Alumni Networks in Venture Capital Financing

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Abstract

One-third of startup deals involve a founder and investor from the same university. Venture capitalists (VCs) are more likely to invest in, and place larger bets on, alumni from their alma mater. Using VC partner turnover, we show a causal link between education ties and funding likelihood. Importantly, startups on the margin, whose founders share an alma mater with a VC partner, have better post-funding outcomes in instrumental variables tests with the supply of funding as an instrument. Furthermore, minority freshmen tend to attend schools with higher same-alma-mater matching rates. Our results imply that university connections facilitate information flow rather than diverting funds towards lower-quality startups.

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I. Introduction

Venture capital funding is considered the lifeblood of entrepreneurial endeavors. VC-backed startups account for an outsized share of innovation (Kaplan and Lerner (2010), Gornall and Strebulaev (2021)) and almost half of all the US IPOs (The National Venture Capital Association, 2020). Yet, despite the importance of innovation for economic growth, many founders of early-stage startups struggle to obtain financing due to severe information frictions between startups and venture capitalists. In this paper, we show that shared professional networks created by university attendance help reduce these information asymmetries, facilitating early-stage investment as well as entrepreneurial success.

We begin by documenting the striking fact that one in three deals in the venture capital market involves 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' tendencies to produce both entrepreneurs and VC investors. We then confirm that this preference reflects an information advantage, as opposed to investors' favoritism toward startups from their alma mater, by showing connected investments have better post-funding exit outcomes. Finally, we show the information advantage provided by shared alma mater is likely more due to superior investment screening than due to enhanced portfolio firm monitoring. Overall, our findings illustrate 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.[1] We further supplement these data with measures of education quality, based on standardized test scores of incoming undergraduates and

[1] PitchBook provides the most comprehensive data available on entrepreneurial financing. We discuss the advantages of PitchBook relative to Crunchbase and VentureXpert in our data section.

(separately) the average early-career pay of alumni. Combined, our data allow us to credibly identify common (i.e., shared) college alumni status between founders and investors, while controlling for school quality, which allows us to hold top schools' tendencies to produce both entrepreneurs and VC investors fixed.

The identification challenge stems from unobservables. For example, in our first tests we explore the influence of shared alma mater on whether an entrepreneur obtains VC funding or not (the extensive margin). But the observed dyads of startups with VCs don't necessarily reflect choices from amongst an otherwise random set of plausible pairings, unless we develop defensible counterfactuals. We therefore build two sets of counterfactuals as follows.

First, we rely on the rich nature of our PitchBook data with more complete coverage of companies and deals. Investors see many more deals than they take. We also know that they tend to consider deals from certain industries and geographies (Gompers et al. (2020)). Therefore, we define a VC investor's consideration set as *all* deals that occurred in a state-industry-year-deal stage, identical to where the focal investor actually participated in a deal. In other words, if *this* investor chooses not to make a deal, but another investor does so in that same state and year and industry and financing stage, then it is likely the non-investing financier at least considered it. The counterfactual set is thus well-populated and based on known opportunities of early-stage investors.

Unfortunately, this empirical strategy still relies on data that may exhibit a selection bias because it inevitably uses only consummated deals. If there is something systematically different between these and unfunded entrepreneurial endeavors, this could bias our extensive margin estimates. We address this concern by forming an alternative dataset that includes entrepreneurs that would likely welcome VC funding, but who do not receive it.

Our data come from LinkedIn with a requirement that the entrepreneur has a company in the LinkedIn Companies dataset and the individual attended a U.S.

university.[2] With these new data, we reconstruct our same alma mater variable and investors' consideration sets using the same intuition described above. We define the set of startups that might be considered by an investor as those companies in the LinkedIn data with similar characteristics (industry, state, *and founding year*[3]) as the companies the investor actually funded. We view this latter analysis as a more reliable extensive margin test. Nearly all prior work in VC funding suffers from potential selection concerns associated with studying consummated deals. Important exceptions study either angel financing (Kerr et al. (2014)) or venture competitions (Howell (2020)), although they do not offer the broad perspective of our LinkedIn data.

The two approaches to developing counterfactuals yield consistent inferences along the extensive margin. Using the first data set (built with PitchBook consummated deals) implies an investor is 10% more likely (relative to the unconditional mean) to match with a startup with founders from their alma mater, than a comparable startup in the same state-industry-year-deal stage, but without shared alumni status. When we study all entrepreneurs in the LinkedIn sample, deal likelihood increases by 0.8% when the founder and investor share an alma mater. Notably, for companies in the LinkedIn sample, the unconditional probability of obtaining VC funding is about 2.57%, implying a 31% increase in funding likelihood due to alumni connections, about 20% greater than our estimate from consummated deals.

Finally, we offer a shock-based view of the role of alumni connections on deal likelihood, by exploring VC partner departures. When a partner leaves an investment firm, this potentially removes same-alma-mater connectivity with startups that the firm may consider funding. In the cases where this does happen, we do indeed observe reduced deal-consummation post-departure.

To lend credence to the value proposition of alumni connections, we also study the intensive margin. The first of these tests examines the quantity of funding raised. Here

[2] Entrepreneurs who list their company in the LinkedIn Companies dataset are presumably seeking capital. We remove publicly traded companies from the set, to reflect their access to public capital markets.

[3] This matching item is crucial to underpin our presumption that the company would welcome early-stage funding.

too, alumni connections matter. When an investor and founder share an alma mater, the investment amount is 18% larger on average. Thus it appears unlikely that the connection merely facilitated a favor, but rather that the investor is willing to backstop with more funding compared to unconnected investments. This positive influence of alumni connection on funding amount importantly survives school fixed effects (which we discuss in more detail later).

While our results describe a positive influence of shared educational background on funding likelihood and amount, the efficiency of such relationships is still unclear. If connections through educational networks help resolve information asymmetry between founders and investors, then connections can 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. We explore this tension by testing whether investors' connected investments perform better or worse than their non-connected investments in the same state-industry-year. We find they perform better.

First we find that VCs' connected investments are 33% more likely to lead to an IPO post-funding.[4] Second, we provide evidence that this improvement is driven by superior deal selection. We demonstrate the latter in two ways: using connected-partner departures, and using Becker-style outcome tests with instrumental variables to identify the marginal deal.

Specifically, the first test explores whether alumni connected VC-partners' *departures* post-funding reduce IPO likelihood. If so, it would suggest that some of the alumni connection's value is due to more/better monitoring by the VC. We find no such deleterious effects. For the Becker-style outcome tests we use instruments to identify "marginal" deals, allowing us to test whether alumni connections lead to better investment outcomes on average. The IVs exploit increased supply of funding available to funds that are employing connected VC partners, and (separately) increased supplies of funds targeting a startup's industry. The IVs build on the idea that increased capital

[4] We also find some weak evidence that M&A outcomes are facilitated by alumni connections.

in hot times shifts investments to more marginal startups (Nanda and Rhodes-Kropf, 2013). In both cases, alumni connections have a positive influence on post-funding IPO likelihood. We conclude that the improved outcomes of alumni-connected deals are driven by better selection and that these connections help resolve information asymmetries on average.

Overall, our results show that early-stage investors tilt their portfolios toward entrepreneurs from their alma mater, and that these bets pay off better. This is new and valuable information regarding the efficient allocation of capital in the early-stage-financing landscape. Crucially, these findings are incremental to known determinants of entrepreneurial fundraising. In particular, we control for the commonly known determinants of early-stage financing: distance between entrepreneur and investor, firm age, founder's university's size, its academic quality, and its number of alumni that are early-stage investors.[5] We find that none of these factors absorb the importance of alumni connections within investor-founder dyads.

Our tests also carefully control for the presence of other networks. These are important because networks overlay each other, and each network could provide information or expertise that substitutes for the benefits of alumni network connections. In particular, we recognize past industry experience by the investor, whether there is a past funding relationship between the investor and founder, and (crucially) whether investors in this round have prior experience working together on other prior deals with a different company. Again, all of these controls fail to absorb the effect of shared alumni networks on both funding (extensive and intensive margins) as well as ex-post performance.

The confirmed importance of alumni connections to early-stage financing success begs the question of a mechanism. While we cannot rule out all possible alternatives, our preferred interpretation of our results is an information channel.[6] To provide analysis

[5] Our robust datasource and development of counterfactuals also enables fixed effect controls to absorb unobservables associated with the VC / investor, which is often a key endogeneity concern.

[6] Other alternatives include a treatment effect (startup founders are more productive when they work alongside investors from their alma mater) and a founder selection effect (more promising founders are more likely to accept deals from investors from their alma mater).

targeting our thesis, we argue that alumni connections inform investors about the quality of founders and their ideas, in ways that may not otherwise be available. We provide several pieces of evidence to support this interpretation.

First, the effect of connections on funding is larger for investor-founder dyads from less prestigious universities (based on SAT scores). So while received wisdom points to elite universities dominating the early-stage landscape through either founder development and/or investor funding, we offer a more nuanced view. Our result suggests that educational connections act as a partial substitute for the public signal about entrepreneurial skills/intelligence provided by a degree from a prestigious school.

Second, our estimated effects at the extensive margin are stronger in the first instance of matching. This is when an investor likely has the least information about a company because they haven't funded it before, so the alumni connection may be viewed as partial certification.

Third, alumni connections matter less to deal consummation when two investors in the current deal had a prior affiliation together on another deal (with a completely different startup). When investors have worked together in the past, it is presumed that they share information. The apparent substitution between the inter-investor information sharing and that through alumni connections, in facilitating deals, again implies an information channel.

Finally, we explore a potential information-sharing event for VC-startup connections; founders' college football teams' success during the season. We show that there are more alumni-connected deals during successful seasons. Based on our discussions with founders and venture capitalists, it appears that this increase in alumni-related deals is likely driven by increased interactions among alumni following successful football seasons.[7]

[7] See Table A.5.

A. *Contributions to Literature*

Our paper makes several important contributions. We first add to studies on the determinants of VC financing.[8] A common thread running through this literature is that resolving information frictions is paramount (see Da Rin et al. (2013) for a review). Bernstein et al. (2017) suggests a broad solution - that information about founding teams is perhaps the most important factor in attracting VC investors. But the ways in which specific founder attributes influence VC investors' decision-making remain unclear. We offer the first broad-sample exploration of a key founder characteristic - their alma mater. We specifically show that founders' connections through alumni networks are an important mechanism working to reduce uncertainty about founding team quality and facilitate VC financing.[9]

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 et al., 2008), sell-side analysts' stock recommendations (Cohen et al., 2010), and banks' loans (Engelberg et al., 2012). However, the influence of these 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 et al., 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

[8] See e.g., (Tian, 2011) for geographic proximity, (Ewens et al., 2018) for technological shocks, (Hellmann and Puri, 2015) for product market strategies, and (Bottazzi et al., 2016) for trust.

[9] We hasten to add that our broad sample evidence allows us to uniquely offer both external validity along with strong identification. This is a rarity in empirical corporate finance. However, in our case the inferences we make with the broadest sample are identical to our conclusions when we progressively tighten our identification.

allocation of capital. We contribute by providing the first direct evidence that alumni networks play a major role in shaping VC investment, and that ultimately, connected investments outperform non-connected ones. [10]

We close with a broader social question and potential contribution of our work. We specifically suggest that alumni connections may offer potential avenues for reducing racial inequality, by helping to bridge the VC funding gap for minority entrepreneurs. We initiate our discussion by acknowledging Okafor's (2023) findings that biases within social networks, driven by in-group referrals, can worsen disparities in access to resources such as venture capital funding. We then investigate whether potential high-growth minority entrepreneurs are more likely to attend universities with a higher frequency of alumni matching, potentially mitigating the referral gap. We find that Black undergraduate students, despite being generally more likely to attend universities with a low rate of alumni matching, are more likely to enroll at universities with a high rate of alumni matching *conditional on school quality*. This higher rate of enrollment in universities with high same alma mater matching could potentially alleviate the referral problem, provided these students are able to derive as much benefit from these alumni networks as students from other groups do.

We then connect this result to potential upward mobility in socioeconomic status, by tying our same alma mater information to Chetty's work. Specifically, we further build upon the findings of Chetty et al. (2022b) and Chetty et al. (2022a) by examining how relationships formed during college can act as a form of social capital, influencing venture capital funding patterns. The authors' analysis of social network data from 72.2 million Facebook users revealed that economic connectedness — the extent to which individuals with low socioeconomic status interact socially with those of high socioeconomic status — is strongly associated with upward income mobility. We link

[10] Our paper was written and posted at least a year earlier than two closely related working papers by Huang (2023) and Koenig (2022). Koenig (2022) uses mostly self-reported data from CrunchBase and Huang (2023) uses a subset of the comprehensive PitchBook data that we use. More importantly, our analysis includes extensive margin tests using LinkedIn data that enables us to control for potential selection bias associated with forming counterfactuals by using only consummated deals. Among other additional tests, we also study the distributional effects of same alma mater matching for minority graduates.

their data[11] with our measure of same-alma-mater relationships at the same (i.e. university) level. We find that the proportion of same-alma-mater deals at the university level is positively related to university-level measures of economic connectedness. Moreover, we find that same alma mater is also significantly related to two of the drivers of economic connectedness - exposure and support ratio. We conclude that an important element of the link between economic connectedness and upward mobility is facilitated by access to VC funding through alumni connections.

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 et al. (2020), Gompers et al. (2021), Ewens et al. (2022)). The College Scorecard data include information on the characteristics of U.S. institutions of higher education such as enrollment, location, and average SAT score of students admitted.[12]

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,

[11] They provided publicly accessible data on various types of social capital at the university level.

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

such as the deal level.

From PitchBook we also collect information on the founding team and partners working for the lead investor. We identify founding team members by keeping company employees with the following titles: Founders, CEO (Chief executive officer), CTO (Chief Technology officer), CMO (Chief Marketing officer), COO (Chief Operating officer), President, 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 of individuals “founding team” or “founders,” although this also can include people who joined the company in early years after its founding. We collect extensive data on the education history of the founders, funding rounds, and whether the company exited via an initial public offering (IPO) or an acquisition as of June 2021. Following a similar process, we collect information on the education history of the partners working for the lead investor in each funding round.[13] Because our data on the quality of education institutions are 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. Hence, 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).

Our final sample comprises the set of deals in PitchBook from 2000 to 2020 where

[13] 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.

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 (for which we have data on enrollment, average SAT score of admitted freshmen, and location of the university).

B. Summary Statistics

B.1. Sample Characteristics

Table 1 presents descriptive statistics at different organizational levels of our samples: startups, founders, investors, deals, and universities. The startup-level statistics generally conform to those documented in extant work. The average startup in our sample has 1.63 rounds, skewed early with nearly two-thirds being seed 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 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.[14]

Moving to founder-level stats, we see that an average founder attended 1.46 higher educational institutions and 5.62% of founders are serial founders. Our investor-level show that the average firm led about 7 deals over our sample period, was formed in 2005 and had an average and median AUM of $2.9 billion and $215 million respectively.

At the deal-level, we emphasize the (marginal) differences between characteristics of all deals vs. first deals for a startup. Since we focus some of our main analysis on first-deals, it is comforting 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 on first deals, implying later deals are larger fundraisings among more valuable companies, which we would also expect.

Finally, our university-level stats indicate two categories of interest. First, there is

[14] 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.

high variation across schools that see their graduates become lead investors at VCs, as well as (separately) variation in those that become founders. This implies a need to control for such variation in our tests of matching of founders and investors that share an alumni connection. Preliminary evidence that high numbers of either investors or founders coming from a particular university does *not* drive our same-alma-mater results, is seen in Figure 1. We reach this conclusion as follows.

[Insert Figure 1 About Here.]

If relationships between an investor and founder were established randomly, we would anticipate that the probability of a founder matching with an investor from their alma mater would equate to the frequency of active investors from that university. On the x-axis, we chart the frequency of investors from each of the 485 universities in our sample. We also show a 45-degree line to indicate the anticipated frequency of matches between a founder and investor from the same alma mater if ties were formed randomly. On the y-axis we show the actual number of same alma mater ties at the university level. Our findings show that the observed same-alma-mater ties considerably exceed the expected frequency. Moreover, these ties are prevalent at both elite schools (Mean SAT >=1400) and non-elite schools (Mean SAT<1400). This ubiquity prompts questions regarding the underlying drivers of these connections and whether they enhance or undermine efficient capital allocation.

[Insert Table 1 About Here.]

Table 2 presents further summary statistics describing startups and their investors in our sample. Here, we focus on the statistics in columns 1-4 describing actual deals (in Section III below we also discuss the counterfactual deals described in columns 5-8). A unit of observation in this table is a startup–lead investor–deal pair. Because 85% of deals have a single lead investor, this data set is similar to a deal level data set. *Same Alma Mater* is the indicator equal to one if at least one founder of the portfolio company attended the same university as at least one of the partner-level executives of the lead investor participating in the deal. The first row of Table 2 shows that 37 percent of deals feature such a connection.

[Insert Table 2 About Here.]

The alumni connection(s) between founders and investors can be analyzed at a more granular level both cross-sectionally and in the time-series. For example, 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 (that is, both graduated within four years of each other).[15] It is also quite common for alumni connections to be within the same school (for example, Columbia Business School rather than Columbia University). We explore the incremental effects of such "tighter" overlaps in our tests.

Table 2 also presents a comparison of the connected and unconnected samples (unconnected meaning the deal does not have a single alumni connection). Several interesting patterns emerge. *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. We use this variable as a proxy for investors' perception of university quality. Deals involving a founder and investor from the same alma mater (connected deals) appear to be more likely at higher-quality schools: the average SAT score for connected deals is higher than for unconnected deals. *University Size* is the class size of graduating students from the founders' alma mater in the year preceding the deal. It is smaller for connected deals. We include this control in our tests to alleviate a mechanical increase in connections for founders from large schools.

Table 2 also reports and compares (across shared alumni status) several 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), Ewens and Townsend (2020))

[15] This measure of overlap is more likely to capture overlapping undergraduate degrees than graduate degrees especially when the founder and investor graduated within 3 and 4 years of each other.

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%). Younger firms are associated with slightly higher incidence of matching alma maters between founders and investors.

Distance is the average distance (in miles) between the portfolio company and the lead investor locations. Numerous papers note the importance of distance to early-stage financing (See, e.g., Sorenson and Stuart (2001), Chen et al. (2010), Tian (2011)). The data indicate that alumni connections are associated with closer geographic location between startup company and investor.

Seed Round indicates the deal is the first recorded venture capital funding round for the company in PitchBook. First deals likely feature more pronounced information asymmetry concerns. Alumni connections should be particularly valuable in providing certification in such cases.

Past Funding Relationship is an indicator for an investor having already invested in the company in an earlier round. This implies less of a concern with asymmetric information in the current funding round, and therefore, potentially less importance to information gleaned through alumni connections. Nevertheless, a past funding relationship still seems to correlate positively with connected deals, at least unconditionally.

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. The data suggest that connected deals are more likely when the investor has already previously invested in the same industry.

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.

Overall, characteristics of deals and investors are significantly correlated with deal connectedness. We therefore include them as controls in our subsequent analysis.

B.2. Alumni Connections by University

Table 3 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 firms founded by alumni of the university (respectively). Columns 6, 7, and 8 present the number of investors per 1,000 students from each school, the number of deals, and the percent of deals that are connected (respectively).

[Insert Table 3 About Here.]

From Table 3, we see that there is substantial variation in the number of deals involving startups and investors from the same alma mater, even amongst 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. We also see that our proxy for school quality (Mean SAT score) is highly correlated with the U.S. News ranking, even though the latter also reflects non-standardized testing factors such as graduation and retention rates, social mobility, faculty resources, alumni giving rate, and graduate indebtedness. This correlation lends credibility to our use of SAT score to proxy for school quality.

III. Results

A. The Effect of Investors' School Ties on Deal Selection — The Extensive Margin

We begin our tests with an extensive margin analysis evaluating whether school connections between early-stage investors and startup founders increase the likelihood of matching. 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. As described earlier, we develop two sets of plausible counterfactuals: one from Pitchbook deals consummated in the same industry, state, year, and stage, but with a different investor; the other from LinkedIn founders (likely) seeking funding, also located in the same industry, state and year of founding as the focal startup. Section A.1. (A.2.) presents the results using the first (second) set of counterfactuals. We then provide an event-based perspective on alumni connections' effects on deal selection by studying VC-partner departure events. See Section A.3. Finally, we close Section A of our results with analysis of the relationship between the frequency of alumni connections at the university level and the racial composition of admitted students. This helps us understand how such connections may influence the VC funding gap.

A.1. The Effect of Investors' School Ties on Deal Selection — PitchBook

We begin by forming the full dataset containing both actual investments and investors' potential/considered deals (those also consummated in the same industry-state-year-stage). 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 set of extensive margin tests, 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. True Ventures did not invest in the other two, and we examine whether this single "yes" as opposed to the two "no's" is influenced by the presence or lack of alumni ties between the partners at True Ventures and the founding team at any of the three companies. Consequently, in our test data, True Ventures will get three observations (one actual and two counterfactual). We then test whether True Venture's 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.

The key variable Same Alma Mater is an indicator equal to one if any of the partners shares an alma mater with any of the founders. Our extensive margin test is then a simple linear probability model explaining whether the deal is actually done, and whether alumni connections increase the likelihood of consummation. From VCs' perspectives, the tests evaluate whether they tilt their portfolios toward startups from their alma mater, relative to similar startups they could have invested in. The regressions also control 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.

Table 4 presents the results. Column 1 shows that a shared alma mater increases the likelihood of investment by 0.22 percentage points. Given the mean probability of investment of 2.03% a shared alma mater correlates with approximately a 10% higher likelihood of an investor deciding to back a startup. Several control variables in the regression carry interesting coefficients. Younger firms associate with higher likelihood of receiving investment. So too do larger founder universities, which would suggest greater opportunities to form alumni connections. Also positively correlated with investment likelihood is a past funding relationship between any of the current-round-investors and the company. This is consistent with information benefits to prior funding relationships, which we emphasize in a broader context next.

Finally, past affiliation positively correlated to funding likelihood. This suggests channels of communication between investors *prior to the current financing round* are important to funding decisions. For example, suppose investor A joins a VC round for startup S, which counts as its other investors, B and C. If B or C have collaborated with A on investments at *other* startup firms before now, past affiliation equals one.

The coefficient on this control is uniformly positive. It suggests that the communication channels forged in prior financing activities (at a shared startup) encourage the investors to work together again on the current (potentially different) startup. Importantly, this control implies that alumni connection information communication is incremental to that contained in prior funding relationships broadly defined.

[Insert Table 4 About Here.]

Column 2 provides another key indicator of information benefits to alumni connections. We include an interactive of SAT score with alumni connection, and the coefficient on it is significantly negative. When SAT scores of the founder's university are higher (lower), alumni connections with investors matter less (more). 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 SAT score provides a public signal about founder or idea quality, the greater importance of alumni connection when the public signal is weaker, implies partial substitution. Put differently, it suggests that connections matter less when founders have strong public signals of their quality, implying connections' importance may stem from their ability to resolve information asymmetries about founder quality.

Columns 3-6 provide results that include more granular measures of alumni connection between founders and VC investors, as interactives. They largely confirm intuition regarding the strength of connection and its influence on investment likelihood. In column 3 for example, we find that the incremental benefit of overlapping timewise at a university (the partner graduated within four years of the founder from the same university), is nearly equal to the average benefit from shared alma mater. Columns 4-6 offer a cross-sectional perspective. The benefits of sharing alma mater are entirely contained in cases where founder and investor both attended the same school (such as Columbia Business School), or both graduated with an MBA from the same university, or both graduated with a bachelors degree from the same university.

We offer two additional cross-sectional perspectives as robustness checks in our appendix. Table A.2 focuses on first deals only. The coefficients on *Same Alma Mater* are roughly five times the magnitude as those found in Table 4. When there is less information known by the investor about the startup through (the absence of) prior deals, the information conveyed through alumni connection has a stronger influence on deal completion likelihood.

The other cross-sectional perspective—presented in the Appendix Table A.3—is again related to the education quality signal, but replaces SAT score with *Early Career Pay* from Payscale. The inferences are the same as before, with higher quality education reducing the influence of alumni connections on the likelihood of a deal. Hence, the inference that alumni connections may substitute for educational quality proxies is robust to measuring the latter with either incoming or outgoing proxies.

We also offer robustness tests centered around the construction of the alumni connection variable. We replace the indicator with a measure of preponderance of such connection. Specifically, *P-Same Alma Mater* is the fraction of founder-investor pairs that attended the same university (See Appendix B for details on how we construct this variable). Appendix Table A.4 shows that it also increases likelihood of investment, and so too do the interactive versions of it (attendance-period overlap, school overlap, MBA overlap, bachelors overlap). Finally, we highlight our hypothesized information benefits (to alumni connections) channel in several ways in Table **??**. Specifically, the positive effect of *P-Same Alma Mater* is increased in the first funding round, and it is reduced when SAT score (of the founder) is higher and when there is a past affiliation between investors, consistent with our information-channel interpretation discussed in the introduction.

We present graphical evidence on the magnitude of connections' impact in Figures 2 and 3. For these tests, we compare actual deals to matched counterfactual deals where we match investors to all of the deals in the same industry-state-year-investment stage as their actual deals. Figure 2 plots the level of investor-founder school connections in the actual and counterfactual deals against the average SAT Score at the founder's school. The figure shows that connections matter for investment throughout the distribution of school quality—actual deals have much higher connection rates than counterfactual deals.

Figure 3 presents similar evidence showing that connections matter at universities of all sizes.

[Insert Figures 2 and 3 About Here.]

A.2. The Effect of Investors' School Ties on Deal Selection — LinkedIn Sample

The results in Table 4 are built on a selected sample - consummated deals. Given the potential bias from ignoring the fact that VCs may see many other potential investment opportunities that do not get funded by anyone, we obtain data from LinkedIn that potentially captures such observations. These data meet the criteria that the founder attended a U.S. university and that they are associated with a company in the LinkedIn "companies" dataset, which we obtain from Datahut, a data aggregator. 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*.[16]

The results are presented in Table 5. In Column (4), our preferred specification, the coefficient on our alumni connection variable is 0.8% and 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 this test investigates the likelihood of an investment by a

[16] 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.

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. Overall, our results show convincing evidence that alumni connections between founders and VC investors are strong predictors of obtaining early-stage financing from VCs.

[Insert Table 5 About Here.]

A.3. The Effect of Partner Turnover at VCs on Likelihood of Deal Completion

We now use a movers strategy to approximate the causal effect of alumni connections on a VC's deal selection. Specifically, we look for changes in the set of partners at VCs. We test whether founders from the same alma mater as the departing partner are less likely to secure funding from the firm previously employing the partner in question. The identifying assumption is that partner departures from VCs are uncorrelated with time-series variation in the number/quality of startups seeking funding from the departing partner's alma mater. We argue that this seems plausible, since departures are likely driven by idiosyncratic factors and partners' career concerns.

Our tests are OLS regressions. We construct an investor-alma mater-year panel, where each investor-year has observations for all of the universities in our sample. This large panel allows us to include explanatory variables for both treatment and post-treatment. *I(Treated)* equals one if a partner from the VC-alma mater pair departed the VC at any time during the sample window. We focus on the years *after* that partner's departure by interacting *I(Treated)* with *I(Post Departure)* as our key explanatory variable in the regression.

To form our dependent variable, we track the proportion of deals allocated to each university by each investor in our sample each year from 2000 to 2020, as well as the proportion of partners who attended a given university and are affiliated with the VC (again in each year). The dependent variable equals the proportion of the VC's deals allocated to founders from a given alma-mater.[17] We always include year FEs, and we varyingly include/exclude investor (VC firm) and/or Investor by University fixed effects.

The results from these regressions are presented in Table 6. Across all specifications, we see the coefficient on the post-treatment key regressor is significantly negative. After a partner leaves a VC, the proportion of deals going to startups formed by founders from the departed partner's alma-mater declines. On average, 0.386% of an investor's deals go to founders from a given university in our sample.[18] In general VC-alma mater pairs where the partner departs the VC (*Treated*) are more likely to attract venture funding. However, following a departure of the partner from the VC firm, the likelihood of getting funding from that VC drops by 23% (from Column (3), -0.5397/2.327).

We can reach our strongest causal conclusions based on the results in Column (4), when we include VC-alma mater fixed-effects. The FEs act as blunt controls for anything unobservable about either the VC or the University that is not time-varying. That means the coefficient on *I(Treated)***I(Post Departure)* is most likely picking up *just* the effect of the VC partner's departure on the proportion of deals that involve a same alma mater matching (of investor and founder) ex post. It is significantly negative. We infer that shared alma mater between investors and founders encourages (extensive margin) deal completion.

[Insert Table 6 About Here.]

In Figure 4, we provide a visual representation of this relationship in event time. First we identify all departures at a VC. Then using the departure year as event-year (0), we calculate the percentage of all deals done by this VC, that were with a founder who attended the same university as the departing partner, in years -3 through +3 inclusive. We average this ratio across all departures, and the calculation remains in event time. The figure's y-axis variable is interpreted as the probability that a deal by the VC was with a founder attending the same alma mater as the departing partner. In event time,

[17] Approximately 0.55% of all investor-alma mater-year pairs have at least one investment.

[18] Given that startup teams can comprise founders from different universities, a deal involving founders from multiple universities will count towards each unique affiliation on the founding team.

we can clearly see a drop in this percentage from event year (inclusive and) onwards.[19]

[Insert Figure 4 About Here.]

A.4. Correlation between Same Alma Mater Ties and Minority Status

Our findings thus far indicate a potential causal relationship between the university a founder attended and their likelihood of receiving early-stage VC funding. It is well-documented that a funding gap persists for minority founders.[20] The distribution of same alma mater ties could either amplify or lessen disparities in access to VC funding. If non-minority entrepreneurs predominantly attend universities with an abundance of alma mater ties, these ties could amplify existing disparities. Conversely, if minority founders preferentially select universities with high frequencies of same alma mater ties, access to VC funding could potentially become more equitable. In this section, we explore the correlation between minority status and same alma mater ties at the university level.

We start our analysis by examining if universities with larger proportions of Black undergraduate students correlate with universities that have a lower prevalence of same alma mater ties. Subsequently, we connect our metric of shared alma mater at the university level with data on economic connectedness at the university level, proposed by Chetty et al. (2022a, 2022b). This step allows us to analyze how the shared alma mater factor is related to networks more broadly.

Our analysis of the association between founder-VC partner matching based on shared alma mater, and the representation of minority students at the undergraduate level of a university, is presented in Table 7. We run OLS regressions at the university level. The dependent variable in this case is the proportion of all deals received by alumni-founders of a given university, where the involved VC partner is also an alum of that same university. Our independent variable is the fraction of undergraduates at the said university who self identify as minorities.[21] We present four panels of regression results, each corresponding

[19] To the extent that there remain doubts about our identifying assumption, we offer two investigations of whether founders that were same alma mater as departing partners, were of lower "quality," in Section C, Figures 5 and 6.

[20] For a comprehensive review, see Ewens (2022).

[21] This data is reported by all 485 universities in our dataset and is sourced from IPEDS.

to undergraduate population racial composition: Black (Panel A), Hispanic (Panel B), Asian (Panel C), and White (Panel D). Each panel contains four specifications, each adding to the set of control variables such as SAT scores, undergraduate population size, and a public university indicator. We do not include fixed effects in this analysis, given the purely cross-sectional nature of the regression, with 485 observations.

[Insert Table 7 About Here.]

In Panel A, specification (1) contains no controls. It strictly measures the correlation between the proportion of deals at a university which include shared alma mater between founder and at least one VC partner, and the percentage of undergraduates who are Black. The correlation is significantly negative. When looking at the entire set of 485 universities, those with higher percentages of Black undergraduates associate with fewer deals between founders and VC partners that both graduated from that university. Given our earlier discussion that sharing an alma mater increases the likelihood of receiving VC funding (and the amount), the negative coefficient (presentation of lower deal likelihood) is likely due to fewer deals overall for founders from universities with larger Black-undergraduate populations. Unconditionally, this suggests that university choice and minority status compound each other, shedding some light on the drivers of the VC funding gap by race.

However, and importantly, the relationship *flips* when we control for school quality via SAT score, implying the negative correlation in specification (1) was mainly driven by the caliber of schools that Black undergraduates get to attend. Once we account for SAT score in specification (2), we see that Black undergraduates are more likely to select into schools that include greater network benefits. There is a significant positive relationship between the proportion of same alma mater deals at the university level and that school's undergraduate Black population percentage. In other words, conditional on school quality, same alma mater matching of founders with investors is more common at schools with a larger percentage Black population. Specifications (3) and (4) include population and public university indicator controls, without changing our inference.

Panels B, C, and D (unsurprisingly), do not show the same pattern. In Panel B, a larger proportion of Hispanic undergrads has no influence on the proportion same alma mater ties, when we look at the simple correlation without controls. And even though the relationship turns positive after controlling for school quality, this does not survive additional controls for undergraduate population size and/or public university indicator. In Panel C, a larger undergraduate proportion of Asian students always associates with higher rates of same alma mater matching. There is no flipping of sign after controlling for school quality, university size, and public university indicator. This suggests that Asian undergraduates select into schools with greater access to VC funding. Finally, larger undergraduate population Caucasian percentages consistently correlate with lower rates of same alma mater matching.

Overall, the results in Table 7 suggest that Black undergraduate students select into schools with stronger alma mater ties *conditional* on school quality (though not unconditionally), which might mitigate the problem of access to VC funding for their early stage business ideas. These network benefits could be one mechanism for improving socioeconomic status among Black populations, since successful entrepreneurship is often linked with upward economic mobility.

To test whether same alma mater ties are related to networks benefits more broadly, we turn to the work (and data) of Chetty et al. (2022a, 2022b). In two influential Nature papers, Chetty and co-authors explore social network determinants of economic mobility. They use extensive FaceBook data to analyze 21 billion friendships (from 72 million U.S. adult observations). Their analysis focuses on low-SES[22] individuals, and the share of high-SES friends among them, which they term "economic connectedness." They find that it is a very strong predictor of upward income mobility. If our same alma mater measure is reliably positively correlated with economic connectedness, then suggests a specific mechanism through which economic connectedness is related to upward mobility: through access to funding for early-stage ideas.

We offer views of the correlation in Figure 7. To link our data with Chetty et al.'s, we collapse our data to the university level (by averaging across years) and then match it to Chetty et al.'s (also) at the university-level. We then show that universities with higher

[22] socio-economic-status

fractions of founder deals from same alma mater investors, also are universities with higher levels of economic connectedness. In short, economic connectedness is positively correlated with same alma mater deals. Therefore, Black entrepreneurs that can select into universities with higher rates of same alma mater matching on early stage venture financing, may be able to overcome barriers to upward economic mobility by accessing more VC funding through partners from their alma mater.

[Insert Figure 7 About Here.]

The remainder of Figure 7 explores which determinants of economic connectedness (that Chetty et al. (2022b) study) are driving its correlation with same alma mater. We find that the strongest links are the "exposure" and "support ratio" measures.

Taken together, this section provides strong evidence that alumni connections between founders and investors facilitate deal completion. We show this through two versions of counterfactual deals, and potentially exogenous shocks to alumni connectivity via partner departures from VCs. We also provide evidence suggesting that alumni connections can help mitigate the VC funding gap experienced by minority founders, once we control for school quality. This is contingent upon minority founders deriving the same average benefits as non-minority founders from attending institutions with high same-alma-mater matching rates.

B. School Connections and Investment Size

Having documented a positive effect of shared educational background between founder and investor on deal consummation, we now turn to the intensive margin and examine whether school connections encourage investors to place larger bets on startups from their alma mater. The sample is actual VC deals and includes an observation for each investor-by-deal combination. A unit of observation in this analysis is a lead investor - deal. Continuing our examples above, the deal in which True Ventures was the lead investor in the 2010 Duo Security seed round will create one observation. 85% of all deals have one lead investor.

The outcome variable in these tests is the *Ln(Funding Raised)* for the deal. We control for the same firm and deal characteristics from prior tests. In Table 8 we present three panels that vary our units of observation to enable varying versions of fixed effects. In Panel A we study our typical 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 regressions run 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* continues to correlate positively with early-stage financing. The coefficient of 0.18 implies 18% more funding when a founder and investor on the deal attended the same university. This effect is clearly important in economic terms. Given the average amount of funding of $17.80 million, an 18% increase in funding implies a $3 million larger investment when an alumni connection is present. We also see that the importance of alumni connection is pronounced when there is overlap in the dates of university attendance between founder and investor; the coefficient on the overlapping graduation indicator is 0.22. And the effect is also pronounced when founder and investor were at the same school (such as Columbia Business School within Columbia University); with the corresponding coefficient equal to 0.155.

[Insert Table 8 About Here.]

In Panel B, collapsing the unit of observation to the deal level creates an interesting effect. The coefficient on *Same Alma Mater* is much larger, often more than twice the size. This is due to the different comparison structure across the two panels. In Panel A there is likely less variation, as the test looks at differences in deals within an investor's portfolio; while in Panel B the variation can be much wider since it compares funding amounts across investors, some of whom funded founders from their alma mater and others who funded founders from different alma maters. In either setting, the inference that alumni connections are correlated with greater funding amounts holds.

Finally, Panel C studies the relationship at the alma mater-deal level. This level allows inclusion of alma mater fixed effects, which is important as a blunt control for school unobservables (such as quality) that could influence funding amounts. Again we see strong influence of *Same Alma Mater* on funding amounts. The coefficients vary between 0.08 and 0.11, continuing to imply a significant positive association between deal size and alumni connections.

We conclude the intensive margin analysis by examining mechanisms driving alumni connections. We hypothesize that such connections become more probable with increased interactions among university alumni. A plausible setting for such interactions is when the college football teams at founders' alma maters are successful. The underlying assumption is that a successful college football season triggers communication among alumni, comprising potential founder-investor pairs.

To run this test, we collect all college football game outcomes from 2010-2019 and compute each school's wins during the current or most recent season.[23] We consider raw number of wins, abnormal wins (demeaned using the school's average), and percentage abnormal wins, as college football team performance metrics. We average football season performance across all founders to collapse the data to the deal level. We then regress an indicator for whether the deal had an alumni connection, on football team performance. The coefficient on the college football team performance variable is significantly positive across all measures. This suggests that universities with high rates of same alma mater matching are likely institutions that encourage interactions among alumni.[24]

We conclude two things. First, shared alma mater associates with greater funds raised. Second, we show that communication amongst alumni is one mechanism facilitating the formation of these same alma mater deals.

[23] College football seasons run from September until January. We apply season win totals to VC deals from September through the following August.
[24] See Table A.5.

C. *Are Connected Investments More Informed?*

Despite the cross-sectional evidence up to this point that alumni connections reduce information frictions, there remains an alternative interpretation. Same alma ties could stem from favoritism, where venture capital partners are choosing founders from their alma mater because of the uncertainty about investing in other startups they have less familiarity with. This favoritism could be driven by in-group bias or overconfidence bias, where venture capitalists overestimate the skills of founders from their university (Kahneman (2011)). To distinguish between this view and the positive information channel we propose, we examine startup outcomes. Our sample is smaller in these tables because we end the sample in 2016 to allow enough time for an exit. Our hypothesis is that more informed funding decisions correlate with a higher likelihood of eventual IPO or other indicators of success.

Table 9 presents simple univariate statistics on various measures of success and failure, stratified by SAT-score bucket, and separately for connected versus unconnected deals. Given multiple founders for a deal, the highest SAT score school across those founders is the one used to place the deal in an SAT range bucket.[25] Each success measure is an indicator with one for affirmative and zero otherwise. The two main success measures in the literature are whether a firm does an IPO post-funding, or whether it gets acquired.[26] Failure is when PitchBook indicates the company is in bankruptcy or is out of business.

[Insert Table 9 About Here.]

The statistics indicate more successes and fewer failures when the deal has at least one alumni connection between a founder and an investor. Even stratifying by school SAT score range, only M&A exits are less common among connected deals in the lowest SAT score bucket.

Interestingly, the effect of alumni connection on better outcomes (more successes or

[25] Our results are similar when we use the average SAT score to place a deal into a bucket.
[26] Recall our restriction on acquisition price of at least twice the invested amount in the company.

fewer failures) appears stronger as school quality declines.[27] For example, post-funding IPOs are 3x more common among connected than unconnected deals in the SAT score bucket (1000 - 1200]. But the same comparison in the top SAT score bucket (1400 - 1600] suggests just a bit more than 2x success in connected deals. Similarly, failure incidence is much lower in connected deals than unconnected deals in the (1000 - 1200] SAT score bucket, while the drop in failures due to alumni connectivity is of much smaller magnitude in the top SAT score bucket.

Table 10 presents a more formal test of the hypothesis that alumni connections are associated with better outcomes, focusing on IPOs. IPOs are the primary benchmark for success after early-stage funding (see e.g., Hochberg et al., 2007; Gompers et al., 2016; Farre-Mensa et al., 2020). In Table 10, we explain IPO likelihood with a linear probability model. Panel A mirrors the approach from Table 8; we continue to set the data at the investor-deal level, and we control for firm and deal characteristics, as well as investor-state-year-industry fixed effects. In other words, the measured effect of alumni connections on IPO likelihood indicates whether investors make funding decisions that lead to better outcomes, *within* an investor's portfolio.

[Insert Table 10 About Here.]

Table 10 column 1 shows that investments in connected startups are 2.6 percentage points more likely to lead to an IPO than non-connected investments. Taking into account that 6% of investments lead to an IPO, the Same Alma Mater coefficient represents nearly a 50% increase in the likelihood of a successful exit via an IPO. This contradicts 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 might be based on shared experiences, values, or knowledge imparted by the same institution, potentially making their partnerships more

[27] Here we are primarily comparing the top SAT score bucket outcomes with the third (of four) SAT score bucket outcomes.

efficient and successful. The former, however, may be primarily driven by comfort and familiarity rather than the startup's merit.

Column 2 examines the effect of founders' school quality, and its interaction with same alma mater, on IPO likelihood. Here we note that Mean SAT Score is zero with a standard deviation of one (i.e., we normalize it to facilitate interpretation of coefficients). Consequently, for deals involving founders from universities with the average SAT score, the impact of same alma mater on the likelihood of an IPO is determined solely by the coefficient on same alma mater. Among founder grads from average-SAT score universities, when the deal is funded by a VC from the same alma mater, their startups are 2% more likely to IPO. On the other hand, the effect is much lower for founders from more prestigious universities. If that university has SAT score that is one standard deviation higher than the average, the effect of same alma mater is (2.055 - 2.33), which is arbitrarily close to zero, in the influence on post-funding IPO likelihood.

Columns 3-5 study the effect of alumni connections on IPO likelihood while separating out the incremental role of overlap in either university attendance window, school within the university, or MBA program. Only the MBA indicator is incrementally important. Results after controlling for these interactives appear weaker in this panel, but this is likely due to tight controls via the investor fixed effects.

Panel B studies the relationship at the deal level, with the slightly less stringent state-year-industry fixed effects. Here the effect of alumni connection on IPO post-funding is consistently strong across all (but one) columns. The appendix Tables A.9 and A.10 study the effect of alumni connections on M&A successful exits and suggest that connections help. The results are weaker than those for IPO exits, but still significant in some cases. As we found for IPOs, the results appear stronger at the deal level rather than at the investor-deal level. We conclude that connected investments outperform non-connected ones. This suggests that reduced information asymmetry outweighs favoritism concerns and is likely an important reason why early-stage investors tilt their portfolios toward startups from their alma mater.

The analysis of IPOs as indicator of successful outcome, allows us to revisit the small concern about our identifying assumption in the extensive margin tests using VC partner departures (see footnote 19). We presumed that these partner departures did not reflect diminished quality of founders from the alma mater of departing partners. We can look for evidence of this in post-funding IPO exits after VC partner departures. However, we must be careful with our sampling. We select all deals by founders who attended the departing partner's alma mater, except we exclude any of these deals that were with the VC from which the partner departed.[28]

Figure 6 shows that IPO counts are actually rising among these likely-similar-quality founders' portfolio companies, in event time throughout the -3 to +3 year window (again with year 0 as the VC partner departure year). Quality does not seem to be diminishing among founders around the time that a same alma mater partner left a VC. Figure 5 shows similar, with a less stringent criteria for assessing quality - number of deals raised by founders from the departing partner's alma mater. Again, we exclude deals with the VC firm from which the departing partner left. Overall, the identifying assumption in our Table 6 and Figure 4 analyses, appears to be met.

[Insert Figures 5 and Figures 6 About Here.]

The outperformance of same alma mater deals raises the question of whether VCs select better deals when they have information provided by shared educational background, or whether these ties, perhaps through a more harmonious working relationship between a venture partner and founder, enable the partner to guide the startup towards exit more smoothly. We revisit our data on VC partner departures to examine this question. If a VC partner departs post-funding but prior to the portfolio company's exit, this would theoretically lessen the monitoring benefit. Consequently, we investigate whether there is a difference in IPO likelihood among deals with a shared alma mater between founder and investor, when the partner (with the same alma mater) departs post-funding, compared to when they remain.

[28] The latter helps satisfy the exclusion restriction.

Table 11 presents the results from this analysis. We run OLS regressions where the dependent variable is an indicator equal to one when the portfolio company exits via IPO before December 2022, zero otherwise. We include our usual same alma mater variable and a partner departure dummy that equals one if the partner departs post-funding but pre-IPO (or pre-sample-end), zero otherwise. The key independent variable is the interactive of these latter two. We also include SAT score control and the size of the first funding amount as controls. There are four specifications with varying controls. Fixed effects are at the state by year by industry level.

[Insert Table 11 About Here.]

The results continue to indicate that same alma mater by itself associates with higher likelihood of exit via IPO. However, neither partner departure (by itself) nor its interactive with same alma mater have any influence on IPO exit probability. We conclude that it is not monitoring/shepherding by connected partners that improves exit. Rather, it appears that same alma mater improves information that the partner may have or glean about founder abilities at the deal selection stage, which likely leads to better exit outcomes.

Our final exploration of whether same alma mater deals are more informed uses a Becker outcomes test framework. We specifically ask whether *marginal* same alma mater deals are associated with higher likelihood of IPO-exit outcomes. If so, this would further challenge a favoritism interpretation that shared alma mater ties encourage inefficient capital allocation. The challenge in such tests lies in proxying for the marginal deal, which we do by employing an instrumental variables strategy, following Benson et al. (2019) and Arnold et al. (2018).

Our first instrument reflects an abundance of funding raised by same alma mater (as the founder on the focal deal) partners, recently but not in the focal year. Specifically, it represents the amount of funding raised by VC funds affiliated with partners from the same alma mater as the focal portfolio company founder, in the four years preceding the focal deal's year. For instance, consider a 2015 deal [focal deal] between a founder and a VC partner, both graduates of Columbia University. We construct our instrument as the total funding raised between 2011 and 2014 by funds employing partners that graduated from Columbia university. The underlying rationale of the instrument is that marginal startups (instrument compliers) are more likely to secure funding from VC partners from the same alma mater only because those partners have more capital to deploy.

We present our results in Table 12, which is at the deal level. The table comprises four regressions, with the dependent variable being an indicator for whether the deal eventually resulted in the portfolio company going public (IPO). Column (1) repeats the OLS specification for ease of comparison with the instrumental variables specifications in Columns (2) to (4). We see that even marginal same alma mater deals are associated with better outcomes. This strongly implies an information benefit interpretation to same alma mater deals, since a favoritism interpretation would suggest that these startups would have worse outcomes.

[Insert Table 12 About Here.]

Our second instrument focuses on the overall supply of funding in the venture capital industry. Specifically, the instrument is the total amount of recent fundraising by firms in the same industry sector as the focal deal portfolio company. Again by example, assume a focal deal in 2015 involving a startup is in the biotech industry. The instrument in this case would be the amount of funds raised by other startups in the biotech industry between 2011 and 2014. Similar to the first instrument, our hypothesis is that a marginal startup is more likely to secure funding when the availability of capital is high.

To test for a favoritism vs. information benefit role of same alma mater, using this instrument to identify the marginal startup, we split the sample. In Column (1), we first regress the IPO indicator on the funding amount instrument for the sample of deals that have shared alma mater between founder and investor. The results, presented in Table 13, reveal a significantly positive coefficient. Then we re-run the regression on the sample of deals that do not have shared alma mater, Column (2). Although the coefficient on the funding amount instrument remains significantly positive, it is significantly smaller than the one in the first regression. The p-value for difference in coefficients (across specifications) is 0.04. Marginal deals—the compliers in our instrumental variables approach—have better outcomes (IPO) when such deals also have shared alma mater between founder and investor. This further confirms our interpretation that same alma mater carries information benefits and these benefits at least outweigh any costs of favoritism. Our finding continue to hold when we include all control variables in Columns (3) and (4).

[Insert Table 13 About Here.]

Our instruments must satisfy two key criteria for correct identification. The first is relevance. In the last row of Table 12 and Table 13, the Cragg-Donald Wald F Statistic, which is a weak-instrument test (Stock and Yogo (2002)), ranges between 299.35 and 765.81. With a 10% Stock-Yogo critical value of 16, it implies that our instrument is not weak, even under generous assumptions of Instrumental Variable (IV) bias relative to Ordinary Least Squares (OLS).

Second, the availability of funding to partners from the same alma mater or within broader industry must be unrelated to the quality of the startup, given our observable covariates (instrument exclusion). We argue that the availability of funding for partners sharing an alma mater or within the industry at large is primarily driven by factors that are exogenous and not tied to the quality of a specific startup. These factors could include shifts in macroeconomic conditions, shifts in the risk appetite of limited partners (LPs), or regulatory changes that affect the venture capital (VC) industry. This would suggest that the amount of funding available to specific partners or sectors is random and unrelated to the quality of any particular startup.

IV. Conclusion

Entrepreneurial ventures are key contributors to technological innovation and long-term economic growth. Yet founders of early-stage ventures 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 an important mechanism working to reduce information asymmetries and facilitate early-stage investment.

Using expansive new data from PitchBook on the education histories of founders and early-stage 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 run by founders from their alma mater, even relative to observably similar startups in the same state-industry-year. This effect occurs at both the extensive margin (deal selection) and the intensive margin (deal size). Both the cross-sectional variation in the effect and the ultimate performance of connected investments suggest that an information advantage 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. This benefit can potentially have far-reaching implications. As one example, we show that the VC funding gap, well documented among Black populations, may be attenuated by such connections (at least at the extensive margin). 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.

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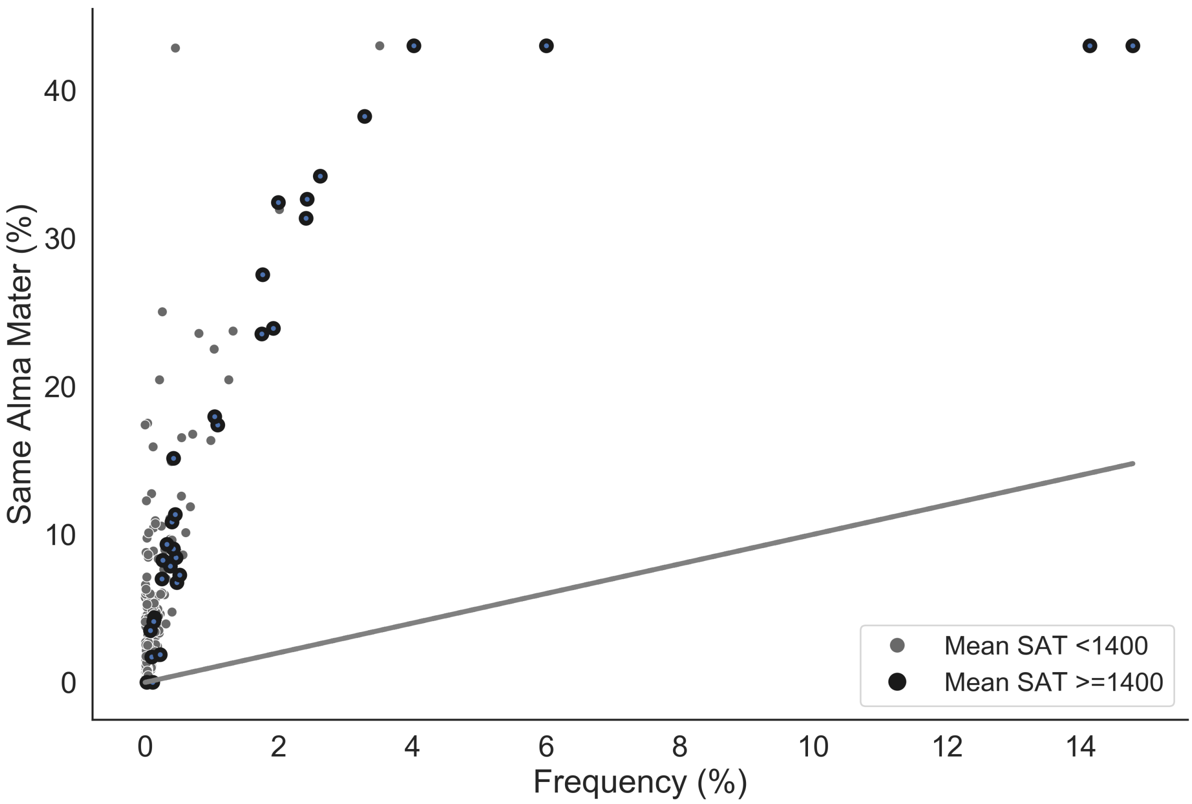

Figure 1: Alma Mater Ties vs. Random Matching
This figure presents a binned scatter plot of the relationship between the frequency of partner-level executives from an alma mater and deals involving founders from the same alma mater. We created this figure using a founder-deal-university dataset that included the number of investment firms in the deal as well as the number of investment firms where at least one partner-level executive working for the investment firm was from the same alma mater as the founder. We then collapsed this data to the university level. *Frequency* is the ratio of partner-level executives from a given university to the total number of partners working for all investment firms during our sample period, which is from 2000 to 2019. If a partner attended several universities, they contribute to each university's total. *Same Alma Mater* for each university represents the average proportion of deals involving founders from that university in which at least one partner-level executive working for the investment firm providing the funding was also an alumnus of the same university. The solid line represents the 45-degree line. Note that if connected ties were formed completely 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; i.e., most points would lie on the 45-degree line. To show most data points, we winsorized *Same Alma Mater* at 43%, which is its 99$^{\text{th}}$ percentile value. The darker dots represent universities with an average SAT score of entering freshmen greater than 1400, while the grey dots represent universities with SAT scores under 1400.

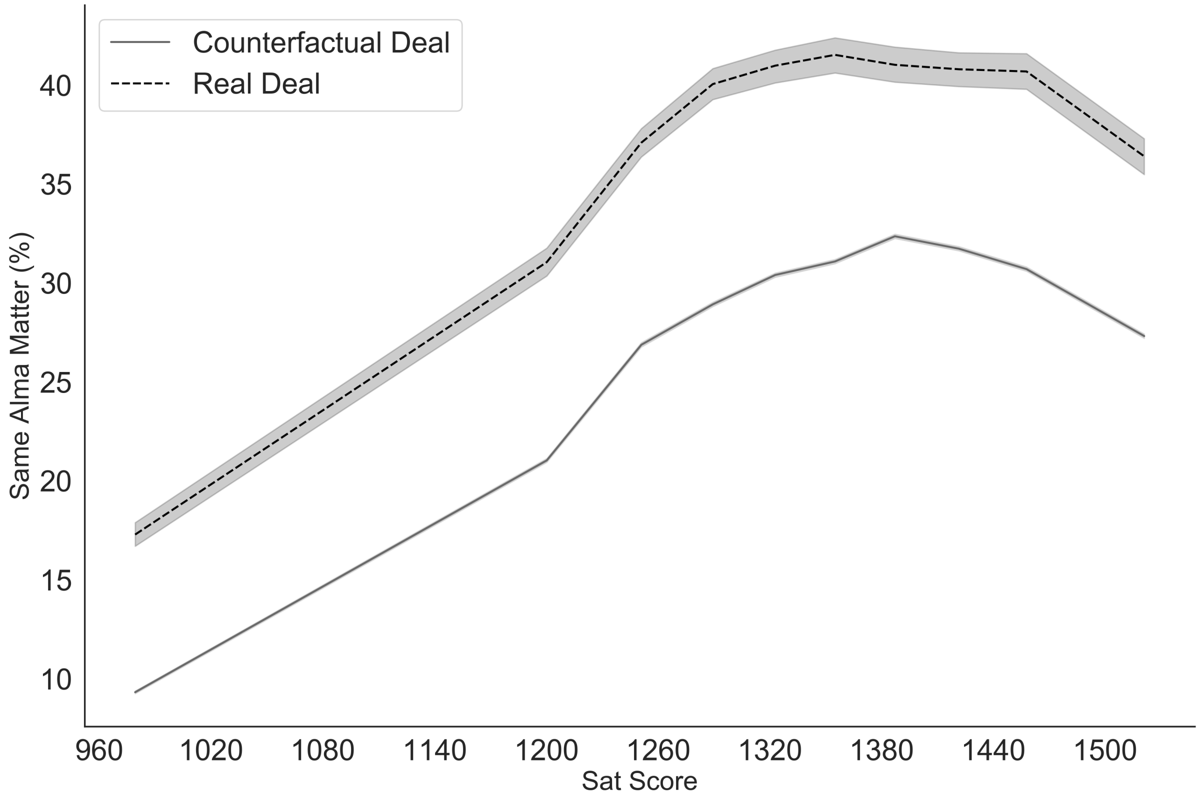

Figure 2: Education networks and school quality
This figure presents a binned scatter plot describing the probability that a deal involves an investment firm where at least one partner-level executive at the firm attended the same university as one of the startup's founders (*Same Alma Mater*). Deals are sorted into decile bins along the horizontal axis based on the most recent data on the average SAT score of accepted students at the founders' alma mater (averaged for startups with multiple founders). *Real Deal* shows the actual fraction of deals with university connections between investors and founders. *Counterfactual Deal* shows the number of university connections amongst 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.

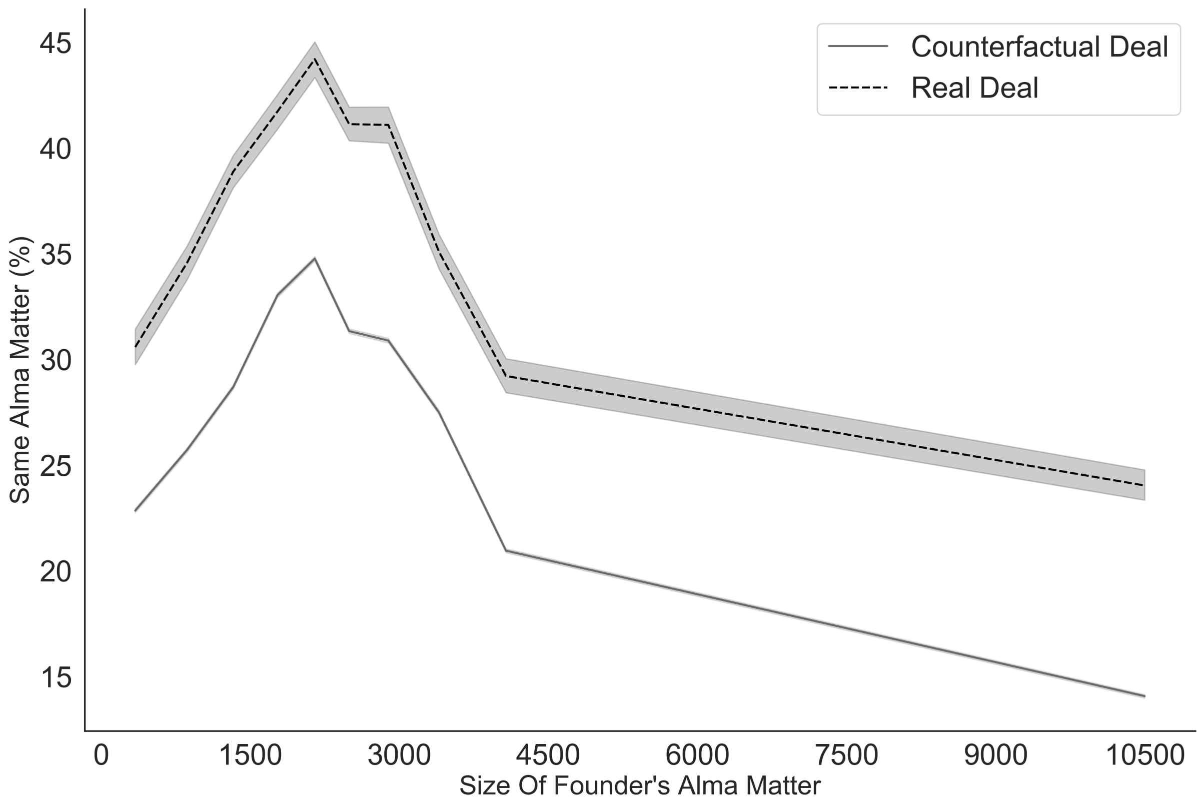

Figure 3: Education networks and investor-firm matching
This figure presents a binned scatter plot describing the probability that a deal involves an investment firm where at least one partner-level executive at the firm attended the same university as one of the startup's founders (*Same Alma Mater*). Deals are sorted into decile bins along the horizontal axis based on the most recent data on the number of graduating students from the founders' alma Mater (averaged for startups with multiple founders). *Real Deal* shows the actual fraction of deals with university connections between investors and founders. *Counterfactual Deal* shows the number of university connections amongst 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 show 95 percent confidence intervals.

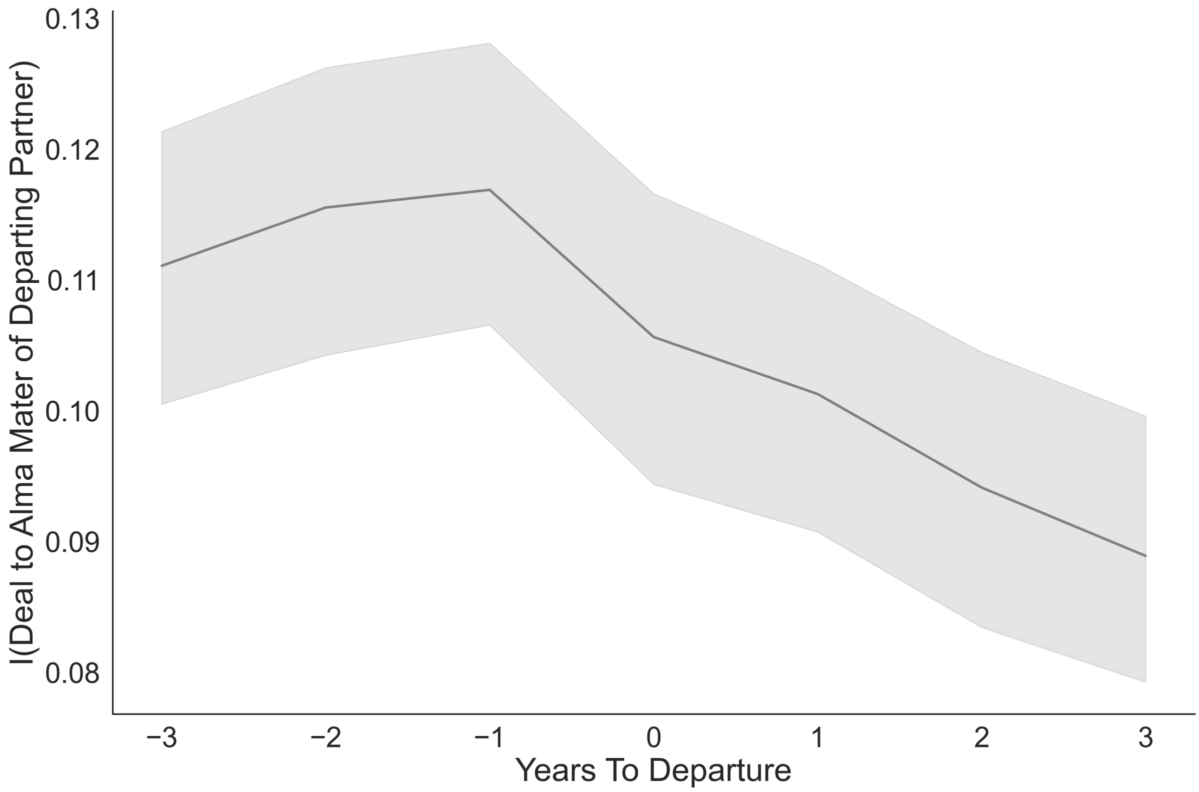

Figure 4: Departures and Alma Mater Deals
This figure presents a binned scatter plot describing the relationship between partners leaving an investment firm and whether the firm continues to fund founders from the departing partners' alma mater. To generate this figure, we create an investor-alma mater-year dataset tracking deals where at least one senior manager of the portfolio company attended the same alma mater as the partner departing the investment firm at $t = 0$. We proxy for a partner's departure using the last year they led a deal involving the investment firm. We generate this figure using only investment firms with at least one departing partner and firms that made at least one investment in each of the six years around a partner's departure at $t = 0$. The figure plots the proportion of the investment firm's deals involving founders from the departing partner's alma mater in event time. The bands around each line represent 95 percent confidence intervals. The grey areas shows the 95 percent confidence interval.

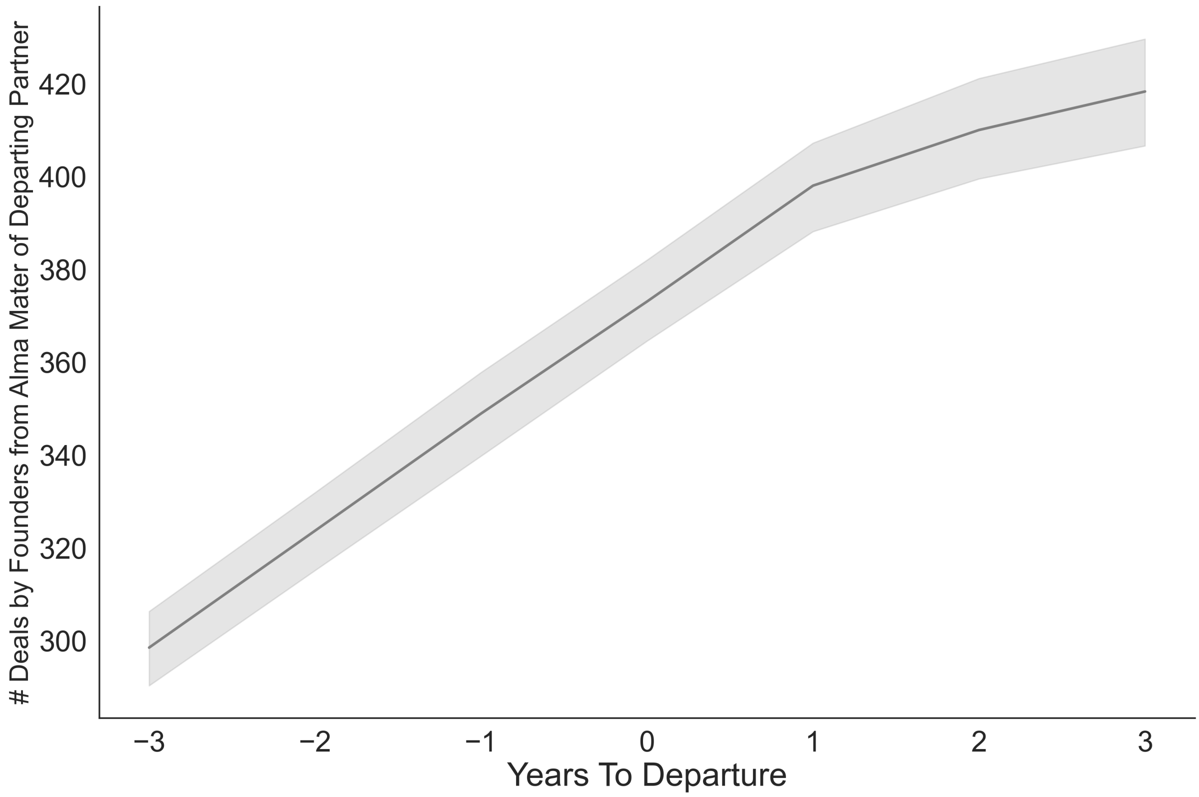

Figure 5: Departures and Alma Mater Deals (Deals by founders from departing partner's alma mater)
This figure presents a binned scatter plot describing the relationship between partners leaving an investment firm and the number of deals involving founders from the departing partner's alma mater. To generate this figure, we create an investor-alma mater-year dataset tracking deals where at least one senior manager of the portfolio company attended the same alma mater as the partner who was departing the investment firm at $t = 0$. *# Deals by Founders from Alma Mater of Departing Partner* counts the total number of deals involving founders from the departing partners alma mater, *excluding the firm from which the departing partner exited*. We proxy for a partner's departure using the last year they led a deal involving the investment firm. The grey areas shows the 95 percent confidence interval.

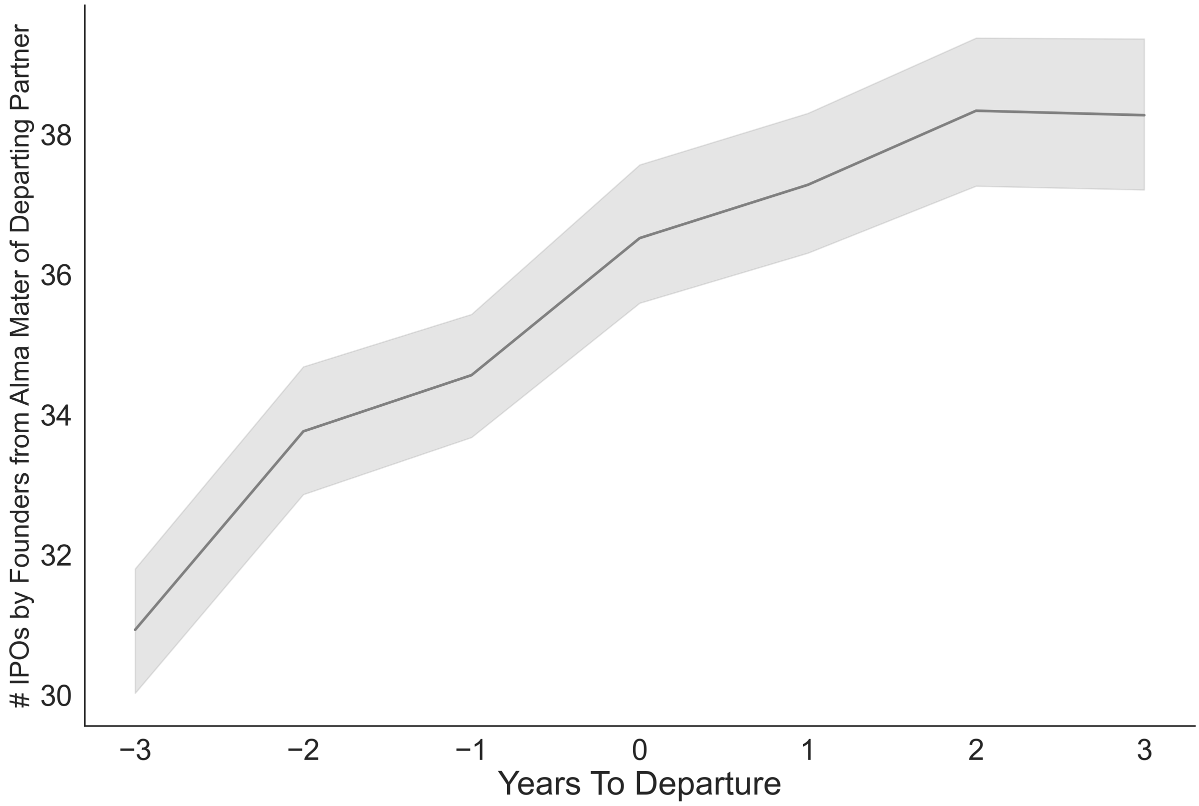

Figure 6: Departures and Alma Mater Deals (IPOs by founders from departing partner's alma mater)
This figure presents a binned scatter plot describing the relationship between partners leaving an investment firm and the total number of IPOs involving founders from the departing partner's alma mater. To generate this figure, we create an investor-alma mater-year dataset tracking IPOs where at least one senior manager of the portfolio company attended the same alma mater as the partner who was departing the investment firm at $t = 0$. *# IPOs by Founders from Alma Mater of Departing Partner* counts the total number of IPOs involving founders from the departing partners alma mater, (crucially) *excluding the investment firm itself from which the departing partner exited.* We proxy for a partner's departure using the last year they led a deal involving the investment firm. The grey areas shows the 95 percent confidence interval.

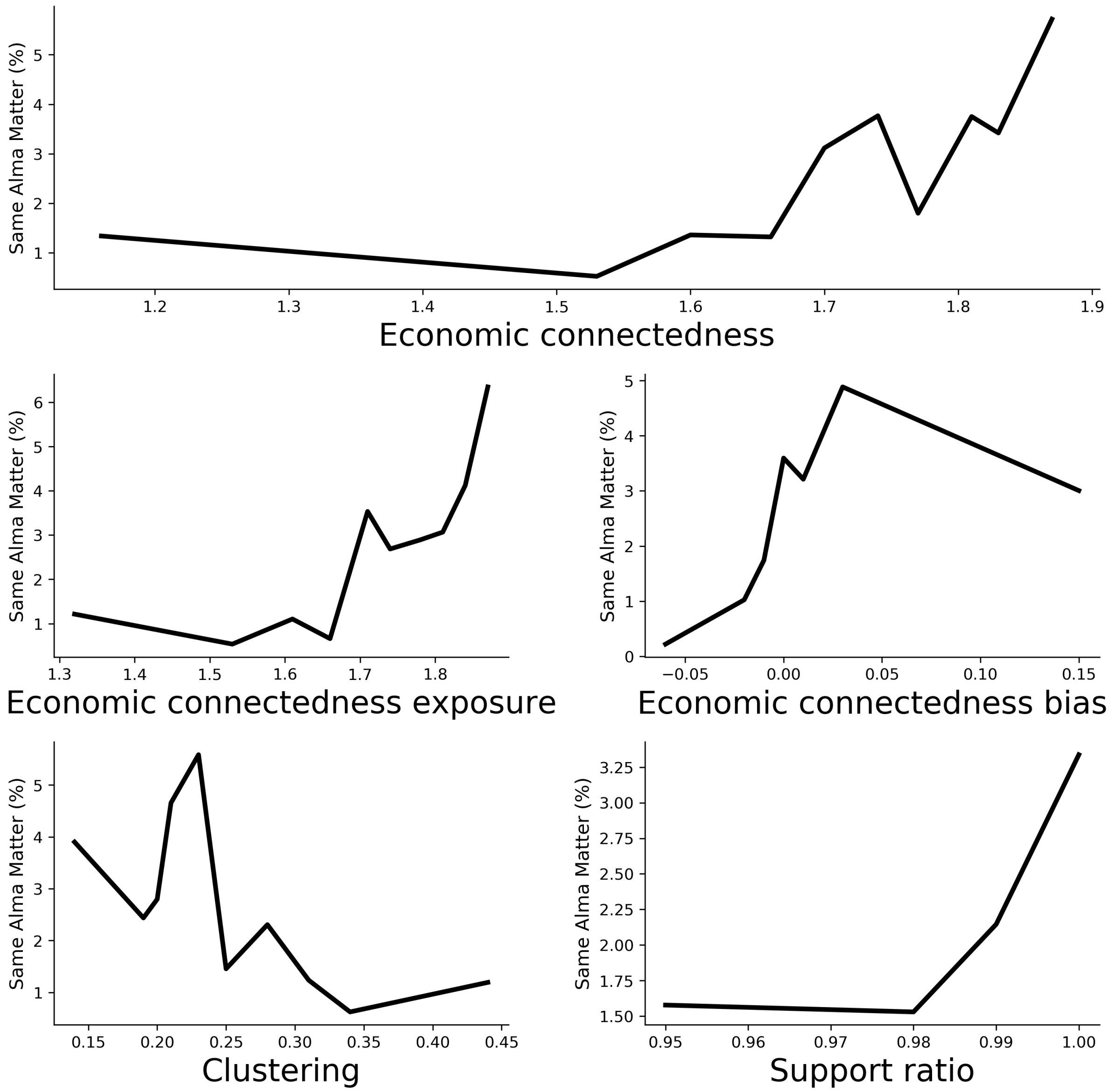

Figure 7: Education networks and social capital measures
This figure shows a binned scatter plot describing the relationship between the proportion of deals founders at a given university received from investment firms with at least one partner-level executive from the *Same Alma Mater*, and various measures of social capital measured using Facebook data from Chetty et al. (2022a). Deals are sorted into decile bins along the horizontal axis based on the different measures of social capital available here: `https://data.humdata.org/dataset/social-capital-atlas`. We matched all 485 universities in the our data to the social capital data. See Chetty et al. (2022a) and Chetty et al. (2022b) for details on how the measures of social capital are constructed using 21 billion friendships from Facebook.

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 company that raised at least one round of 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(Califoria 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: Characteristics of Startups and their Investors

This table reports summary statistics for our sample of early-stage equity financing deals. The sample is collected from PitchBook and is restricted to firms receiving funding from 2000-2020, with founders from U.S. universities and 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).

	Real 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			
I(Bachelors)	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***
Past Funding Relationship	0.23	0.26	0.22	6.26***	0.01	0.01	0.01	25.93***
Seed Round	0.17	0.13	0.19	-11.23***	0.15	0.1	0.17	-96.69***
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 3: 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 SAT score of accepted 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	Massachusetts Institute of Technology	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 Technology	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 University in St Louis	1506	31.60	329	17.43	528	20.83
20	University of California-Los Angeles	1423	20.47	1132	8.56	1872	28.42
	University of Michigan-Ann Arbor	1434	26.31	1110	13.74	1836	27.56
	Southern Methodist University	1395	19.40	201	17.83	340	13.53
	University of Iowa	1233	4.07	174	2.35	268	14.93

Table 4: Do Investors Tilt their Portfolios Toward Startups from their Alma Mater? (Lead Investors 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 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	0.2176***	0.2341***	0.1751***	0.0192	0.0637	0.0860
	(0.0341)	(0.0357)	(0.0371)	(0.0617)	(0.0587)	(0.0593)
Mean SAT Score	-0.0274	-0.0135	-0.0284*	-0.0267	-0.0274*	-0.0280*
	(0.0167)	(0.0172)	(0.0167)	(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)	
I(Bachelors)						0.1666***
						(0.0633)
Ln(University Size)	0.0451***	0.0414***	0.0450***	0.0441***	0.0449***	0.0461***
	(0.0150)	(0.0151)	(0.0150)	(0.0150)	(0.0150)	(0.0150)
Young Firm	0.2673***	0.2708***	0.2705***	0.2691***	0.2686***	0.2687***
	(0.0421)	(0.0421)	(0.0421)	(0.0421)	(0.0421)	(0.0421)
Ln(distance)	-0.5154***	-0.5151***	-0.5141***	-0.5139***	-0.5141***	-0.5133***
	(0.0283)	(0.0283)	(0.0283)	(0.0283)	(0.0283)	(0.0283)
Past Funding Relationship	34.0103***	34.0086***	34.0050***	34.0077***	34.0080***	34.0086***
	(0.5073)	(0.5073)	(0.5073)	(0.5073)	(0.5073)	(0.5073)
I(Seed Round)	1.3828***	1.3855***	1.3881***	1.3852***	1.3845***	1.3846***
	(0.0708)	(0.0708)	(0.0708)	(0.0708)	(0.0708)	(0.0708)
Past Affiliation	0.5868***	0.5866***	0.5863***	0.5865***	0.5866***	0.5866***
	(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 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 set 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	0.0140***		0.0102***	0.0088***
	(0.0018)		(0.0019)	(0.0023)
Mean SAT Score		0.0059***	0.0047***	0.0044***
		(0.0006)	(0.0006)	(0.0006)
Same Alma Mater x Mean SAT Score				0.0027
				(0.0024)
Ln(# Founders)	0.0209***	0.0224***	0.0209***	0.0211***
	(0.0018)	(0.0018)	(0.0018)	(0.0018)
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 6: The Influence of Shared Alma Mater on Investment Allocation (Investor-University-Year)

This table explores the relationship between a partner's departure from an investment firm and the proportion of founders from the departing partner's alma mater who continue to secure funding from the firm that the departing partner was associated with. We run OLS regressions at the investor-alma mater-year level, pairing each investment firm with each of the 485 alma maters for which we have SAT scores. We track the proportions of deals allocated to founders from each university by the investment firm in each year from 2000 to 2020. The dependent variable, *P(Investment)*, represents the proportion of the investor's deals allocated to founders from a particular alma mater. Approximately 0.55% of all investor-alma mater-year pairs have at least one investment. The key independent variable, *I(Treated)*, which is at the Investor X University level, is an indicator of whether a partner at the investment firm, who attended a specific university, left the firm over the sample period. *I(Post Departure)* is an indicator that equals one in the years following the partner's departure. *SAT Score* is the SAT score of entering freshmen at the university in a given year. Standard errors are clustered by investment firm.

Dependent Variable:	P(Investment)			
	(1)	(2)	(3)	(4)
I(Treated) X I(Post Departure)	-0.6722***	-0.6776***	-0.5397***	-0.5799***
	(0.1769)	(0.1766)	(0.1735)	(0.1955)
I(Treated)	2.8873***	2.4646***	2.3265***	
	(0.1413)	(0.1373)	(0.1333)	
SAT Score		0.2746***	0.2760***	
		(0.0098)	(0.0098)	
Adjusted R^2	0.004	0.007	0.011	0.073
# Investment Firms	715	715	715	715
# Alma Mater	485	485	485	485
# Observations	2440665	2440665	2440665	2440665
Year FE	Yes	Yes	Yes	Yes
Investor FE	No	No	Yes	No
Investor X University FE	No	No	No	Yes

Table 7: Distributional Consequences of Same Alma Mater Deals

This table investigates the relationship between the proportion of same alma mater deals by founders from a specific alma mater and the racial distribution of students at that alma mater. We run OLS regressions at the alma mater level. We first track the proportions of deals involving all founders from a given alma mater where at least one partner working for the investment firm that led the deal was from the same alma mater, *P(Same Alma Mater Deals)*. The independent variables are the proportions of undergraduate students at the university that are Black (Panel A), Hispanic (Panel B), Asian (Panel C), and White (Panel D). *SAT Score* refers to the average SAT score of entering freshmen at the university over our sample period, *Ln(Undergraduate Population)* is the log number of undergraduate students over our sample period, and *I(Public School)* is an indicator for a public school. Standard errors are clustered by university.

Panel A:	P(Same Alma Mater Deals)			
	(1)	(2)	(3)	(4)
P(Black Undergrads)	-6.6460**	8.6948**	7.7391**	7.4807**
	(2.8961)	(3.4216)	(3.4769)	(3.5086)
SAT Score		4.2121***	4.2709***	4.1607***
		(0.6358)	(0.6245)	(0.6208)
Ln(Undergraduate Population)			1.6578***	1.8626***
			(0.2609)	(0.4276)
I(Public School)				-0.6718
				(0.8812)
Panel B:				
P(Hispanic Undergrads)	0.4779	5.8821**	2.9494	2.5083
	(2.7875)	(2.8477)	(2.9716)	(3.0891)
Panel C:				
P(Asian Undergrads)	42.8117***	23.5543***	17.1043**	17.1301**
	(9.7324)	(6.8988)	(6.8126)	(6.7952)
Panel D:				
P(White Undergrads)	-9.5011***	-7.8230***	-6.2896***	-6.2133***
	(2.8167)	(2.1245)	(2.1278)	(2.2692)
Adjusted R^2	0.002	0.244	0.293	0.292
# Alma Mater	485	485	485	485
# Observations	485	485	485	485

Table 8: 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 8 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
F.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 9: Exit Outcomes of Same Alma Mater Deals (Univariate Analysis)

This table investigates the relationship between same-alma mater deals, exit outcomes of startups, and the quality of universities, where we use the average SAT score of admitted freshmen as a proxy for quality. The unit of observation is a U.S.-based portfolio company that received VC backing. For these schools, we first take the average SAT score between 2000 and 2019 from the College Board. Using these average scores, we categorize schools into four buckets based on their average SAT scores. We then match these schools to our company-level dataset. For each company, we retain the highest-ranking school (by SAT score bucket) that any of the founders attended. For instance, if one founder attended Stanford and the other Southern Methodist University (SMU), we assign that company the average SAT score for Stanford. *Any Success* is an indicator for whether the company was acquired (*Acquisition*) or went public (*IPO*) before the end of our sample, June 2021. *Failure* is an indicator for instances where PitchBook classifies the company as "Out of Business," "Bankruptcy: Liquidation," or "Bankruptcy: Admin/Reorg." For each SAT score bucket, we report the average number of company exits in each exit type for unconnected and connected deals, with the connected deal statistics reported in parentheses.

SAT score sort Outcomes	[1600 to 1400)	[1400 to 1200)	[1200 to 1000)	[1000 and below]
IPO	3.55% (7.75%)	3.55% (6.48%)	2.46% (7.53%)	1.56% (3.33%)
Acquisition	23.68% (25.69%)	25.26% (26.70%)	24.79% (27.39%)	25.00% (16.67%)
Failure	9.16% (7.27%)	9.73% (9.49%)	11.94% (7.53%)	10.15% (10.00%)
Any Success	27.24% (33.45%)	28.82% (33.18%)	27.25% (34.93%)	26.56% (20.00%)

Table 10: 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 following the initial investment. 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. *Ln(Funding Raised FD)* is the amount of funding the startup raised from the lead investor in the first funding round. Compared to Table 8, 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. 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)		
	(1)	(2)	(3)	(4)	(5)
Same Alma Mater	2.5675***	2.0554***	2.6066***	1.8463	-0.0300
	(0.5985)	(0.6030)	(0.6866)	(1.2930)	(1.0635)
Mean SAT Score	0.6265**	1.2823***	0.6274**	0.6329**	0.6215**
	(0.2954)	(0.3184)	(0.2957)	(0.2951)	(0.2953)
Same Alma Mater x Mean SAT Score		-2.3305***			
		(0.6362)			
I(Overlapping Graduation)			-0.1085		
			(0.9699)		
I(Same School)				0.8320	
				(1.3362)	
I(MBA)					3.1134***
					(1.1327)
Ln(Investors Alma Mater)	0.0090	-0.0524	0.0091	0.0065	0.0103
	(0.2868)	(0.2875)	(0.2868)	(0.2870)	(0.2868)
Young Firm	0.1193	0.1504	0.1183	0.1233	0.1387
	(0.7309)	(0.7296)	(0.7309)	(0.7308)	(0.7313)
Ln(distance)	-0.3194	-0.3097	-0.3199	-0.3178	-0.3145
	(0.2670)	(0.2668)	(0.2669)	(0.2671)	(0.2670)
I(Seed Round)	1.6391***	1.6693***	1.6373***	1.6410***	1.6803***
	(0.5336)	(0.5334)	(0.5336)	(0.5337)	(0.5341)
Past Affiliation	-0.0405	-0.0460	-0.0402	-0.0409	-0.0427
	(0.0572)	(0.0574)	(0.0573)	(0.0572)	(0.0571)
Ln(Funding Raised FD)	3.2411***	3.2442***	3.2434***	3.2401***	3.2386***
	(0.3070)	(0.3069)	(0.3080)	(0.3070)	(0.3068)
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	7110	7110	7110	7110	7110
# Investors	857	857	857	857	857
Observations	10012	10012	10012	10012	10012

(Table 10 Continued)

B. Startup-Level Tests					
Dependent Variable:			I(IPO)		
	(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

Table 11: Selection or Treatment?

The tests in this table examines the relationship between a partner's departure from an investment firm and the likelihood that a company funded by the investment firm exits via in 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 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 12: Selection or Treatment (Marginal Deal)

This table presents Instrumental Variable (IV) regressions examining the effect of educational connections between founders and investors on the likelihood a company exits via an IPO. The tests are conducted at the deal level, and we instrument for the key independent variable *Same Alma Mater* (which indicates whether any of the founders share the same alma mater as a partner at the investment firm) with the amount of funding raised by funds employing partners from the same alma mater as the founders over the previous four years from when the deal was raised, *excluding* the year of the deal. The dependent variable, *I(IPO)*, is an indicator for whether the deal exits via an IPO or Acquisition by June 2021. Standard errors are clustered by startup.

Dependent Variable:	I(IPO)			
	(1)	(2)	(3)	(4)
Same Alma Mater	3.525***	7.340***	7.893***	6.751**
	(0.706)	(1.806)	(2.619)	(2.685)
Mean SAT Score			-0.175	0.327
			(0.493)	(0.509)
Ln(University Size)				0.549
				(0.347)
Young Firm				-2.078**
				(0.994)
Ln(distance)				0.559*
				(0.316)
Past Funding Relationship				-2.126**
				(0.987)
I(Seed Round)				-2.467***
				(0.684)
Past Affiliation				0.168**
				(0.067)
# Deals	6736	6736	6736	6736
Adjusted R^2	0.10	-0.12	-0.12	-0.11
State x Year x Industry FE	Yes	Yes	Yes	Yes
Cragg-Donald Wald F	.	765.81	395.79	377.00

Table 13: Selection or Treatment (Marginal Deal — Instrument Supply of Funding)

This table presents Instrumental Variable (IV) regressions examining the effect of funding raised by founders through educational connections between founders and investors on the likelihood a company exits via an Initial Public Offering (IPO). The tests are conducted at the deal level, and the key independent variable *Ln(Funding)* (which represents the total amount of funding raised from the deal) is instrumented with the amount of funding raised by startups in that industry sector over the previous four years from when the deal was raised, *excluding* the year of the deal. The dependent variable, *I(IPO)*, is an indicator for whether the deal exits via an Initial Public Offering by June 2021. Columns (1) and (3) are for *Same Alma Mater* deals, while columns (2) and (4) are for unconnected deals. *P Value Diff. Coef* is a p-value for a test of the difference in coefficients on *Ln(Funding)* between columns (1) and (2), and columns (3) and (4). Standard errors are clustered by startup.

Dependent Variable:	I(IPO)			
	(1)	(2)	(3)	(4)
Ln(Funding)	11.964***	6.642***	13.512***	7.306***
	(1.792)	(1.841)	(2.072)	(2.012)
Mean SAT Score			0.147	0.982**
			(0.900)	(0.436)
Ln(University Size)			-1.033	0.519
			(0.927)	(0.415)
Young Firm			1.884	2.436
			(2.304)	(1.544)
Ln(distance)			-1.543**	-0.298
			(0.618)	(0.433)
Past Funding Relationship			0.380	0.914
			(1.970)	(1.362)
I(Seed Round)			15.680***	8.015***
			(3.381)	(2.925)
Past Affiliation			-0.146	0.041
			(0.142)	(0.074)
State x Year x Industry FE?	Yes	Yes	Yes	Yes
Adjusted R^2	-0.18	-0.23	-0.17	-0.23
# Deals	2349	4064	2349	4064
Observations	2349	4064	2349	4064
Cragg-Donald Wald F	446.70	309.93	424.99	299.35
Same Alma Mater Deal?	Yes	No	Yes	No
P Value Diff. Coef		0.04		0.03

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. [29] 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.[30] 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. Moreover, Table A.7 in the Internet Appendix reveals that firms missed by CrunchBase 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.

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

[29] 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.

[30] 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.

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 company's funding round, we calculate the metric of potential matches as:

$$\text{Potential Matches}_{ijt} = \prod N_{it} E_i N_{jt} E_j, \tag{B1}$$

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 number 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 amongst 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:

$$\text{Past Affiliation}_{ij} = \frac{\sum_k \sum_p I_{ij} I_{kj} I_{ip} I_{kp}}{\sum_{kj} I_{kj}}, \tag{C1}$$

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.

For example, consider a startup 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.

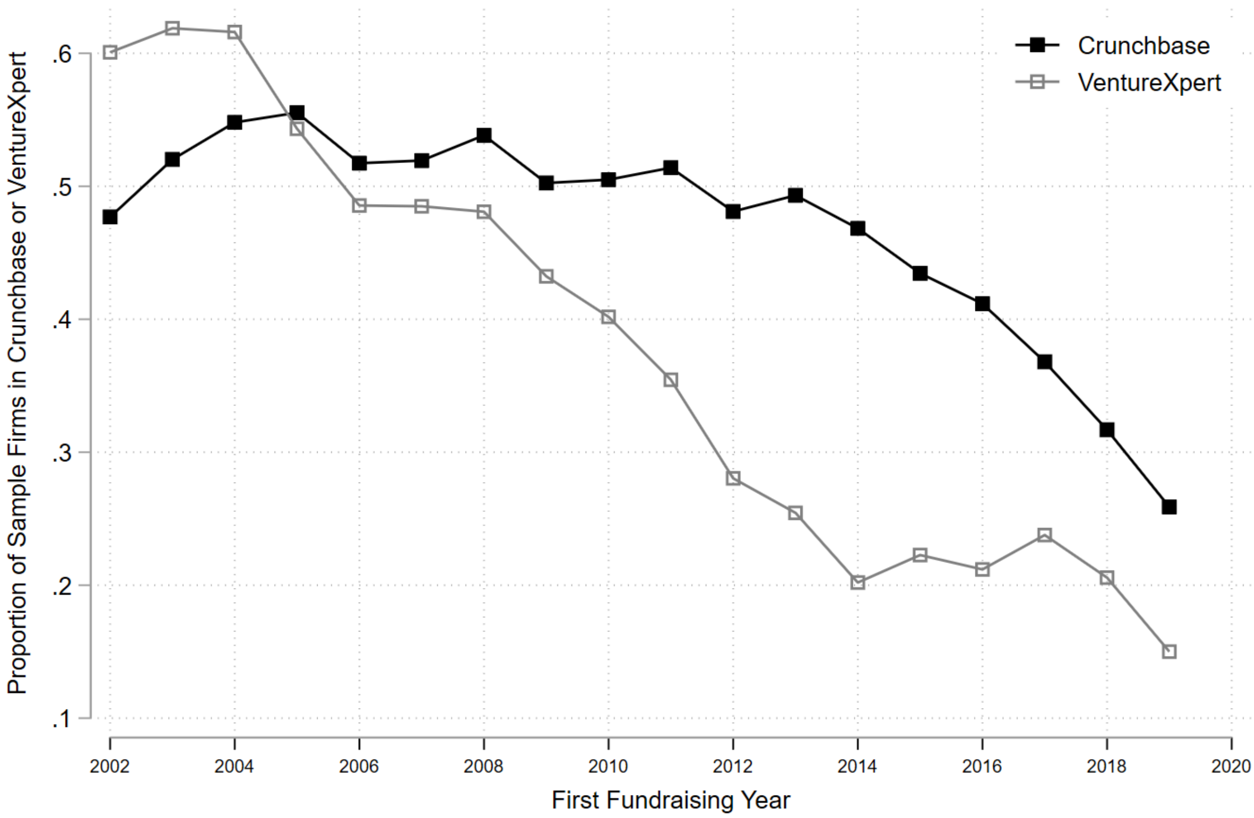

Figure A.1: PitchBook relative to other databases

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*. Our 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.

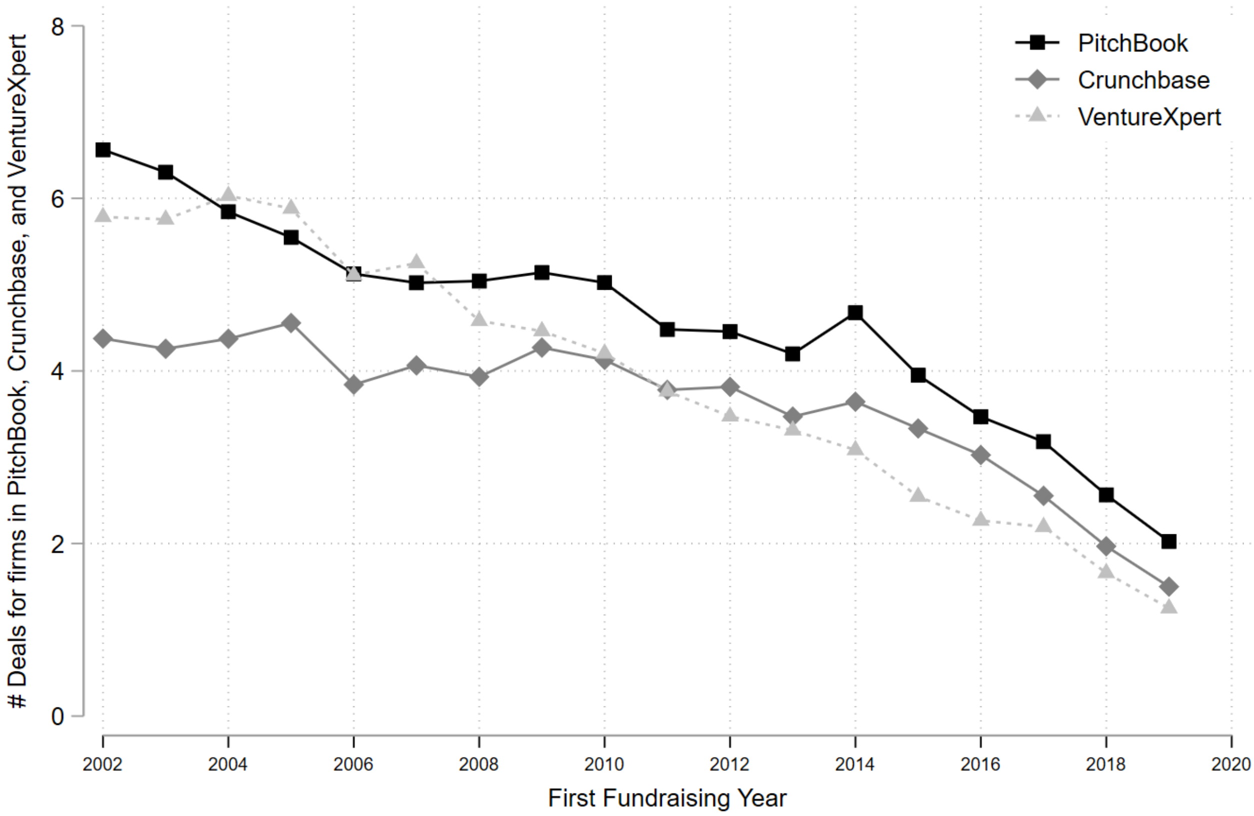

Figure A.2: PitchBook relative to other databases (Matched Sample)
This figure shows the number of deals for firms in our sample in Crunchbase and VentureXpert. We match the startups to VentureXpert and CrunchBase on founding year, state, and then require a 100 percent fuzzy match on the standardized 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 to one if any of the founders share the same alma mater as an investor in the deal.
Mean 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 to 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 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 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: College Football wins and Alumni Networks

This table presents regressions examining the effect of college football wins on the likelihood of alumni connections. The tests are conducted at the deal level. The dependent variable is the fraction of founder-investor pairs with school ties. The independent variable captures several measures of the success of the football teams at the founders' alma maters during the current season. Specifically, we calculate the total number of wins in the current season, and the abnormal number of wins relative to past seasons, as a fraction of the number of games played in the season or just the raw number. The sample includes all VC deals from 2010-2019, where at least one founder attended a university with a college football program, and the requisite data are available from PitchBook. Standard errors are clustered by startup.

Dependent Variable:	Same Alma Mater		
	(1)	(2)	(3)
Abnormal FB Wins (N)	0.0278***		
	(0.0027)		
Abnormal FB Wins (%)		0.1461***	
		(0.0165)	
FB Wins (N)			0.0205***
			(0.0023)
# Deals	8,868	8,868	8,868
Adjusted R^2	0.020	0.017	0.016
Observations	8,868	8,868	8,868

Table A.6: How comprehensive is PitchBook's coverage? Evidence from hand collected data on Unicorn Founders.

	Hand Collection	PitchBook Overlap
Unique Companies	518	518
Unique Founders	1,257	1,017
Companies with information on at least one founder	518	464

Table A.7: 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 startupss (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.8: 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 Matter	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***

Table A.9: Connections, School Quality, and Exit via Acquisition (Investor-Deal Level)

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 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 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 8, 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.

Dependent Variable:	I(Acquisition)				
	(1)	(2)	(3)	(4)	(5)
Same Alma Mater	2.5675***	-0.3167	0.6291	2.4202	1.8650
	(0.5985)	(0.9354)	(1.0419)	(1.9697)	(1.8213)
Mean SAT Score	0.6265**	-0.9671	-0.8465	-0.8959*	-0.8665*
	(0.2954)	(0.5912)	(0.5246)	(0.5248)	(0.5247)
Same Alma Mater x Mean SAT Score		0.3421			
		(0.9968)			
I(Overlapping Graduation)			-2.8326**		
			(1.3167)		
I(Same School)				-3.2439	
				(2.0140)	
I(MBA)					-2.7051
					(1.8732)
Ln(Investors Alma Mater)	0.0090	-1.3276**	-1.3335**	-1.3267**	-1.3377**
	(0.2868)	(0.5312)	(0.5308)	(0.5309)	(0.5311)
Young Firm	0.1193	1.4005	1.3783	1.3894	1.3882
	(0.7309)	(1.0277)	(1.0275)	(1.0272)	(1.0274)
Ln(distance)	-0.3194	0.2025	0.1897	0.1976	0.1996
	(0.2670)	(0.4142)	(0.4140)	(0.4140)	(0.4141)
I(Seed Round)	1.6391***	-0.9811	-1.0236	-0.9840	-1.0125
	(0.5336)	(1.1947)	(1.1946)	(1.1957)	(1.1958)
Past Affiliation	-0.0405	0.3013***	0.3073***	0.3019***	0.3024***
	(0.0572)	(0.1089)	(0.1086)	(0.1087)	(0.1088)
Ln(Funding Raised FD)	3.2411***	2.5149***	2.5741***	2.5194***	2.5175***
	(0.3070)	(0.3810)	(0.3812)	(0.3807)	(0.3811)
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	7110	7110	7110	7110	7110
# Investors	857	857	857	857	857
Observations	10012	10012	10012	10012	10012

Table A.10: Connections, School Quality, and Exit via Acquisition (Startup Level)

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 a startup level, with standard errors reported in parentheses. 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 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 8, 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 startup.

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