)* across the founders. The mean of *P(Partners in Sector)* is 11.98%.

[Insert Table 6 Here.]

Lastly, we turn to column 5 of Table 6. Here, we focus on startups founded immediately prior to and during the Covid-19 Pandemic, limiting the sample to those founded between 2018 and 2021. We then implement a difference-in-differences test, where we interact *P(Partners in Sector)* with an indicator for the startup being founded in 2020 or later. The results show that the positive effect of alumni networks on startups' chances of receiving VC funding declined by roughly two-thirds during the pandemic. These results are consistent with in-person interactions and university alumni gatherings contributing to the positive effect of alumni networks on startups' access to VC funding.

B. School Connections and Investment Size

We now turn to the intensive margin of venture capital investment and examine whether school connections encourage investors to place larger bets on startups from their alma mater. We again use data on VC deals from PitchBook. The dependent variable in these tests is the *Ln(Funding Raised)* for the deal, and we control for the same firm and deal characteristics from prior tests.

In Table 7, we present three panels that vary our units of observation to enable various layers of fixed effects. In Panel A, we study the sample at the investor-deal level, and include investor-state-year-industry fixed effects. Panel B collapses the sample to the deal level and *Same Alma Mater* indicates whether any of the founders share the same alma mater as any partners working for the lead investor in the deal. Panel C presents tests at the alma mater-deal level, which permits the use of alma mater fixed effects. In the alma mater-deal data, a unit of observation is a deal and a university attended by at least one of the founders—a deal involving three founders that attended three different universities will have three unique observations.

In Panel A column 1, we see that *Same Alma Mater* predicts larger venture capital investments. The coefficient of 0.18 implies 18% more funding when a founder and investor on the deal attended the same university. This effect is meaningful in economic terms. Given the average funding amount of $17.80 million, an 18% increase represents $3 million in additional investment. Importantly, the tight fixed effects ensure that these tests only exploit variation within investor-state-year-industry, helping to reduce omitted variable concerns. Columns 2-5 explore cross-sectional variation in the effect and show that connections have the largest effect on funding when there is overlap in the dates of university attendance, and when the founder and investor were at the same school within the university (such as the business school within the university).

[Insert Table 7 Here.]

In Panel B, we collapse the sample to the deal level and find similar results. In fact, the coefficient on *Same Alma Mater* is slightly larger. This is due to the fact that Panel A intentionally limited the analysis to study variation within investors, whereas Panel B exploits more of the variation in the data and allows for comparisons across investors. In either setting, we find that alumni connections lead to significantly larger venture capital investments. Moreover, the cross-sectional variation in each setting lines up with an explanation based on human connections rather than omitted variables.

Finally, Panel C studies the relationship at the alma mater-deal level. This level of analysis allows for the inclusion of alma mater fixed effects, which are important as flexible controls for school unobservables (such as quality) that could influence funding amounts. These tests continue to show a strong positive effect of *Same Alma Mater*. Overall, we find that alumni network connections influence not only the extensive, but also the intensive margin of venture capital investment.

C. Are Connected Investments More Informed?

In this section, we study the important question of whether the documented effects of alumni connections represent informational advantages versus favoritism. A favoritism explanation could be grounded in either in-group bias or overconfidence bias, where VCs overestimate the skills of founders from their university (e.g., Kahneman (2011)). To distinguish between an information channel versus favoritism, we examine post-funding outcomes for the startups in our sample that received funding in 2016 or earlier (to allow time to observe exits). If an information advantage is the primary mechanism, we would expect connected investments to perform at least as well as non-connected investments. In contrast, if favoritism is driving the tilt in investors' portfolios, we would expect connected investments to underperform.

Table 8 presents tests examining startups' likelihood of an IPO—the primary benchmark for success following early-stage funding (e.g., Hochberg et al. (2007), Gompers et al. (2016), and Farre-Mensa et al. (2020)). The tests examine the effect of *Same Alma Mater* on IPO likelihood with a linear probability model that controls for firm and deal characteristics. In Panel A, we conduct tests at the investor-deal level and include investor fixed effects so that we draw inferences based on variation in outcomes *within* an investor's portfolio. In Panel B, we collapse the data to the deal level and conduct similar tests using the broader variation across investors.

Panel A column 1 shows that investments in connected startups are 2.7 percentage points more likely to lead to an IPO than non-connected investments. Taking into account that 7.4% of investments lead to an IPO, the *Same Alma Mater* coefficient represents over a 36% increase in the likelihood of a successful exit via an IPO. This contrasts (indirectly) with Gompers et al. (2016), who report a cost of homophily among venture capitalists collaborating on deals by demonstrating that such deals are less likely to result in an IPO. Our findings suggest that relationships between co-investing VCs of the same ethnicity, as explored by Gompers et al. (2016), and those between founders and investors from the same university are fundamentally different. The latter may be based on shared experiences, values, or knowledge imparted by the same institution, potentially making partnerships more efficient. Whereas the former may be driven by comfort or familiarity. Our findings here also suggest that networks connecting VC partners and founders may play an important role in VC firm performance, complementing work by Hochberg et al. (2007) who document the performance implications of VC firm networks formed by portfolio investment syndication.

[Insert Table 8 Here.]

Columns 2-5 explore cross-sectional variation in the effect of *Same Alma Mater* on IPO likelihood. The results in column 2 show that the effect is stronger at schools with lower average SAT scores.[15] Importantly, this matches the cross-sectional variation in the effect of alumni connections on funding likelihood and deal size, suggesting a common mechanism is at work. Columns 3-5 test for incremental effects of overlap in terms of university attendance window, school within the university, or MBA program. Here, only the MBA indicator is statistically significant.

Panel B studies the relationship at the deal level and implements state-year-industry fixed

[15] Mean SAT Score is standardized to have a mean of zero and standard deviation of one.

effects. We find broadly similar effects using this sample construction and control strategy. Overall, the tests in this section provide evidence that VCs' connected investments outperform their non-connected ones on average. This finding suggests that reduced information asymmetry, rather than favoritism, is likely the primary reason why venture capital investors tilt their portfolios toward startups from their alma mater.

We conduct two additional tests and report the results in the Internet Appendix. First, in Table A.6, we examine the effect of alumni connections on the likelihood of a successful exit via M&A. The results are weaker than those for IPO exits, but still suggest a positive effect of connections. Second, we conduct a test to distinguish whether the positive effect of *Same Alma Mater* on IPO likelihood is due to ex ante screening (as prior results suggest) versus ex post monitoring or guidance to startups. Specifically, we ask whether following a VC partner departure, the VC firm's existing portfolio companies from the departing partner's alma mater become less likely to exit via IPO (as one would expect if the performance effect were driven by monitoring). Table A.7 reports these tests, which do not find significant evidence for this ex post monitoring channel.

1. Legacy Admissions and Access to Valuable Education Networks

Our final set of tests starts with a striking observation: the percentage of deals involving a same-alma-mater-investor is over twice as high when the founders are from universities that allow legacy admissions.[16] We document this finding in Figure 4 Panel A, which shows a binned scatter plot of the percentage of deals that are same-alma-mater against the average SAT Score at the founder's alma mater. We split the graph into cases where legacy is considered in admissions

[16] Schools that allow legacy admissions can consider the applicant's familial relationship to alumni of the institution in their admissions process.

versus cases where it is not. The plot shows that throughout the school quality distribution, the deals involving founders from legacy schools are much more likely to have a same-alma-mater-investor, compared to deals of startups from non-legacy schools. Further tests in Table A.8 confirm that this pattern holds even after controlling for a rich set of university and startup characteristics as well as state-year-industry fixed effects.

[Insert Figure 4 Here.]

While striking, there could be several explanations for this pattern in the data. First, the pattern could arise because startups from legacy admissions schools are of higher quality and attract within-network investment. Second, it could arise due to favoritism in VC investment within legacy school networks. Or third, this pattern could arise because education networks at legacy admissions schools are particularly thick, well-developed, and valuable to entrepreneurs looking to connect with venture capital investors.

We offer one view on this in Figure 4 Panel B. It plots the percentage of deals where the startup ultimately conducted an IPO against the SAT Score of the founder's alma mater, split by legacy versus non-legacy schools. The plot shows that the likelihood of an IPO is nearly identical for legacy and non-legacy schools across the school quality distribution. This finding cuts against explanations where legacy school startups are systematically better (which would lead to higher IPO likelihoods), or where legacy school startups receive significant favoritism from VC investors (which would lead to lower IPO likelihoods). Instead, the particularly strong tilt in investors' portfolios at legacy schools, combined with the similar startup performance at these schools, suggests that these education networks are particularly information-rich and valuable to aspiring entrepreneurs.

Our findings here highlight the importance of access to well-developed alumni networks for prospective entrepreneurs looking to obtain VC funding. The benefits hold even after conditioning on school academic quality, naturally raising the question of which students benefit from this increased access to entrepreneurial finance. Table A.9 summarizes student demographics at legacy admissions schools versus non-legacy schools. The statistics (from the more recent time period) show that legacy schools have a slightly lower percentage of students from underrepresented minority groups (e.g., 19% of their students are Black or Hispanic, compared to 22% at non-legacy schools). An even larger difference arises based on socioeconomic status: legacy schools have far fewer first-generation college students (20% versus 30%) and legacy school students are from families with 28% higher incomes ($103K versus $80K). As large as these current differences are, Table A.9 shows that in most cases, they were even larger historically (in the early 2000s when the data begins). Overall, these patterns highlight the importance of equitable access to valuable university networks when discussing equality of opportunity in entrepreneurship.

IV. Conclusion

Entrepreneurial ventures are key contributors to innovation and long-term economic growth. Yet, founders of early-stage firms often struggle to obtain financing due to the severe information frictions between themselves and venture capitalists. In this paper, we present novel evidence that professional networks created by university attendance are a major force working to reduce information asymmetries and facilitate early-stage investment.

Using expansive new data from PitchBook on the education histories of founders and venture capital investors, we document that roughly one-third of VC investments involve a shared university connection between a founder and investor. Our tests show that VCs tilt their portfolios toward startups from their alma mater, even relative to observably similar startups in the same state-industry-year. This occurs at both the extensive margin (deal selection) and the intensive margin (deal size). The superior performance of connected investments suggests that an information advantage, rather than favoritism, drives the tilt in portfolios.

Our findings demonstrate that university networks play an economically important role in reducing information frictions and supporting the flow of capital to early-stage ventures. Further exploration of network effects in early-stage financing, and of the distributional consequences of access to these networks is a promising area for future research.

References

Baker, A. C.; D. F. Larcker; and C. C. Wang. "How much should we trust staggered difference-in-differences estimates?" *Journal of Financial Economics*, 144 (2022), 370–395.

Bengtsson, O., and D. H. Hsu. "How do venture capital partners match with startup founders?" (2010). Available at SSRN 1568131.

Bernstein, S.; A. Korteweg; and K. Laws. "Attracting early-stage investors: Evidence from a randomized field experiment." *The Journal of Finance*, 72 (2017), 509–538.

Bottazzi, L.; M. Da Rin; and T. Hellmann. "The Importance of Trust for Investment: Evidence from Venture Capital." *The Review of Financial Studies*, 29 (2016), 2283–2318.

Brown, G. W.; S. Kenyon; and D. Robinson. "Filling the U.S. Small Business Funding Gap." *Frank Hawkins Kenan Institute of Private Enterprise Report. UNC Kenan Institute of Private Enterprise*, (2020).

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

Cengiz, D.; A. Dube; A. Lindner; and B. Zipperer. "The effect of minimum wages on low-wage jobs." *The Quarterly Journal of Economics*, 134 (2019), 1405–1454.

Chen, H.; P. Gompers; A. Kovner; and J. Lerner. "Buy local? The geography of venture capital." *Journal of Urban Economics*, 67 (2010), 90–102.

Cohen, L.; A. Frazzini; and C. Malloy. "The small world of investing: Board connections and mutual fund returns." *Journal of Political Economy*, 116 (2008), 951–979.

Cohen, L.; A. Frazzini; and C. Malloy. "Sell-side school ties." *The Journal of Finance*, 65 (2010), 1409–1437.

Da Rin, M.; T. Hellmann; and M. Puri, "A survey of venture capital research." In *Handbook of the Economics of Finance*, Vol. 2, Elsevier (2013), 573–648.

Denes, M.; S. T. Howell; F. Mezzanotti; X. Wang; and T. Xu. "Investor tax credits and entrepreneurship: Evidence from U.S. states." *The Journal of Finance*, 78 (2023), 2621–2671.

Duchin, R., and D. Sosyura. "Divisional managers and internal capital markets." *The Journal of Finance*, 68 (2013), 387–429.

Engelberg, J.; P. Gao; and C. A. Parsons. "Friends with money." *Journal of Financial Economics*, 103 (2012), 169–188.

Ewens, M.; A. Gorbenko; and A. Korteweg. "Venture capital contracts." *Journal of Financial Economics*, 143 (2022), 131–158.

Ewens, M., and M. Marx. "Founder replacement and startup performance." *The Review of Financial Studies*, 31 (2018), 1532–1565.

Ewens, M.; R. Nanda; and M. Rhodes-Kropf. "Cost of experimentation and the evolution of venture capital." *Journal of Financial Economics*, 128 (2018), 422–442.

Ewens, M., and M. Rhodes-Kropf. "Is a VC Partnership Greater than the Sum of its Partners?" *The Journal of Finance*, 70 (2015), 1081–1113.

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

Farre-Mensa, J.; D. Hegde; and A. Ljungqvist. “What is a patent worth? Evidence from the U.S. patent “lottery”.” *The Journal of Finance*, 75 (2020), 639–682.

Gompers, P.; W. Gornall; S. N. Kaplan; and I. A. Strebulaev. “Venture capitalists and COVID-19.” *Journal of Financial and Quantitative Analysis*, 56 (2021), 2474–2499.

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

Gompers, P. A.; V. Mukharlyamov; and Y. Xuan. “The cost of friendship.” *Journal of Financial Economics*, 119 (2016), 626–644.

Goodman-Bacon, A. “Difference-in-differences with variation in treatment timing.” *Journal of Econometrics*, 225 (2021), 254–277.

Gornall, W., and I. A. Strebulaev. “The economic impact of venture capital: Evidence from public companies.” (2021). Available at SSRN 2681841.

Hellmann, T., and M. Puri. “The Interaction between Product Market and Financing Strategy: The Role of Venture Capital.” *The Review of Financial Studies*, 13 (2015), 959–984.

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

Howell, S. T. “Financing innovation: Evidence from R&D grants.” *American Economic Review*, 107 (2017), 1136–64.

Huang, C. “Networks in Venture Capital Markets.” (2023). Available at SSRN 4501902.

Ivashina, V., and J. Lerner. “Pay now or pay later? The economics within the private equity partnership.” *Journal of Financial Economics*, 131 (2019), 61–87.

Kahneman, D. *Thinking, fast and slow*, Macmillan (2011).

Kaplan, S. N., and J. Lerner. “It ain’t broke: The past, present, and future of venture capital.” *Journal of Applied Corporate Finance*, 22 (2010), 36–47.

Kerr, W. R.; J. Lerner; and A. Schoar. “The consequences of entrepreneurial finance: Evidence from angel financings.” *The Review of Financial Studies*, 27 (2014), 20–55.

Koenig, L. “Cut From the Same Cloth: The Role of University Affiliations in Venture Capital Investments.” (2022). Available at SSRN 4248420.

Kuhnen, C. M. “Business networks, corporate governance, and contracting in the mutual fund industry.” *The Journal of Finance*, 64 (2009), 2185–2220.

Puri, M., and R. Zarutskie. “On the life cycle dynamics of venture-capital- and non-venture-capital-financed firms.” *The Journal of Finance*, 67 (2012), 2247–2293.

Retterath, A., and R. Braun. “Benchmarking venture capital databases.” (2020). Available at SSRN 3706108.

Sorenson, O., and T. E. Stuart. “Syndication networks and the spatial distribution of venture capital investments.” *American Journal of Sociology*, 106 (2001), 1546–1588.

The National Venture Capital Association, “Venture Capital Yearbook, Washington: National Venture Capital Association.”Available at https:

//nvca.org/wp-content/uploads/2020/04/NVCA-2020-Yearbook.pdf Accessed: 10/12/2020 (2020).

Tian, X. "The causes and consequences of venture capital stage financing." *Journal of Financial Economics*, 101 (2011), 132–159.

Townsend, R. R. "Propagation of financial shocks: The case of venture capital." *Management Science*, 61 (2015), 2782–2802.

Yimfor, E., and J. A. Garfinkel. "Predicting success in entrepreneurial finance research." *Journal of Corporate Finance*, (2023), 102,359.

Figure 1: Alma Mater Ties vs. Random Matching

This figure presents a binned scatter plot of the fraction of deals by founders from a given university that involve a same-alma-mater investor, against the fraction of all venture capital (VC) partners that attended that university. The solid line represents the 45-degree line. Note that if ties were formed at random, we would expect *Same Alma Mater* to equal *Frequency*, as the likelihood that a founder draws a partner from their alma mater would equal the frequency of partners from their alma mater in the data. To show most data points, we winsorize *Same Alma Mater* at 43%, which is its 99th percentile value. The darker dots represent universities with an average scholastic assessment test (SAT) score of entering freshmen greater than 1400, while the grey dots represent universities with SAT scores under 1400.

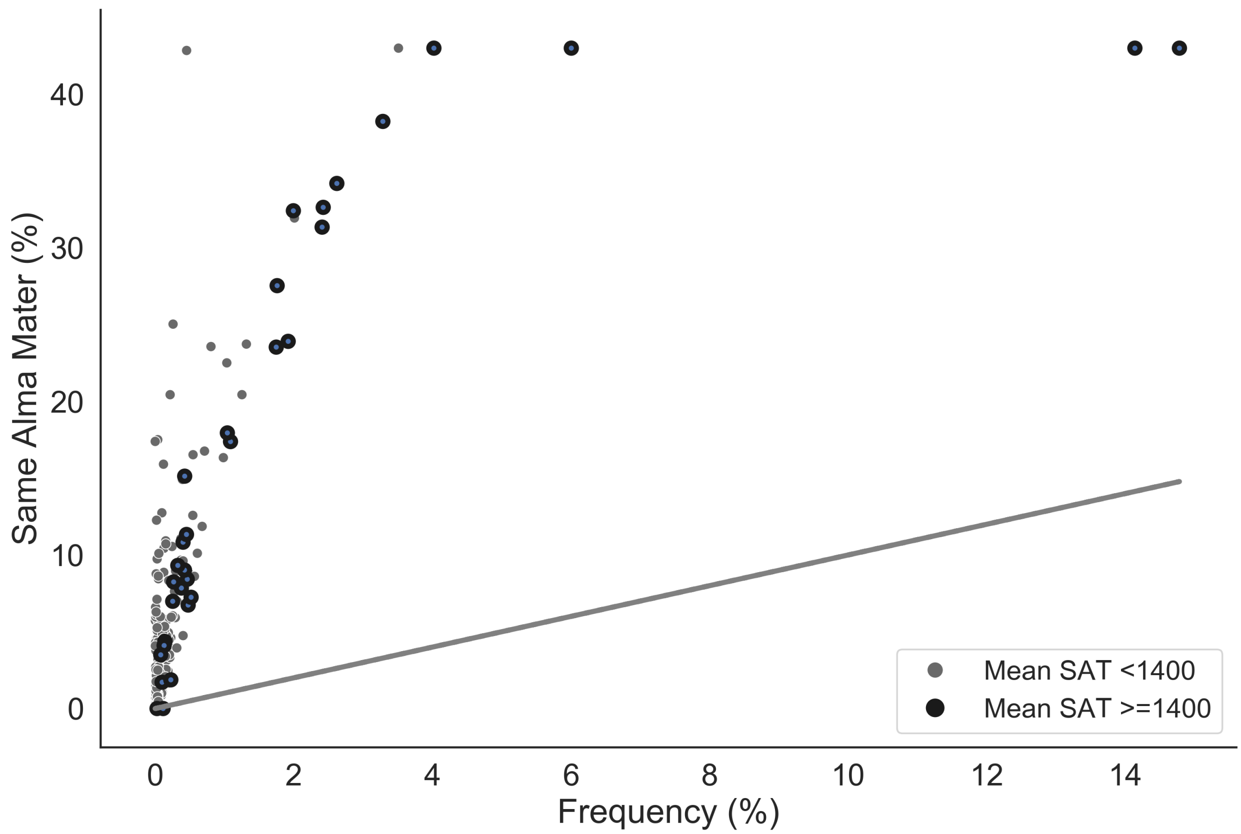
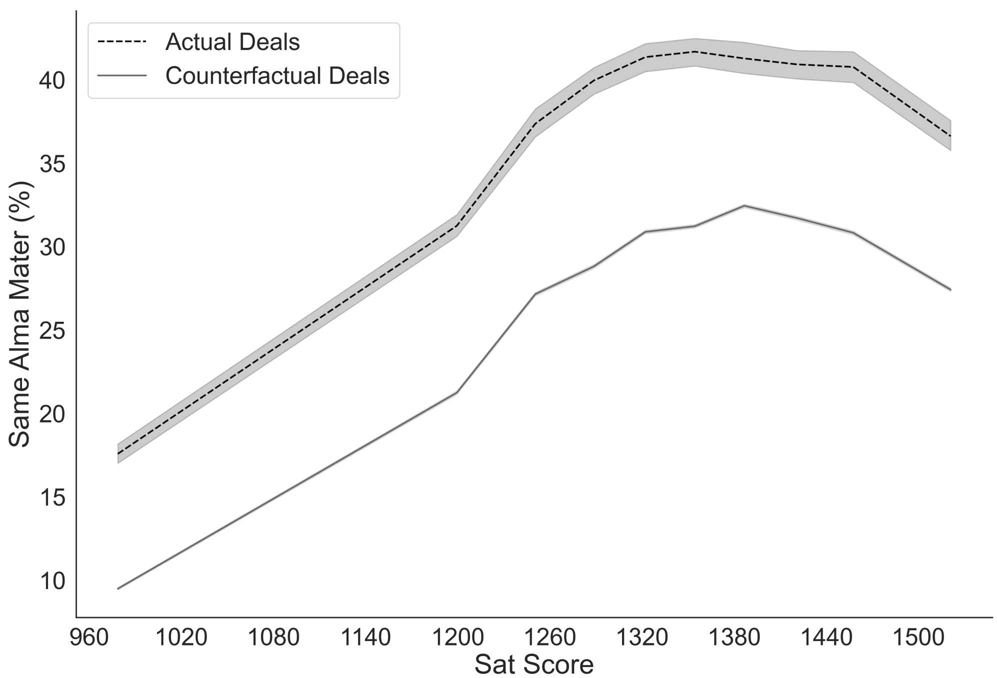


Figure 2: Education networks based on school quality and size

This figure presents a binned scatter plot describing the probability that a deal involves an investment firm where at least one partner attended the same university as one of the startup's founders (*Same Alma Mater*). In Panel A, deals are sorted into decile bins along the horizontal axis based on the most recent data on the average scholastic assessment test (SAT) score of entering freshmen at the founders' alma mater (averaged for startups with multiple founders). In Panel B, deals are sorted into decile bins along the horizontal axis based on the most recent data on the number of graduating students from the founders' alma mater (averaged for startups with multiple founders). *Actual Deals* shows the actual fraction of deals with university connections between investors and founders. *Counterfactual Deals* shows the number of university connections among founders and investors where, in addition to the actual deal, investors are also assigned all active deals in the same industry, year, state, and investment stage as the deal that they were actually involved in. The bands around each line represent 95 percent confidence intervals.

Panel A: Education networks and school quality



Panel B: Education networks and university size

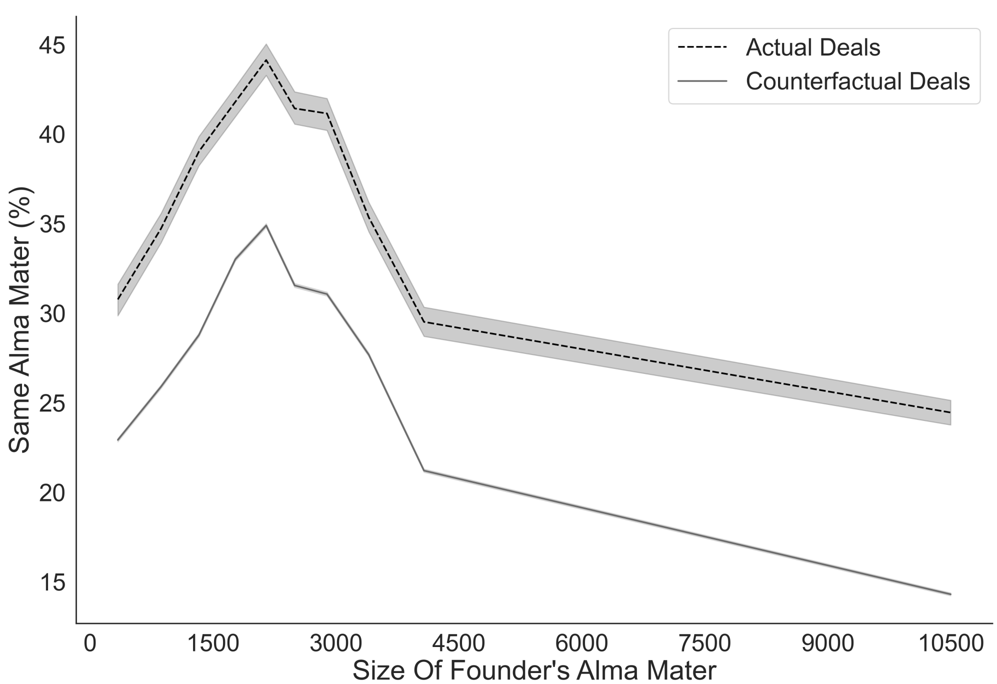
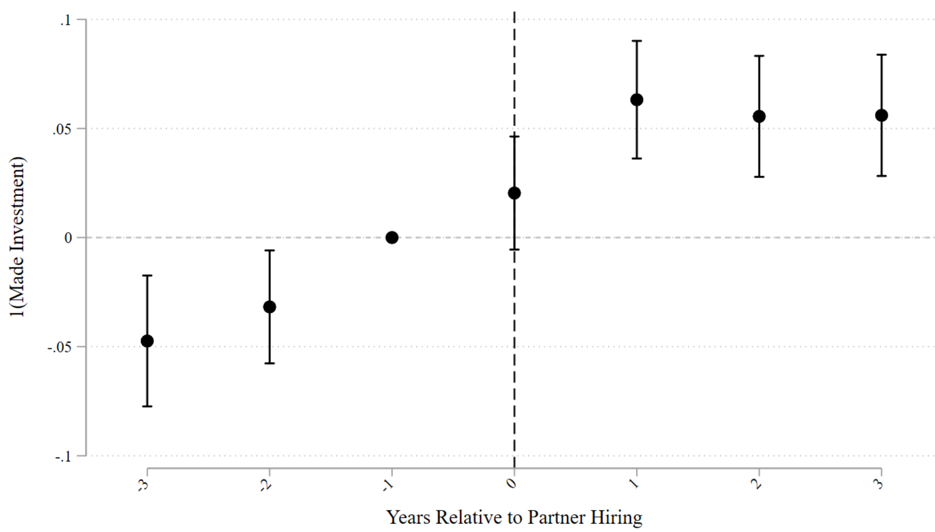


Figure 3: Partner Transitions and Same Alma Mater Investment Patterns

This figure presents event study analyses examining how venture capital (VC) firms' investment patterns change around partner hiring and departure events. Both panels show stacked differences-in-differences estimates with investor-cohort-university and year-cohort fixed effects, using matched control firms based on deal timing, investor type, headquarters location, and cumulative deal count. The dependent variable is an indicator for whether the firm made an investment in a startup founder from a specific university in a given year. Panel A examines investment patterns around partner hiring events, where treatment occurs when a VC firm hires a partner from a particular university. Panel B analyzes investment patterns around partner departure events, where treatment occurs when a partner leaves the firm. The departure analysis excludes receiving firms from the control group to address potential SUTVA (Stable Unit Treatment Value Assumption) violations. Event time -1 is omitted as the reference category. The vertical dashed line indicates the treatment year (hiring or departure). Error bars represent 95 percent confidence intervals with standard errors clustered by investor firm. Sample period covers 2005-2018 treatment cohorts with a three-year window around each event.

Panel A: Investment Patterns Following Partner Hiring



Panel B: Investment Patterns Following Partner Departures

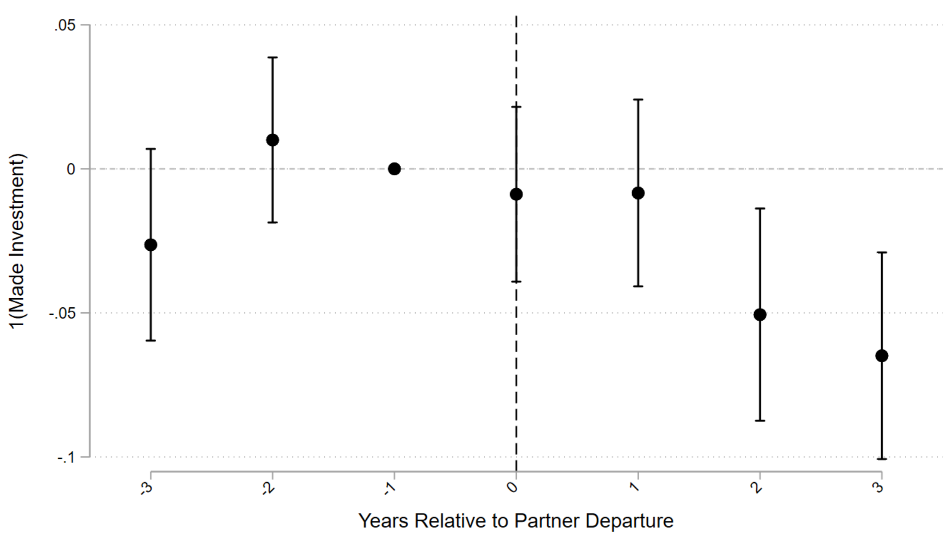
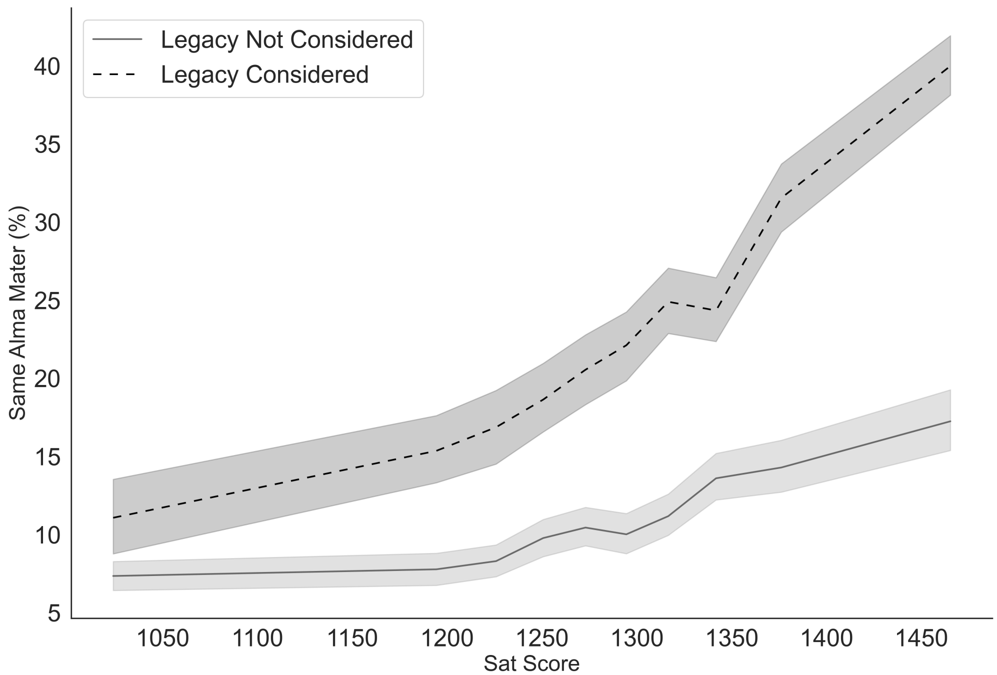


Figure 4: Legacy, Same Alma Mater, and Outcomes

This figure examines the relationship between universities' legacy admissions policies, academic quality, and startup outcomes. Panel A presents a binned scatter plot describing the probability that a deal involves an investment firm where at least one partner attended the same university as one of the startup's founders (*Same Alma Mater*). Deals are sorted into decile bins along the horizontal axis based on the most recent data on the average scholastic assessment test (SAT) score of entering freshmen at the founders' alma mater (averaged for startups with multiple founders). *Legacy Considered* shows the likelihood of a Same Alma Mater match for founders who attended a university that considers legacy admissions. *Legacy Not Considered* shows the results for founders that attended a school that does not consider legacy admissions. Panel B presents a similar plot, where the dependent variable is an indicator for whether the startup exited via an IPO, times 100. The bands around each line represent 95 percent confidence intervals.

Panel A: Education networks, School quality, and Legacy Admissions



Panel B: Performance, School quality, and Legacy Admissions

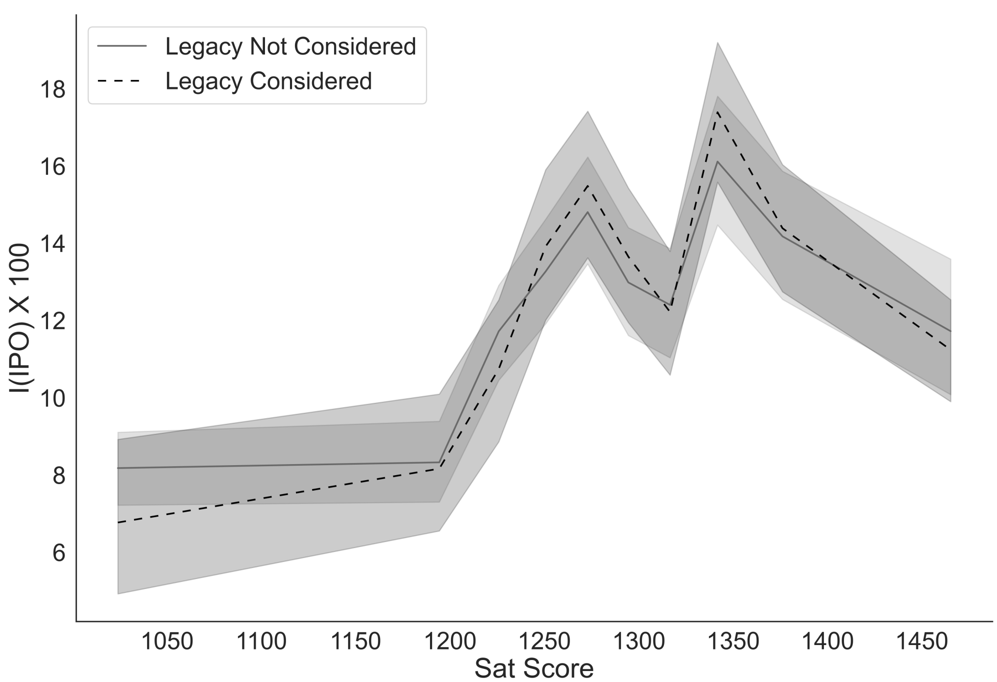


Table 1: Summary Statistics

This table reports summary statistics for startups, founders, investors, deals, and universities appearing in the PitchBook data. In Panel A, the unit of observation is a startup that raised at least one round of VC funding. In Panel B, the unit of observation is a founder of a startup that raised at least one round of venture capital (VC) funding. Founders are individuals whose title contains the following keywords: "founder," "founding," or "owner." In Panel C, the unit of observation is an investment firm that led at least one round of VC funding. In Panel D, the unit of observation is a VC deal, where the requisite data are available for our tests. In Panel E, the unit of observation is a university that at least one founder or investor participating in a VC deal attended. We define all variables in Table A.1.

	N	**Mean**	**Std**	**25%**	**50%**	**75%**	**Max**
A. Startup-level statistics							
Year Founded	18,022	2010.15	6.41	2007.00	2011.00	2015.00	2021.00
I(U.S. Headquarters)	18,022	1.00	0.00	1.00	1.00	1.00	1.00
I(California Headquarters)	18,022	0.42	0.49	0.00	0.00	1.00	1.00
# Rounds	18,022	1.63	1.00	1.00	1.00	2.00	9.00
# Seed/Early stage Rounds	18,022	1.04	0.79	1.00	1.00	1.00	7.00
# Late Stage Rounds	18,022	0.59	0.91	0.00	0.00	1.00	8.00
Cumulative Amount Raised ($ Millions)	18,022	26.37	90.72	1.50	6.53	22.50	4911.94
Year First Funding Round	18,022	2013.91	4.64	2011.00	2015.00	2018.00	2021.00
I(M&A)	18,022	0.26	0.44	0.00	0.00	1.00	1.00
I(IPO)	18,022	0.06	0.23	0.00	0.00	0.00	1.00
# Founders	16,774	2.33	1.16	2.00	2.00	3.00	14.00
B. Founder-level statistics							
# Startups Formed	37,107	1.05	0.26	1.0	1.0	1.0	14.0
# Education Institutions	28,007	1.46	0.61	1.0	1.0	2.0	6.0
# Education Institutions Sample	25,078	1.37	0.56	1.0	1.0	2.0	5.0
C. Investor-level statistics							
# Lead Partners	1,662	6.77	10.35	2.00	4.0	7.00	168.0
AUM ($ Millions)	1,372	2906.18	21930.75	65.88	215.5	851.69	649000.0
Year Founded	1,626	2005.05	10.66	1999.00	2007.0	2013.00	2021.0

(Table 1 Continued)

	N	Mean	Std	25%	50%	75%	Max
D. Deal-level statistics							
All Deals							
# Lead Investors	29,421	1.14	0.43	1.00	1.00	1.0	7.00
# Partners at lead investors	18,673	5.28	4.66	2.00	4.00	7.0	41.00
# Founders	27,590	2.38	1.17	2.00	2.00	3.0	14.00
Amount Raised ($ Millions)	26,694	17.80	53.12	2.30	6.80	17.1	3400.00
Post Money Valuation ($ Millions)	18,070	151.56	1202.67	13.41	32.08	85.0	74314.06
First Deals Only							
# Lead Investors	18,022	1.12	0.40	1.00	1.00	1.0	7.0
# Partners at lead investors	10,865	4.87	4.29	2.00	4.00	6.0	35.0
# Founders	16,774	2.33	1.16	2.00	2.00	3.0	14.0
Amount Raised ($ Millions)	15,977	10.10	33.57	1.58	4.16	10.0	3000.0
Post Money Valuation ($ Millions)	10,070	48.46	337.08	9.25	18.20	40.0	30750.0
E. University-level statistics							
# Lead Investors	361	13.25	37.76	1.00	3.00	10.00	395.00
# Founders	442	26.05	55.22	3.00	6.00	22.00	574.00
Early Career Pay	474	61667.09	8533.82	55625.00	60000.00	65375.00	98900.00
Mid-Career Pay	474	113990.30	19675.16	99700.00	110700.00	124750.00	173700.00
Admission Rate	485	0.61	0.23	0.46	0.66	0.78	0.98
SAT Score	485	1221.95	134.03	1129.00	1198.00	1307.00	1566.00
University Size	485	2041.57	2147.34	497.00	1151.00	3106.00	15078.00

Table 2: Entrepreneurs and Investors from Top 20 Universities

This table presents statistics on founders and investors in our sample from the top 20 universities (according to U.S. News' 2019 rankings). Our sample is collected from PitchBook, and is restricted to firms receiving funding from 2000-2020, with founders/investors from U.S. universities, and with the required data for our tests. Columns 1, 2, and 3 present the rank, name, and the most recent data (2019) on the mean scholastic assessment test (SAT) score of entering freshmen at these universities. Columns 4 and 5 present the number of founders per 1000 students enrolled at the university and the number of startups founded by alumni of the university. Columns 6, 7, and 8 present the number of partners per 1000 students from each school, the number of deals, and the percent of deals by the school's partners that are connected (involve at least one founder from the same university).

Alma mater			Entrepreneurs		Investors		
Rank	University Name	Mean SAT	# Founders Per 000s	# Firms	# Partners Per 000s	# Deals	% Same Alma Mater
1	Princeton University	1503	151.75	646	92.00	1075	30.14
2	Harvard University	1520	290.15	2589	213.70	4440	44.98
3	Columbia University	1512	134.44	1208	98.11	2030	27.98
4	MIT	1545	75.07	603	27.61	1022	20.35
5	Yale University	1517	72.79	746	43.84	1303	27.78
6	Stanford University	1497	336.59	2959	128.90	5143	49.06
7	University of Chicago	1520	68.45	671	63.80	1066	22.98
8	University of Pennsylvania	1492	82.28	1739	62.63	2925	36.17
9	Northwestern University	1508	43.71	656	21.08	1077	22.75
10	Duke University	1516	71.73	754	42.25	1208	24.42
11	Johns Hopkins University	1513	43.64	442	16.17	784	21.17
12	California Institute of Tech.	1566	203.09	224	43.30	375	22.13
13	Dartmouth College	1488	82.82	517	58.18	844	29.03
14	Brown University	1492	63.07	515	28.65	872	25.57
15	University of Notre Dame	1502	39.05	343	32.46	571	17.69
16	Vanderbilt University	1514	32.73	291	18.35	471	16.77
17	Cornell University	1471	48.57	1092	22.39	1785	24.48
18	Rice University	1513	33.59	202	14.17	334	14.97
19	Washington Univ. in St. Louis	1506	31.60	329	17.43	528	20.83
20	UCLA	1423	20.47	1132	8.56	1872	28.42

Table 3: Characteristics of Startups and their Investors

This table reports summary statistics for our sample of venture capital deals. The sample is collected from PitchBook, and is restricted to firms receiving funding from 2000-2020, with founders/investors from U.S. universities, and with the required data for our tests. Columns 1-4 focus on actual deals and report the mean for the full sample, the mean for the set of deals with a founder-investor alma mater connection, the mean for the set of unconnected deals, and a t-test for differences between the connected and unconnected deals. Columns 5-8 report the same statistics for the sample of counterfactual deals. These counterfactual deals are selected by pairing each actual deal with other deals in PitchBook that the investor likely considered, i.e., those in the same State X Year X Industry X Stage (see Section III.A for details).

	Actual Deals (N = 18351)				**Counterfactual Deals (N = 885640)**			
	Full Sample	SAM Sample	DAM Sample	t-stat	Full Sample	SAM Sample	DAM Sample	t-stat
Same Alma Mater	0.37				0.33			
I(Overlapping Graduation)	0.14				0.10			
I(Same School)	0.32				0.27			
I(MBA)	0.31				0.26			
Mean SAT Score	1313.39	1343.59	1295.59	26.40***	1328.73	1361.73	1312.6	177.24***
University Size	2590.02	2300.33	2760.88	-18.26***	2536.30	2207.09	2695.71	-133.88***
Young Firm	0.72	0.73	0.72	0.60	0.75	0.72	0.77	-45.84***
Distance (miles)	1267.66	1131.5	1347.97	-7.89***	1276.56	1096.6	1363.59	-59.86***
Seed Round	0.17	0.13	0.19	-11.23***	0.15	0.1	0.17	-96.69***
Past Funding Relationship	0.23	0.26	0.22	6.26***	0.01	0.01	0.01	25.93***
Past Industry Experience	0.96	0.98	0.96	6.66***	0.98	0.99	0.97	47.01***
Past Affiliation	2.53	2.94	2.29	7.01***	0.64	0.97	0.48	69.18***

Table 4: Do Investors Tilt their Portfolios Toward Startups from their Alma Mater?

The tests in this table examine the effect of founders' and investors' shared educational backgrounds on the likelihood that investors fund startups. The table presents coefficients from OLS regressions run at the investor-deal level, with standard errors reported in parentheses. We focus on venture capital deals from 2000-2020, where the requisite data is available from PitchBook. A unit of observation is an investor-deal. The sample includes an observation for each actual deal and synthetic deals constructed by pairing each investor with all deals in that same State X Year X Industry X Stage. The dependent variable is an indicator for being an actual deal, times 100. The key independent variable, *Same Alma Mater*, indicates whether any of the founders share the same alma mater as an investor in the deal. *Mean SAT Score* is the average SAT score at the founder's alma mater in the year the startup raised funding (averaged for startups with multiple founders). We cluster standard errors by startup-investor pair.

Dependent Variable:	I(Investment) X 100				
	1	2	3	4	5
Same Alma Mater	0.2176***	0.2341***	0.1751***	0.0192	0.0637
	(0.0341)	(0.0357)	(0.0371)	(0.0617)	(0.0587)
Mean SAT Score	-0.0274	-0.0135	-0.0284*	-0.0267	-0.0274*
	(0.0167)	(0.0172)	(0.0167)	(0.0167)	(0.0167)
Same Alma Mater x Mean SAT Score		-0.0819**			
		(0.0379)			
I(Overlapping Graduation)			0.1461**		
			(0.0586)		
I(Same School)				0.2434***	
				(0.0655)	
I(MBA)					0.1936***
					(0.0631)
Ln(University Size)	0.0451***	0.0414***	0.0450***	0.0441***	0.0449***
	(0.0150)	(0.0151)	(0.0150)	(0.0150)	(0.0150)
Young Firm	0.2673***	0.2708***	0.2705***	0.2691***	0.2686***
	(0.0421)	(0.0421)	(0.0421)	(0.0421)	(0.0421)
Ln(distance)	-0.5154***	-0.5151***	-0.5141***	-0.5139***	-0.5141***
	(0.0283)	(0.0283)	(0.0283)	(0.0283)	(0.0283)
Past Funding Relationship	34.0103***	34.0086***	34.0050***	34.0077***	34.0080***
	(0.5073)	(0.5073)	(0.5073)	(0.5073)	(0.5073)
I(Seed Round)	1.3828***	1.3855***	1.3881***	1.3852***	1.3845***
	(0.0708)	(0.0708)	(0.0708)	(0.0708)	(0.0708)
Past Affiliation	0.5868***	0.5866***	0.5863***	0.5865***	0.5866***
	(0.0149)	(0.0149)	(0.0149)	(0.0149)	(0.0149)
Investor x State x Year x Industry FE	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.16	0.16	0.16	0.16	0.16
# Deals	29,421	29,421	29,421	29,421	29,421
# Startups	18,022	18,022	18,022	18,022	18,022
# Investment Firms	1670	1670	1670	1670	1670
Observations	903991	903991	903991	903991	903991

Table 5: Alumni Networks and Investment: Evidence from VC Partner Hiring and Departures

This table examines VC investment patterns following partner hiring and departure events (see Section III.A.2 for detailed data construction). The dataset is at the investor-university-year level. The dependent variable is an indicator for whether the VC firm made an investment that year in founders who attended a given university (multiplied by 100). The key independent variable is the interaction term *Treated* × *Post*, where *Treated* indicates that the investor-university pair is one where a hiring (departure) event takes place, and *Post* indicates the period following the event. Column 1 examines hiring effects on investment patterns. Columns 2–6 analyze different departure specifications: all departures (2), departures excluding "receiving firms" from controls (3), exogenous departures including retirements, deaths, and exits from VC industry (4), strict exogenous departures limited only to retirement and death events (5), and endogenous departures (6). All specifications employ a stacked difference-in-differences methodology with control VCs matched on state, deal stage, and first deal year. We include investor-cohort-university and year-cohort fixed effects, with standard errors clustered by investor. The bottom of Panel A reports the number of unique treated/control VC firms, alma maters, and events. Panel B presents the classification of all 1,007 departure events in our sample.

Dependent Variable:	**1(Made Investment) X 100**					
	Hiring	**Departures**	**SUTVA**	**Exogenous**	**Exogenous-Strict**	**Endogenous**
	1	2	3	4	5	6
Treated × Post	7.103***	-2.823**	-2.443**	-3.731*	-7.914***	-2.498*
	(0.948)	(1.138)	(1.142)	(2.007)	(2.654)	(1.352)
Adjusted-R^2	0.357	0.381	0.379	0.389	0.454	0.379
# VC Firms	981	591	591	279	95	432
# Alma Mater	485	485	485	485	485	485
Observations	6,656,702	3,322,243	3,293,230	1,092,314	378,696	2,307,806
Cohort X Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort X Investor X University FE	Yes	Yes	Yes	Yes	Yes	Yes
# Events	2,374	1,007	1,007	707	140	300
Mean of **1(Made Investment)**	0.039	0.041	0.044	0.046	0.058	0.046

Panel B: Distribution of Departure Events by Type		
Departure Type	N	%
(1) Retirement/Death	140	14%
(2) Moving to Non-VC Industries	567	56%
(3) Founding a VC Firm	105	10%
(4) Promotion at Another VC Firm	71	7%
(5) Demotion at Another VC Firm	66	7%
(6) Lateral Move to Another VC Firm	58	6%
Total	1,007	100.0

Table 6: Founders' Alumni Networks and Access to VC Funding

The tests in this table examine the effect of founders' educational backgrounds on the probability that the founder raises a round of venture capital funding. The table presents OLS regressions run at the startup level. We use the entire PitchBook database of companies formed between 2000 and 2021 where the founder attended at least one school on our list of U.S. universities. Our dependent variable is an indicator for whether the company raised a round of VC funding in the year of founding or the following year (23.48% of startups raised a round of VC funding within this timeframe). The key independent variable, *P(Partners in Sector)*, is the proportion of deals led by partners from the same alma mater as the founder's, in the startup's industry sector, during the calendar year that the focal company was formed (averaged across founders when there are multiple). The average value of this variable is 11.98%. *Mean SAT Score* is the average scholastic assessment test (SAT) score at the founder's alma mater in the year the startup was formed. *Ln(# University Size)* is the log of the number students graduating from the founder's alma mater. *I(Founded >= 2020)* is an indicator for startups formed in 2020 or later, a proxy for startups most exposed to the effects of the Covid-19 pandemic. The sample in column 5 only includes startups formed in 2018 or later. Standard errors are clustered by startup.

Dependent Variable:	I(VC Funding) X 100				
	1	2	3	4	5
P(Partners in Sector)	20.7161***		8.7425***	34.3342***	17.3587***
	(1.2577)		(1.6992)	(3.6845)	(5.3526)
Mean SAT Score		3.7137***	2.8216***	2.5513***	1.8012**
		(0.1786)	(0.2453)	(0.2481)	(0.7299)
Ln(University Size)			0.2277	-0.6894***	-1.1930*
			(0.2294)	(0.2514)	(0.6484)
P(Partners in Sector) X Mean SAT Score				-20.4713***	
				(2.6648)	
I(Founded >= 2020) X P(Partners in Sector)					-12.7134*
					(6.5123)
Adjusted R^2	0.08	0.08	0.08	0.08	0.08
# Startups	71509	71509	71509	71509	11840
State x Year x Industry FE	Yes	Yes	Yes	Yes	Yes

Table 7: Do Investors Place Larger Bets on Startups from their Alma Mater?

The tests in this table examine the effect of educational connections between founders and investors on the amount of funding raised. Panel A presents OLS regressions run at the investor-deal level. The sample includes investor-deal combinations for VC deals from 2000-2020, where the requisite data is available from PitchBook. The dependent variable is the log amount of funding raised, and the key independent variable, *Same Alma Mater*, indicates whether any of the founders share the same alma mater as a partner working for the investment firm at the time of the deal. Panel B presents similar OLS regressions run at the deal level. Panel C presents similar OLS regressions run at the alma mater-deal level, which permits the use of alma mater fixed effects. Standard errors are clustered by investor in Panel A, and by startup in Panels B, and C.

A. Investor-Deal Level Tests					
Dependent Variable:	Ln(Funding Raised)				
	1	2	3	4	5
Same Alma Mater	0.1825***	0.1837***	0.0976**	0.0460	0.2124***
	(0.0367)	(0.0369)	(0.0393)	(0.0743)	(0.0705)
Mean SAT Score	-0.0133	-0.0067	-0.0140	-0.0117	-0.0134
	(0.0241)	(0.0259)	(0.0240)	(0.0241)	(0.0241)
Same Alma Mater x Mean SAT Score		-0.0212			
		(0.0376)			
I(Overlapping Graduation)			0.2208***		
			(0.0465)		
I(Same School)				0.1552**	
				(0.0755)	
I(MBA)					-0.0346
					(0.0692)
Ln(University Size)	0.0149	0.0141	0.0137	0.0147	0.0148
	(0.0202)	(0.0204)	(0.0202)	(0.0202)	(0.0202)
Young Firm	-0.4117***	-0.4109***	-0.4031***	-0.4141***	-0.4114***
	(0.0431)	(0.0431)	(0.0431)	(0.0430)	(0.0430)
Ln(distance)	0.0052	0.0054	0.0052	0.0061	0.0051
	(0.0346)	(0.0346)	(0.0347)	(0.0346)	(0.0346)
Past Funding Relationship	0.0573	0.0573	0.0546	0.0558	0.0577
	(0.0386)	(0.0386)	(0.0385)	(0.0386)	(0.0386)
I(Seed Round)	-1.2019***	-1.2012***	-1.1952***	-1.2025***	-1.2023***
	(0.0528)	(0.0529)	(0.0529)	(0.0528)	(0.0528)
Past Affiliation	0.0219***	0.0217***	0.0211***	0.0219***	0.0218***
	(0.0038)	(0.0038)	(0.0038)	(0.0038)	(0.0038)
Investor x State x Year x Industry FE	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.69	0.69	0.69	0.69	0.69
# Startups	5677	5677	5677	5677	5677
# Deals	6047	6047	6047	6047	6047
# Investors	1514	1514	1514	1514	1514
# Observations	6379	6379	6379	6379	6379

(Table 7 Continued)

B. Deal Level Tests					
Dependent Variable:	Ln(Funding Raised)				
	1	2	3	4	5
Same Alma Mater	0.3436***	0.3442***	0.2662***	0.2947***	0.2391***
	(0.0232)	(0.0232)	(0.0256)	(0.0431)	(0.0434)
Mean SAT Score	0.0039	0.0071	0.0022	0.0044	0.0038
	(0.0159)	(0.0173)	(0.0159)	(0.0159)	(0.0159)
Same Alma Mater x Mean SAT Score		-0.0122			
		(0.0244)			
I(Overlapping Graduation)			0.2217***		
			(0.0331)		
I(Same School)				0.0567	
				(0.0432)	
I(MBA)					0.1244***
					(0.0436)
Controls	Yes	Yes	Yes	Yes	Yes
State x Year x Industry FE	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.40	0.40	0.40	0.40	0.40
# Startups	10232	10232	10232	10232	10232
# Deals	15535	15535	15535	15535	15535
# Observations	15535	15535	15535	15535	15535

C. **Alma mater-Deal Level Tests**			
Dependent Variable:	Ln(Funding Raised)		
	(1)	(2)	(3)
Same Alma Mater	0.1073***	0.0950***	0.0793***
	(0.0188)	(0.0240)	(0.0206)
Year x Industry FE	Yes	No	No
Alma Mater x Year x Industry FE	No	Yes	Yes
Controls	No	No	Yes
Adjusted R^2	0.05	0.07	0.32
# Startups	10054	10054	10054
# Universities	485	485	485
# Observations	52808	52808	52808

Table 8: The Performance of Connected vs. Non-connected Investments

The tests in this table examine the effect of educational connections between founders and investors on the probability of an IPO post-funding. Panel A presents OLS regressions run at the investor-startup level. We keep the first investment by the lead investor in the startup and track whether the investment exits via an IPO. The sample includes investor-deal combinations for VC deals from 2000-2016, where the requisite data are available from PitchBook. We end the sample in 2016 to allow enough time for an exit. The dependent variable is an indicator for whether the startup in the deal eventually exits via an IPO by June 2021 (see the appendix for exits via successful acquisitions). The key independent variable, *Same Alma Mater*, indicates whether any of the founders share the same alma mater as a partner at the investment firm. Panel B presents similar OLS regressions run at the deal level. Standard errors are clustered by investor in Panel A and by startup in Panel B.

A. Investor-Startup Level Tests					
Dependent Variable:			I(IPO) X 100		
	1	2	3	4	5
Same Alma Mater	2.7417***	2.4340***	2.8081***	2.2441*	-0.1540
	(0.6212)	(0.6314)	(0.7127)	(1.3641)	(1.1163)
Mean SAT Score	0.7511**	1.1450***	0.7526**	0.7553**	0.7443**
	(0.3063)	(0.3342)	(0.3064)	(0.3062)	(0.3062)
Same Alma Mater x Mean SAT Score		-1.3886**			
		(0.6482)			
I(Overlapping Graduation)			-0.1847		
			(1.0135)		
I(Same School)				0.5726	
				(1.4040)	
I(MBA)					3.4608***
					(1.1857)
Ln(Investors Alma Mater)	0.1005	0.0645	0.1004	0.0991	0.1035
	(0.3008)	(0.3011)	(0.3008)	(0.3010)	(0.3007)
Young Firm	0.0173	0.0349	0.0147	0.0219	0.0381
	(0.7602)	(0.7597)	(0.7607)	(0.7603)	(0.7605)
Ln(distance)	-0.2529	-0.2465	-0.2538	-0.2516	-0.2453
	(0.2788)	(0.2787)	(0.2787)	(0.2788)	(0.2788)
I(Seed Round)	1.1769**	1.1999**	1.1755**	1.1765**	1.2020**
	(0.5883)	(0.5877)	(0.5885)	(0.5884)	(0.5882)
Past Affiliation	-0.0051	-0.0083	-0.0047	-0.0053	-0.0074
	(0.0624)	(0.0624)	(0.0624)	(0.0624)	(0.0623)
Ln(Funding Raised)	3.3764***	3.3758***	3.3804***	3.3756***	3.3746***
	(0.3200)	(0.3199)	(0.3211)	(0.3200)	(0.3197)
Investor FE	Yes	Yes	Yes	Yes	Yes
First Deal Year FE	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.08	0.08	0.08	0.08	0.08
# Startups	7058	7058	7058	7058	7058
# Investors	851	851	851	851	851
Observations	9930	9930	9930	9930	9930

(Table 8 Continued)

B. Startup-Level Tests					
Dependent Variable:	I(IPO) X 100				
	1	2	3	4	5
Same Alma Mater	1.9230***	1.7750**	2.5560***	2.3208	-0.1752
	(0.7123)	(0.7124)	(0.8332)	(1.7893)	(1.4353)
Mean SAT Score	0.8367**	1.0416***	0.8552**	0.8330**	0.8385**
	(0.3573)	(0.4029)	(0.3572)	(0.3577)	(0.3573)
Same Alma Mater x Mean SAT Score		-0.7631			
		(0.7551)			
I(Overlapping Graduation)			-1.8707		
			(1.1934)		
I(Same School)				-0.4553	
				(1.8277)	
I(MBA)					2.4931*
					(1.4962)
Ln(University Size)	0.4754	0.4461	0.4718	0.4760	0.4855
	(0.3441)	(0.3453)	(0.3441)	(0.3442)	(0.3440)
Young Firm	-0.2518	-0.2325	-0.2459	-0.2508	-0.2858
	(0.9846)	(0.9839)	(0.9842)	(0.9849)	(0.9846)
Ln(distance)	-0.0637	-0.0568	-0.0639	-0.0647	-0.0615
	(0.2940)	(0.2942)	(0.2942)	(0.2938)	(0.2939)
I(Seed Round)	2.1798***	2.2101***	2.1484***	2.1771***	2.2269***
	(0.6140)	(0.6149)	(0.6145)	(0.6133)	(0.6152)
Past Affiliation	0.1016*	0.1016*	0.1072*	0.1020*	0.0973
	(0.0598)	(0.0599)	(0.0599)	(0.0598)	(0.0596)
Ln(Funding FD)	3.3567***	3.3628***	3.3838***	3.3560***	3.3557***
	(0.3155)	(0.3157)	(0.3172)	(0.3157)	(0.3154)
Controls	Yes	Yes	Yes	Yes	Yes
State x Year x Industry FE	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.10	0.10	0.10	0.10	0.10
# Startups	6736	6736	6736	6736	6736
Observations	6736	6736	6736	6736	6736

Alumni Networks in Venture Capital Financing

Internet Appendix

Appendix A. PitchBook's Coverage

Figures A.1 and A.2 compare the coverage of startups and early-stage financing deals in PitchBook with Crunchbase and VentureXpert, other frequently used datasets of early-stage high-growth companies.[17] Figure A.1 shows that VentureXpert and Crunchbase include at most 60 percent of the deals in our sample in any given year, with this percentage decreasing over time. Figure A.2 shows that PitchBook has better deal coverage for the firms listed in all three databases.[18] This is especially important given that it affects the construction of variables such as past collaboration between investors, or past funding relationships, which are likely correlated with shared education networks. Tables A.10 and A.11 provide summary statistics across databases. The statistics show that the startups missed by Crunchbase in particular tend to be smaller and secure less funding. These are the types of firms most likely to benefit from alumni connections due to their high levels of information asymmetry. A database missing deals would limit the external validity of the results, and could lead researchers to miscalculate important controls, potentially confounding the effect of alumni networks on funding and entrepreneurial outcomes.

[17] An important caveat that this analysis does not consider is the possibility of VC-backed deals existing in Crunchbase and VentureXpert that do not appear in PitchBook for our data period. For a comparative analysis of coverage across various databases, see Retterath and Braun (2020). These authors gather deal data from a large venture capital firm in Europe to examine how comprehensively different databases cover the deals. They consistently rank PitchBook above the other databases, particularly when comparing coverage of startup founders.

[18] We match the firms to VentureXpert and Crunchbase on founding year, state, and then require a 100 percent fuzzy match on the standardized name, which we verify for accuracy.

Appendix B. Constructing P-Same Alma Mater

Our aim is to construct a measure of alumni connections between founders and partners employed by the lead investor. Naturally, larger founding teams or lead investors employing many partners would be more likely to have an alumni connection. To ensure that our results are robust to this consideration, we normalize the number of alumni connections as follows.

We begin by constructing potential matches between founders and investors. The number of unique founder-university and partner-university pairs (for each deal) is our target measure. For instance, if a founder attended two universities and a partner affiliated with the lead investor also attended two universities, then the number of potential matches would be four. Formally, for portfolio company i and lead investor j in the year t of the company's funding round, we calculate the metric of potential matches as:

$$\text{Potential Matches}_{ijt} = \prod N_{it} E_i N_{jt} E_j, \tag{B.1}$$

where N_{it} is the count of the founding team of company i, and N_{jt} is the count of senior team members working for the fund within the lead investment firm j in year t, and E_i and E_j are the numbers of unique universities associated with the founders of company i and partners of investment firm j, respectively.

Then, for each portfolio company and lead investor, we use the number of potential matches to scale the actual connection count between founders and lead partners associated with a deal. In other words, we calculate a probability that the deal involves an alumni match between the founder and the lead investor. This probability is size-independent.

We present robustness checks of our main result using this probability measure in our Appendix Table A.4. Our findings remain consistent with our benchmark results that use a simple indicator for the existence of an alumni connection between the founder and the lead investor.

Appendix C. Constructing Past Affiliation

We construct a measure of past collaborations among investors in a company. This measure captures collaborations between the lead VC firm in the current round of funding and other lead investors that funded the startup in previous rounds. We define past affiliation as follows:

$$\text{Past Affiliation}_{ij} = \frac{\sum_k \sum_p I_{ij} I_{kj} I_{ip} I_{kp}}{\sum_{kj} I_{kj}}, \tag{C.1}$$

where i stands for the lead investor in startup j, k indexes all past investors in startup j, p indexes previous investments in other startups, and I_{kj} takes a value of one when VC firm k previously funded startup j. Thus, Past Affiliation captures the strength of relations between VC firm i and other past investors in startup j.

For example, consider a startup that has raised a Seed and a Series A round, where the Seed round was led by investor k, and the Series A round by investor i. Further, suppose that this deal occurred in 2010. If VC firm i and k have never previously invested in the same startup p prior to 2010, past affiliation is zero. If they had jointly invested in 2 startups prior to 2010, then past affiliation is 2.

Appendix D. Replication in the LinkedIn Sample

In this Appendix, we extend the main result from Table 4 to a potentially broader universe of young firms. We obtain LinkedIn data from a data aggregator called Datahut. We then examine startups that meet the criteria that the founder attended a U.S. university and that they are associated with a company in the LinkedIn "companies" dataset. We further require that the company is U.S.-based, and not missing data on location and founding year. Our final sample comprises 11,157 companies formed between 2000 and 2015 by founders attending one of the 485 schools in our sample. The presumption is that these companies would welcome VC funding.

We then reconstruct our *Same Alma Mater* variable, using a similar approach as we did for the Table 4 analysis. First, we match the set of companies from LinkedIn to PitchBook on founding year, state, and name to build a dataset of companies that got VC funding. Then we define counterfactuals as all LinkedIn companies in the same state, industry, and founding year as the company that had an actual VC funding event. Presumably, they would all welcome VC funding, but only one (or some) received it. Recipients of VC funding are the "ones" and non-recipients are the "zeroes" in this extensive margin test. The key independent variable is again *Same Alma Mater*.[19]

The results are presented in Table A.5. In column 4, the preferred specification, the coefficient on *Same Alma Mater* is 0.88% and is statistically significant. Since the unconditional probability that a company in these data receives VC funding is 2.57%, alumni connections correlate with a 31% increase in the likelihood of getting VC funding. It is important to note that

[19] Most of our Table 4 controls are unavailable because our analysis here is a true extensive margin—the counterfactuals do not receive any VC funding.

this test investigates the likelihood of an investment by a VC (Investor FE) considering two startups in the same state (State FE), formed in the same year (Founding Year FE), and operating in the same industry (Industry FE) that differ by whether the startup founders attended the same alma mater as the partners at the investment firm. Our fixed effects absorb time-varying investment preferences across investors, industries, geographies, and founding year. The results here are consistent with our main results using the PitchBook universe, providing further evidence of the effect of alumni connections on the extensive margin of VC investment.

[Insert Table A.5 Here.]

Figure A.1: PitchBook relative to other databases

This figure shows the proportion of startups in our sample that are also covered by Crunchbase and VentureXpert. We match the startups to VentureXpert and Crunchbase on founding year, state, and then require a 100 percent fuzzy match on the standardized name, which we verify for accuracy. For each startup in our sample, we keep the first year in which it raises funding, *First Fundraising Year*. Out of the 28,277 startups in our sample (before any filtering on covariates available for our tests), 12,102 matched to Crunchbase and 8,081 matched to VentureXpert. We see that less than 60 percent of firms in our sample are covered by VentureXpert or Crunchbase in a given year. However, post 2005, Crunchbase appears to have better coverage than VentureXpert.

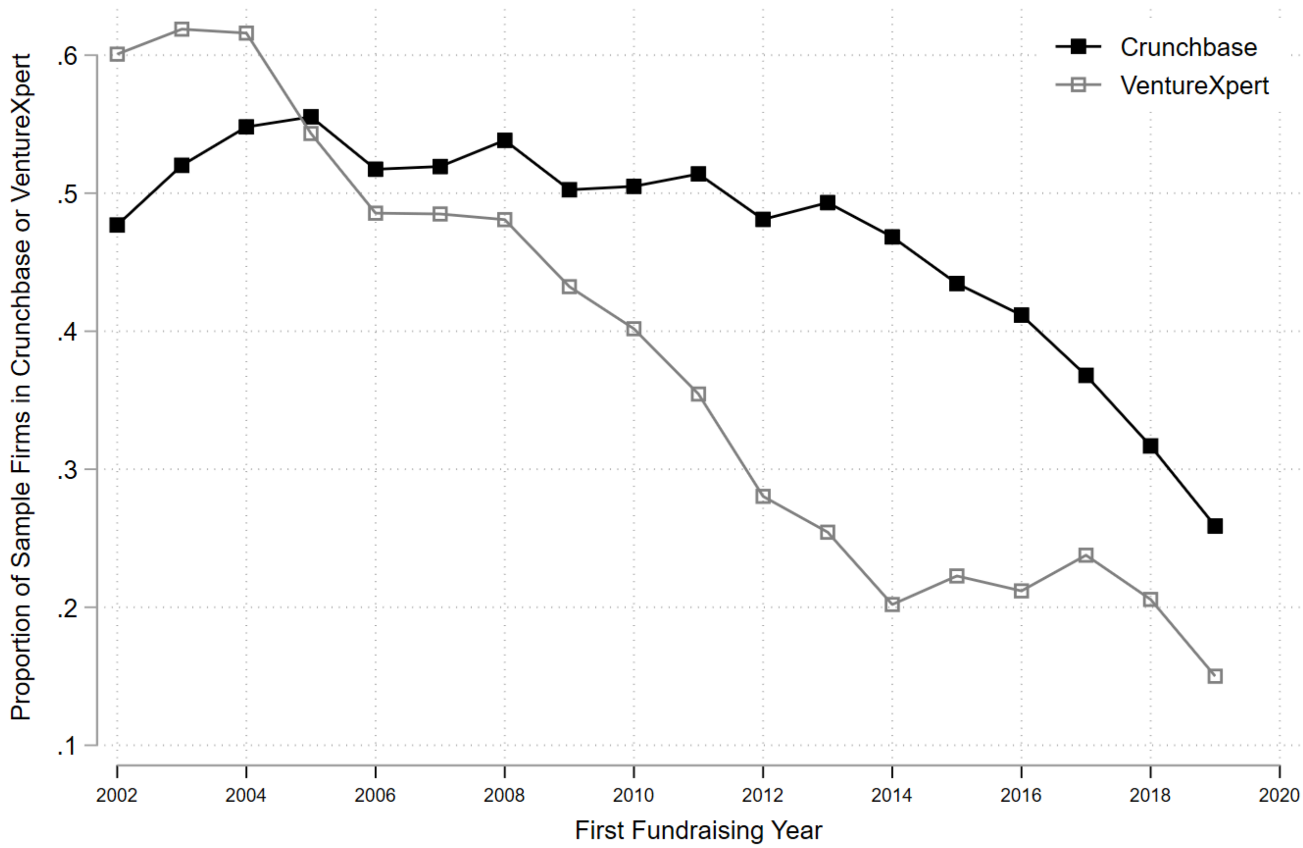


Figure A.2: PitchBook relative to other databases (Matched Sample)

This figure shows the number of deals for firms in our sample in Crunchbase and VentureXpert. We match the startups to VentureXpert and Crunchbase on founding year, state, and then require a 100 percent fuzzy match on the standardized name, which we verify for accuracy. Out of the 28,277 startups in our sample, 4,918 matched to Crunchbase and VentureXpert. For each of these startups, we keep the first year in which it raises funding, *First Fundraising*, and count the number of deals in PitchBook, Crunchbase, and VentureXpert. Besides 2004 and 2005, PitchBook appears to have better coverage of deals than either VentureXpert or Crunchbase.

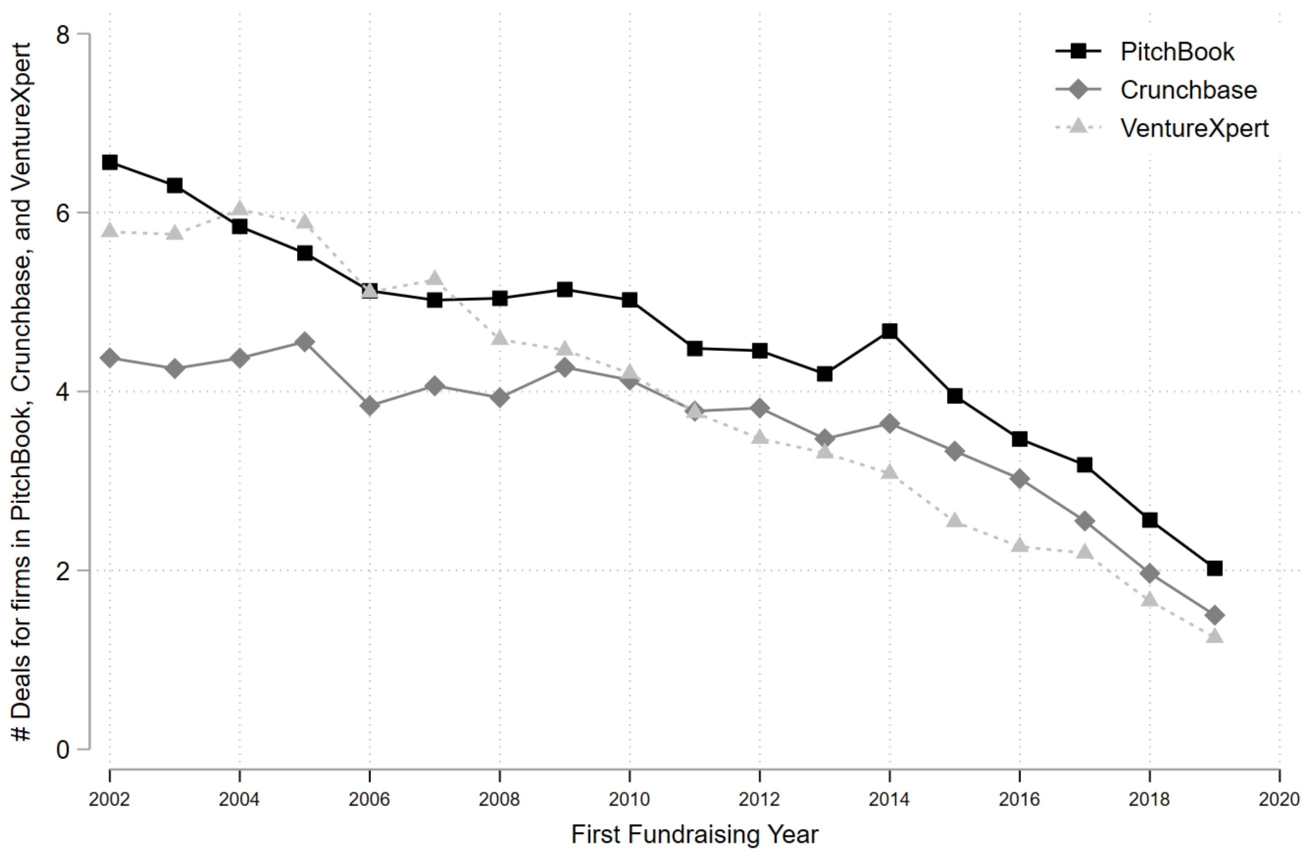


Table A.1: Variable Definitions

Variable Name	Definition
Same Alma Mater	Indicator that equals one if any of the founders share the same alma mater as an investor in the deal.
Mean scholastic assessment test (SAT) Score	Average SAT score of entering freshmen at the university attended by the founder of the portfolio company (averaged for companies with multiple founders)
University Size (000s)	The number of graduating students from the founders' alma mater in the year preceding the deal.
Young Firm	An indicator that equals one if the firm was formed less than five years before the date of financing
Distance (miles)	The average distance (in miles) between the portfolio company and the investors participating in the deal.
Past Funding Relationship	An indicator that equals one if any investor in the current deal already invested in the company in an earlier round.
First Funding Round	Indicator equals one if the deal is the first recorded funding round for the company in PitchBook.
Past Industry Experience	An indicator that equals one if an investor in a given deal already previously invested in a portfolio company in the same industry as the firm currently receiving the investment.
Past Affiliation	Indicator that equals one if an investor in a current round has previously collaborated with the startup's existing investors, in other rounds excluding the current round, on prior deals involving other startups.
I(Overlapping Graduation Years)	Indicator that equals one if any of the founders share the same alma mater as an investor in the deal and they graduated within four years of each other.
# Investors	The number of investors participating in the deal.
IPO	Indicator equals one if the firm goes public in the years following the funding round but before the second quarter of 2021
Acquired	Indicator equals one if the firm is acquired in the years following the funding round but before the second quarter of 2021
Funds Raised ($ Millions)	Amount of funding raised by the firm in the current funding round

Table A.2: Do Investors Tilt their Portfolios Toward Startups from their Alma Mater? (First Deals Only)

The tests in this table examine the effect of founders' and investors' shared educational backgrounds on the likelihood that investors fund startups. The table presents coefficients from OLS regressions run at an investor-deal level, with standard errors reported in parentheses. We focus on early-stage equity financing deals from 2000-2020, where the requisite data is available from PitchBook. A unit of observation is an investor deal. The sample includes an observation for each actual deal and synthetic deals constructed by pairing each investor with all deals in that same State X Year X Industry X Stage. The dependent variable is an indicator for being a real deal. The key independent variable, *Same Alma Mater*, indicates whether any of the founders share the same alma mater as an investor in the deal. *Mean SAT Score* is the average scholastic assessment test SAT score at the founder's alma mater in the year the startup raised funding (averaged for startups with multiple founders). We cluster standard errors by startup-investor pair.

Dependent Variable:	I(Investment)					
	1	2	3	4	5	6
Same Alma Mater	1.0669***	1.1653***	0.8053***	0.2763	0.4239*	0.6324***
	(0.1293)	(0.1423)	(0.1400)	(0.2413)	(0.2391)	(0.2338)
Mean SAT Score	-0.0654	-0.0262	-0.0701	-0.0615	-0.0644	-0.0671
	(0.0539)	(0.0549)	(0.0539)	(0.0539)	(0.0539)	(0.0539)
Same Alma Mater x Mean SAT Score		-0.3215**				
		(0.1526)				
I(Overlapping Graduation)			1.0562***			
			(0.2545)			
I(Same School)				0.9713***		
				(0.2629)		
I(MBA)					0.8039***	
					(0.2607)	
I(Bachelors)						0.5561**
						(0.2563)
Ln(University Size)	0.1112**	0.0988**	0.1092**	0.1099**	0.1112**	0.1148**
	(0.0493)	(0.0494)	(0.0492)	(0.0493)	(0.0493)	(0.0493)
Young Firm	-0.5823*	-0.5858*	-0.5649	-0.5844*	-0.5842*	-0.5803*
	(0.3524)	(0.3525)	(0.3524)	(0.3525)	(0.3524)	(0.3524)
Ln(distance)	-1.7541***	-1.7519***	-1.7502***	-1.7493***	-1.7494***	-1.7485***
	(0.0922)	(0.0922)	(0.0922)	(0.0922)	(0.0922)	(0.0922)
I(Seed Round)	0.1790	0.1904	0.2082	0.1810	0.1824	0.1874
	(0.2305)	(0.2304)	(0.2305)	(0.2305)	(0.2305)	(0.2306)
Past Affiliation	0.9725***	0.9724***	0.9718***	0.9723***	0.9725***	0.9724***
	(0.0356)	(0.0356)	(0.0356)	(0.0356)	(0.0356)	(0.0356)
Investor x State x Year x Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.13	0.13	0.13	0.13	0.13	0.13
# Deals	8767	8767	8767	8767	8767	8767
# Startups	8767	8767	8767	8767	8767	8767
# Investment Firms	1181	1181	1181	1181	1181	1181
Observations	138807	138807	138807	138807	138807	138807

Table A.3: Do Investors Tilt their Portfolios Toward Startups from their Alma Mater? (Early Career Pay in lieu of SAT Score)

The tests in this table examine the effect of founders' and investors' shared educational backgrounds on the likelihood that investors fund startups. The table presents coefficients from OLS regressions run at an investor-deal level, with standard errors reported in parentheses. We focus on early-stage equity financing deals from 2000-2020, where the requisite data is available from PitchBook. A unit of observation is an investor deal. The sample includes an observation for each actual deal and synthetic deals constructed by pairing each investor with all deals in that same State X Year X Industry X Stage. The dependent variable is an indicator for being a real deal. The key independent variable, *Same Alma Mater*, indicates whether any of the founders share the same alma mater as an investor in the deal. *Early Career Pay* is the average early career pay of graduates of the founder's alma mater according to PayScale (averaged for startups with multiple founders). We cluster standard errors by startup-investor pair.

Dependent Variable:	I(Investment)					
	1	2	3	4	5	6
Same Alma Mater	0.6209***	0.7037***	0.4595***	0.1978**	0.1707*	0.3044***
	(0.0580)	(0.0668)	(0.0616)	(0.0939)	(0.0880)	(0.0958)
Ln(Early Career Pay)	-0.1140***	-0.0884***	-0.1150***	-0.1120***	-0.1127***	-0.1153***
	(0.0226)	(0.0231)	(0.0226)	(0.0226)	(0.0226)	(0.0226)
Same Alma Mater x Ln(Early Career Pay)		-0.2267***				
		(0.0686)				
I(Overlapping Graduation)			0.7199***			
			(0.1253)			
I(Same School)				0.5746***		
				(0.1083)		
I(MBA)					0.6294***	
					(0.1034)	
I(Bachelors)						0.4321***
						(0.1090)
Ln(University Size)	0.0187	0.0133	0.0181	0.0172	0.0178	0.0194
	(0.0221)	(0.0221)	(0.0221)	(0.0221)	(0.0221)	(0.0221)
Young Firm	0.1353**	0.1443**	0.1412**	0.1373**	0.1382**	0.1373**
	(0.0568)	(0.0569)	(0.0568)	(0.0568)	(0.0568)	(0.0568)
Ln(distance)	-0.7585***	-0.7585***	-0.7569***	-0.7568***	-0.7564***	-0.7554***
	(0.0416)	(0.0416)	(0.0416)	(0.0416)	(0.0416)	(0.0416)
Past Funding Relationship	39.5813***	39.5750***	39.5716***	39.5781***	39.5754***	39.5795***
	(0.6071)	(0.6071)	(0.6071)	(0.6071)	(0.6071)	(0.6071)
I(Seed Round)	2.4529***	2.4588***	2.4652***	2.4587***	2.4587***	2.4551***
	(0.1329)	(0.1329)	(0.1329)	(0.1329)	(0.1329)	(0.1329)
Past Affiliation	0.6620***	0.6618***	0.6611***	0.6618***	0.6615***	0.6618***
	(0.0210)	(0.0210)	(0.0210)	(0.0210)	(0.0210)	(0.0210)
Investor x State x Year x Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.18	0.18	0.18	0.18	0.18	0.18
# Deals	18930	18930	18930	18930	18930	18930
# Startups	11942	11942	11942	11942	11942	11942
# Investment Firms	2449	2449	2449	2449	2449	2449
Observations	609868	609868	609868	609868	609868	609868

Table A.4: Do Investors Tilt their Portfolios Toward Startups from their Alma Mater? (Alma Mater Scaled by Potential Pairs)

The tests in this table examine the effect of founders' and investors' shared educational backgrounds on the likelihood that investors fund startups. The table presents coefficients from OLS regressions run at an investor-deal level, with standard errors reported in parentheses. We focus on early-stage equity financing deals from 2000-2020, where the requisite data is available from PitchBook. A unit of observation is an investor deal. The sample includes an observation for each actual deal and synthetic deals constructed by pairing each investor with all deals in that same State X Year X Industry X Stage. The dependent variable is an indicator for being a real deal. The key independent variable, *P-Same Alma Mater*, is the fraction of founder-investor pairs that attended the same university. *Mean SAT Score* is the average scholastic assessment test SAT score at the founder's alma mater in the year the startup raised funding (averaged for startups with multiple founders). We cluster standard errors by startup-investor pair.

Dependent Variable:	I(Investment)					
	1	2	3	4	5	6
P-Same Alma Mater	0.1288***	0.2429***	0.1043***	0.0392	0.0358	0.0805***
	(0.0161)	(0.0289)	(0.0173)	(0.0283)	(0.0263)	(0.0292)
Mean SAT Score	-0.0307*	-0.0717***	-0.0312*	-0.0287*	-0.0291*	-0.0302*
	(0.0166)	(0.0189)	(0.0166)	(0.0166)	(0.0166)	(0.0166)
P-Same Alma Mater x Mean SAT Score		-0.1330***				
		(0.0247)				
P-Overlap			0.0620***			
			(0.0187)			
P-Institute				0.1046***		
				(0.0290)		
P-MBA					0.1099***	
					(0.0275)	
P-Bachelors						0.0574**
						(0.0291)
Ln(University Size)	0.0579***	0.0458***	0.0578***	0.0562***	0.0568***	0.0586***
	(0.0151)	(0.0152)	(0.0151)	(0.0151)	(0.0151)	(0.0151)
Young Firm	0.2522***	0.2565***	0.2533***	0.2529***	0.2528***	0.2522***
	(0.0420)	(0.0420)	(0.0420)	(0.0420)	(0.0420)	(0.0420)
Ln(distance)	-0.5133***	-0.5070***	-0.5130***	-0.5133***	-0.5134***	-0.5125***
	(0.0282)	(0.0282)	(0.0282)	(0.0282)	(0.0282)	(0.0282)
Past Funding Relationship	34.0176***	34.0088***	34.0147***	34.0167***	34.0163***	34.0174***
	(0.5071)	(0.5071)	(0.5071)	(0.5071)	(0.5071)	(0.5071)
I(Seed Round)	1.3633***	1.3725***	1.3661***	1.3632***	1.3627***	1.3636***
	(0.0707)	(0.0707)	(0.0707)	(0.0707)	(0.0707)	(0.0707)
Past Affiliation	0.5874***	0.5868***	0.5872***	0.5874***	0.5875***	0.5874***
	(0.0149)	(0.0149)	(0.0149)	(0.0149)	(0.0149)	(0.0149)
Investor x State x Year x Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.16	0.16	0.16	0.16	0.16	0.16
# Deals	29,421	29,421	29,421	29,421	29,421	29,421
# Startups	18,022	18,022	18,022	18,022	18,022	18,022
# Investment Firms	1670	1670	1670	1670	1670	1670
Observations	903991	903991	903991	903991	903991	903991

Table A.5: Do Investors Tilt their Portfolios Toward Startups from their Alma Mater? (LinkedIn Data)

The tests in this table examine the effect of founders' educational backgrounds on the probability that the founder raises a round of venture capital funding. The table presents OLS regressions run at the investor-startup level. We use the entire LinkedIn database (from Datahut) as of 2017 to select companies formed by founders that attended the schools in our sample. We further restrict the universe to U.S.-based companies formed between 2002 and 2015 that are "Privately Held," and are not missing data on industry, or state where the company is located. Next, we match this set of companies to PitchBook to isolate companies that raised venture capital funding. For companies that raised a venture round, we obtain the alma mater associated with the partners of the lead investor. Next we pair each lead investment firm with all *other* companies in our LinkedIn sample that were formed in the same year, operate in the same industry, and are located in the same state. We assume that these are the sets of companies the lead investor potentially *considered* investing in. The dependent variable, *I(Investment)*, is an indicator for whether the lead investor actually invested in the deal. About 2.57% of all investor-startup pairs are actual investments. The key independent variable, *Same Alma Mater*, indicates whether any of the founders share the same alma mater as the partners working for the lead investor. *Mean SAT Score* is the average SAT score at the founder's alma mater in the year the startup was formed (averaged for startups with multiple founders). *Ln(# Founders)* is the log of the number of startup founders. Standard errors are clustered by investment firm.

Dependent Variable:	I(VC Investment)			
	1	2	3	4
Same Alma Mater	1.4050***		1.0217***	0.8790***
	(0.1847)		(0.1923)	(0.2318)
Mean SAT Score		0.5950***	0.4736***	0.4432***
		(0.0588)	(0.0609)	(0.0624)
Same Alma Mater x Mean SAT Score				0.2671
				(0.2369)
Ln(# Founders)	2.0940***	2.2376***	2.0924***	2.1131***
	(0.1830)	(0.1831)	(0.1830)	(0.1832)
Adjusted R^2	0.09	0.09	0.09	0.09
# Startups	49,037	49,037	49,037	49,037
Observations	49,037	49,037	49,037	49,037
State x Founding Year x Industry FE x Investor	Yes	Yes	Yes	Yes

Table A.6: Connections, School Quality, and Exit via Acquisition

The tests in this table examine the effect of school ties between founders and investors on the probability of an Acquisition post-funding. The table presents coefficients from OLS regressions run at the investor-startup level, with standard errors reported in parentheses. We keep the first investment by the lead investor in the startup and track whether the investment exits via an acquisition following the initial investment. We focus on early-stage equity financing deals from 2000-2016, where the requisite data is available from PitchBook. We end the sample in 2016 to allow enough time for an exit. The dependent variable is an indicator for whether the startup in the deal eventually exits via an acquisition by June 2021. The key independent variable, *Same Alma Mater*, indicates whether any of the founders share the same alma mater as an investor in the deal. *Mean SAT Score* is the average scholastic assessment test (SAT) score at the founder's alma mater in the year the startup raised funding (averaged for startups with multiple founders). *Ln(Funding Raised FD)* is the amount of funding the startup raised from the lead investor in the first funding round. Compared to Table 7, this table is missing the control for *Past Funding Relationship* because this variable are not defined for an investor's first financing of the startup. We cluster standard errors by investment firm.

Panel A. Investor-Deal Level Tests					
Dependent Variable:			I(Acquisition)		
	1	2	3	4	5
Same Alma Mater	2.7417***	-0.8504	0.2842	2.4253	1.9482
	(0.6212)	(0.9953)	(1.1039)	(2.0880)	(1.9285)
Mean SAT Score	0.7511**	-0.3785	-0.3708	-0.4231	-0.3889
	(0.3063)	(0.6164)	(0.5468)	(0.5470)	(0.5471)
Same Alma Mater x Mean SAT Score		-0.0595			
		(1.0469)			
I(Overlapping Graduation)			-3.1200**		
			(1.3843)		
I(Same School)				-3.7541*	
				(2.1302)	
I(MBA)					-3.3289*
					(1.9816)
Ln(Investors Alma Mater)	0.1005	-1.1719**	-1.1710**	-1.1613**	-1.1733**
	(0.3008)	(0.5588)	(0.5583)	(0.5585)	(0.5586)
Young Firm	0.0173	1.4074	1.3632	1.3763	1.3866
	(0.7602)	(1.0869)	(1.0868)	(1.0862)	(1.0866)
Ln(distance)	-0.2529	0.4834	0.4670	0.4750	0.4758
	(0.2788)	(0.4359)	(0.4356)	(0.4357)	(0.4357)
I(Seed Round)	1.1769**	-0.7179	-0.7424	-0.7160	-0.7430
	(0.5883)	(1.3052)	(1.3043)	(1.3065)	(1.3065)
Past Affiliation	-0.0051	0.2826**	0.2894**	0.2840**	0.2850**
	(0.0624)	(0.1133)	(0.1127)	(0.1131)	(0.1132)
Ln(Funding Raised)	3.3764***	2.7533***	2.8218***	2.7584***	2.7550***
	(0.3200)	(0.4035)	(0.4035)	(0.4030)	(0.4036)
Investor FE	Yes	Yes	Yes	Yes	Yes
First Deal Year FE	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.08	0.08	0.08	0.08	0.08
# Startups	7058	7058	7058	7058	7058
# Investors	851	851	851	851	851
Observations	9930	9930	9930	9930	9930

(Table A.6 Continued)

Panel B. Startup Level Tests					
Dependent Variable:	I(Acquisition)				
	1	2	3	4	5
Same Alma Mater	1.8000*	1.8147*	2.2426*	2.5097	1.7290
	(1.0189)	(1.0301)	(1.1624)	(2.2676)	(1.9494)
Mean SAT Score	-0.2904	-0.3108	-0.2779	-0.2970	-0.2904
	(0.5575)	(0.6127)	(0.5579)	(0.5580)	(0.5575)
Same Alma Mater x Mean SAT Score		0.0758			
		(1.1156)			
I(Overlapping Graduation)			-1.3057		
			(1.5746)		
I(Same School)				-0.8121	
				(2.3150)	
I(MBA)					0.0844
					(2.0255)
Ln(University Size)	-0.4783	-0.4754	-0.4801	-0.4769	-0.4780
	(0.5702)	(0.5702)	(0.5702)	(0.5700)	(0.5704)
Young Firm	2.2631*	2.2612*	2.2669*	2.2651*	2.2620*
	(1.2109)	(1.2114)	(1.2108)	(1.2114)	(1.2123)
Ln(distance)	0.6679	0.6672	0.6674	0.6663	0.6680
	(0.4233)	(0.4234)	(0.4232)	(0.4233)	(0.4233)
I(Seed Round)	0.0739	0.0713	0.0526	0.0669	0.0755
	(1.1910)	(1.1903)	(1.1910)	(1.1927)	(1.1909)
Past Affiliation	0.2488**	0.2488**	0.2528**	0.2498**	0.2486**
	(0.1030)	(0.1030)	(0.1030)	(0.1030)	(0.1030)
Ln(Funding FD)	3.1377***	3.1371***	3.1563***	3.1362***	3.1377***
	(0.3547)	(0.3547)	(0.3555)	(0.3548)	(0.3547)
State x Year x Industry FE	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.03	0.03	0.03	0.03	0.03
# Startups	6736	6736	6736	6736	6736
Observations	6736	6736	6736	6736	6736

Table A.7: Selection or Treatment?

The tests in this table examine the relationship between a partner's departure from an investment firm and the likelihood that a company funded by the investment firm exits via an initial public offering (IPO). The table presents OLS regressions run at the startup level. The dependent variable, *I(IPO)*, is an indicator for whether the startup exits via an IPO by June 2021. The key independent variable, *I(Partner Departure)*, indicates whether the departing partner *from the same alma mater as the founder* left the investment firm three years or fewer following the investment but before the exit date or June 2021. *SAT Score* is the scholastic assessment test (SAT) score of entering freshmen at the alma mater in a given year. Standard errors are clustered by investment firm.

Dependent Variable:	I(IPO)			
	1	2	3	4
Same Alma Mater	3.5757***	3.3847***	2.0619***	2.0638***
	(0.7159)	(0.7369)	(0.7223)	(0.7214)
Same Alma Mater X Partner Departure	-1.9674	-1.9773	-1.2537	-1.4820
	(4.7254)	(4.7309)	(4.6882)	(4.6891)
Partner Departure	0.5585	0.5456	-1.4948	-1.3654
	(3.5356)	(3.5452)	(3.5480)	(3.5279)
Mean SAT Score		0.4054	0.6856**	0.8428**
		(0.3421)	(0.3404)	(0.3573)
Ln(Funding FD)			3.1338***	3.3351***
			(0.2802)	(0.3164)
State x Year x Industry FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.10	0.10	0.12	0.12
# Firms	6736	6736	6736	6736
Observations	6736	6736	6736	6736
Other Controls?	No	No	No	Yes

Table A.8: Educational Networks and Legacy Admissions

This table presents OLS regressions examining the relationship between educational connections and legacy admission policies. The tests are conducted at the deal level. The dependent variable, *Same Alma Mater*, is an indicator for whether any founder shares the same alma mater as an investor in the deal. The key independent variable, *Legacy Considered*, equals one if any of the founders attended a university that considers legacy admissions. Column (1) presents results without controls, and column (2) includes additional controls. Other Controls includes the same control variables as previous analyses, whose coefficients are not reported here. Standard errors are clustered by startup.

Dependent Variable:	Same Alma Mater	
	1	2
Legacy Considered	0.3012***	0.1868***
	(0.0119)	(0.0151)
I(Public University)		-0.0668***
		(0.0165)
Top SAT Quintile		0.2712***
		(0.0239)
Second SAT Quintile		0.2177***
		(0.0181)
Third SAT Quintile		0.1786***
		(0.0166)
Fourth SAT Quintile		0.1006***
		(0.0152)
Adjusted R^2	0.12	0.18
# Startups	6868	6868
# Deals	9426	9426
Other Controls	No	Yes
State x Year x Industry FE	Yes	Yes

Table A.9: Characteristics of Universities with Legacy admissions

This table shows the characteristics of students attending the universities attended by the founders in our sample, split by whether the university considers legacy admissions. *P(White)*, *P(Asian)*, *P(Hispanic)*, and *P(Black)* are the proportions of undergraduate students at the university that are White, Asian, Black, and Hispanic respectively. *SAT Score* refers to the average scholastic assessment test (SAT) score of entering freshmen at the university over our sample period, *University Size* is the average number of undergraduate students attending the university, *Admission Rate* is the average admissions rate for the university and *I(Public School)* is an indicator for a public university. For the Legacy sample (Universities that consider Legacy in their admissions process), N = 146 and for the Non-Legacy sample (Universities that do not consider Legacy in their admissions process), N = 339.

	2003 to 2008 (N = 485)				**2016 to 2021 (N = 485)**			
	Full Sample	Legacy Sample	Non Legacy Sample	t-stat	Full Sample	Legacy Sample	Non Legacy Sample	t-stat
P(White)	0.59	0.58	0.59	-0.33	0.59	0.58	0.59	-0.59
P(Asian)	0.05	0.06	0.05	1.49	0.07	0.09	0.07	2.23**
P(Hispanic)	0.05	0.05	0.06	-1.93*	0.13	0.11	0.13	-2.49**
P(Black)	0.06	0.05	0.07	-1.37	0.09	0.08	0.09	-0.56
I(Public University)	0.44	0.16	0.55	-9.16***	0.51	0.24	0.58	-6.18***
University Size	8960.13	6089.50	10038.69	-5.35***	11304.23	9452.92	11786.15	-1.95*
Average SAT	1135.24	1240.33	1095.75	12.94***	1201.82	1311.24	1173.34	9.51***
Admission Rate	0.63	0.52	0.68	-8.66***	0.65	0.50	0.69	-6.50***
Pell Grant	0.20	0.15	0.22	-9.02***	0.28	0.20	0.30	-8.63***
First Generation	0.29	0.20	0.33	-14.62***	0.28	0.20	0.30	-10.50***
Income	73944.34	85671.98	69538.01	11.47***	85164.13	103227.79	80461.84	8.49***

Table A.10: Characteristics of Startup Firms and Investors for Sample firms in Crunchbase

This table reports summary statistics for startups in our sample split by whether we matched the startup to Crunchbase, another database covering startup financing. Our sample is collected from PitchBook, and is restricted to firms receiving funding from 2000-2020, with founders from U.S. universities, and with the required data for our tests. We match startups in PitchBook to CrunchBase on founding year, state, and then require a 100 percent fuzzy match on the standardized name, which we verify for accuracy. A startup that is matched to Crunchbase is assigned all deals in PitchBook, even though Crunchbase might not cover all the deals PitchBook covers. All continuous variables are winsorized at the 1% and 99% levels to minimize the influence of outliers.

	All startups (N = 46,466)		**CrunchBase & PitchBook (N = 21,512)**		**PitchBook Only (N = 24,954)**		**Tests**	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Diff	T-stat
Same Alma Mater	0.35	0.48	0.40	0.49	0.32	0.47	0.16	12.90***
Mean SAT Score	1304.24	122.34	1294.99	117.66	1310.28	124.92	-0.13	-8.55***
University Size	2618.39	1763.52	2591.02	1614.47	2636.23	1854.02	-0.03	-1.81*
Young Firm	0.72	0.45	0.66	0.47	0.76	0.43	-0.21	-16.29***
Distance (miles)	755.70	769.44	769.63	738.63	746.62	788.74	0.03	2.30**
Past Funding Relationship	0.38	0.49	0.50	0.50	0.31	0.46	0.40	40.29***
First Funding Round	0.23	0.42	0.18	0.38	0.27	0.45	-0.23	-26.61***
Past Industry Experience	0.96	0.20	0.97	0.16	0.95	0.23	0.13	14.70***
Past Affiliation	0.17	0.37	0.21	0.41	0.14	0.34	0.21	18.29***
# Investors	4.26	3.94	4.57	3.69	4.05	4.08	0.13	11.45***
Outcomes								
IPO	2.83	16.59	4.59	20.93	1.68	12.87	0.18	8.64***
Acquired	8.59	28.02	12.38	32.94	6.12	23.96	0.22	12.83***
Has Patent	25.16	43.39	36.08	48.02	18.05	38.46	0.42	26.15***
Funds Raised ($ Millions)	16.49	63.49	20.58	62.23	13.82	64.16	0.11	8.52***

Table A.11: Characteristics of Startup Firms and Investors for Sample firms in VentureXpert

This table reports summary statistics for startup firms in our sample split by whether we matched the firm to VentureXpert, a widely used database for studies on earlystage funding. Our sample is collected from PitchBook, and is restricted to firms receiving funding from 2000-2020, with founders from U.S. universities, and with the required data for our tests. We match startups in PitchBook to VentureXpert on founding year, state, and then require a 100 percent fuzzy match on the standardized name, which we verify for accuracy. A startup that is matched to VentureXpert is assigned all deals in PitchBook, even though VentureXpert typically has lower deal coverage. All continuous variables are winsorized at the 1% and 99% levels to minimize the influence of outliers.

	All firms (N = 46,466)		**VentureXpert & PitchBook (N = 18,334)**		**PitchBook Only (N = 28,132)**		**Tests**	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Diff	T-stat
Same Alma Mater	0.35	0.48	0.37	0.48	0.33	0.47	0.07	5.64***
Mean SAT Score	1304.24	122.34	1290.49	118.58	1316.11	124.27	-0.21	-15.02***
University Size	2618.39	1763.52	2637.21	1716.98	2602.17	1802.54	0.02	1.44
Young Firm	0.72	0.45	0.72	0.45	0.71	0.45	0.02	1.46
Distance (miles)	755.70	769.44	717.57	753.63	788.57	781.32	-0.09	-7.36***
Past Funding Relationship	0.38	0.49	0.40	0.49	0.37	0.48	0.07	6.92***
First Funding Round	0.23	0.42	0.23	0.42	0.24	0.43	-0.02	-2.57**
Past Industry Experience	0.96	0.20	0.96	0.20	0.96	0.21	0.01	0.83
Past Affiliation	0.17	0.37	0.17	0.38	0.16	0.37	0.03	3.17***
# Investors	4.26	3.94	4.18	3.74	4.32	4.10	-0.03	-3.03***
Outcomes								
IPO	2.83	16.59	3.47	18.30	2.28	14.94	0.07	3.90***
Acquired	8.59	28.02	12.26	32.79	5.43	22.65	0.25	15.08***
Has Patent	25.16	43.39	31.66	46.52	19.56	39.67	0.28	18.51***
Funds Raised ($ Millions)	16.49	63.49	13.45	52.66	19.11	71.42	-0.09	-7.44***