VCs, Founders, and the Performance Gender Gap

Sahil Raina*

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Abstract

VC-financed startups founded by women perform worse than startups founded exclusively by men. Do VCs influence this performance gap? To answer this question, I compare the gender gap in performance between startups initially financed by syndicates led by VCs with only male general partners (GPs) and startups financed by syndicates led by VCs with female GPs. I find a much larger performance gap among startups financed by syndicates with only male lead GPs. I show this disparity is driven by differences in VCs' ability to evaluate female-led startups. These findings imply that VCs contributed to the performance gender gap in startups.

Keywords: Venture capital, Entrepreneurship, Gender gap, Firm performance
JEL Codes: G24, J16, G11, G32

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Anecdotally, Silicon Valley is a harsh environment for female entrepreneurs. An article published in *The New York Times* in April 2014 noted that "sexism exists in many places, but start-up companies have particular qualities that can allow problems to go unchecked." A January 2015 *Newsweek* article described the venture capital (VC) industry in northern California as a "boys' club" and asserted that the industry's actions create "a particularly toxic atmosphere for women in Silicon Valley." A survey of female founders showed that founders who experienced discrimination or harassment from an investor usually chose to end those relationships,[1] which could hurt their startups' future success. At the same time, a number of VCs led by female general partners have arisen recently, with the purpose of financing female-led startups,[2] which suggests mainstream VC somehow invests suboptimally in female entrepreneurs. Taken together, these facts imply that VC financing may be an impediment to the success of female-led startups. Given that many of the most important firms in the modern economy started their lives as VC-financed startups,[3] such impediments could severely hurt the future prospects of the economy.

While anecdotes and surveys provide some insight into the impact of the VC sector's interactions with female founders, they do not provide systematic evidence of how VC influences the future success of female-led startups. Do VC-financed female-led startups succeed less often? If so, does the reduced likelihood of success arise due to VC financing? This paper addresses the above questions by evaluating whether VC financing affects the success of female- and male-led startups differently.

To establish whether female- and male-led VC-financed startups differ in performance, I compare successful exits from VC financing via IPO or acquisition[4] for startups with all male founders with successful exits of startups with at least one female founder. I find that

[1] See Inc.com's 2018 Women Entrepreneurship Report, `https://www.inc.com/women-entrepreneurship-report/index.html`.

[2] Some examples of such VCs include Rethink Impact, Merian Ventures, Female Founders Fund, and BBG Ventures.

[3] For instance, Amazon, Apple, Dell, Facebook, Google, Intel, Microsoft, Netflix, Starbucks, and Uber all went through a VC-financed stage.

[4] Successful exit from VC financing via IPO or acquisition is a standard measure of performance in the VC literature (for example Hochberg et al., 2007; Cockburn and MacGarvie, 2009; Puri and Zarutskie, 2012).

female-led startups are 20% less likely to successfully exit than male-led startups, which is a sizeable performance gap.[5]

While this performance gap establishes that female entrepreneurs' projects systematically fare worse when using venture capital, it does not tell us whether VCs, through their actions, impact this performance gap or whether there is some innate difference in female- and male-led VC-financed startups that drives the gap. To assess whether VCs impact the performance gender gap, I compare the difference in likelihoods of exit between female- and male-led startups initially financed by syndicates led by VCs with and without female general partners (GPs). If intrinsic differences between female- and male-led startups fully explain the performance gap, the gap should be the same across startups financed by the two sets of syndicates. In my analyses, however, I find that, among startups financed by syndicates with all male lead GPs, female-led startups are 63% less likely to exit in a given year than male-led startups. Strikingly, there is no such gap among startups financed by syndicates with female lead GPs.[6] The difference in performance gaps arises from significantly higher exit rates for female-led startups financed by syndicates with female lead GPs. In contrast, male-led startups' exit rates are the same regardless of the gender composition of the lead VC in the syndicate.

Aside from VC impact, another possible explanation for the performance gap difference between syndicates with and without female lead GPs is that higher quality female-led startups preferentially seek financing from syndicates with female lead GPs, which I refer to as the "founder preference" hypothesis. To rule out this hypothesis, I compare the performance gender gap among startups financed by syndicates whose GP gender composition changes after startups submit their financing requests to the gap among startups financed by syndicates whose gender composition did not change in that same period. As VCs must analyze

[5] To my knowledge, this is the first paper to empirically document this performance gap between female- and male-led VC-financed startups.

[6] This finding may seem at odds with Ewens and Townsend's finding that female-led startups perform better when financed by female angels and vice versa, which led those authors to conclude that angel investors are biased towards founder of their own gender. In Section 1, I discuss, in detail, the different settings of the two papers, which explain their different findings.

funding requests before making their financing decisions but startups are essentially "locked in" to their VCs after requesting financing, a change in GP composition in the "locked in" period excludes the effect of founders' choice of VC while having an impact on VCs' evaluation and advising of startups. This analysis shows that there is a substantial widening of the performance gender gap when syndicates lose female lead GP representation in the "locked in" period. These results imply that founder preferences do not drive the performance gap difference. As a result, differences in VC actions must influence the performance gap among female- and male-led startups as well.[7]

The findings above indicate that the performance gender gap is impacted by VC actions. But *how* do VCs influence to the gap? Is it as evaluators of potential investments or as advisors to financed startups (or both)? I find that syndicates with female GPs narrow the performance gender gap by evaluating female-led startups better. I compare differences in the performance gender gap between syndicates with and without female lead GPs in initial versus second financing rounds based on the notion that evaluation is far more important relative to advising in the initial round than in the second round. The test shows that female GP presence in the second round does not impact the performance gap, which strongly suggests that female GPs narrow the gap by evaluating female-led startups better. I perform three additional analyses, studying proportions of female-led startups in syndicates with and without female lead GPs, differences in exits between female- and male-led startups financed by syndicates that appoint female or male board members, and differences in subsequent financing by syndicates with female lead GPs between startups financed by syndicates with and without female lead GPs. The results of all three analyses also suggest that the performance gender gap differences arise from syndicates with female lead GPs more accurately evaluating female-led startups. This, in turn, implies that VC impact on the performance gender gap arises from differences in VCs' ability to evaluate female-led startups.

[7] As female presence in a VC is correlated with VC age, size, and experience, another potential explanation is that one of those correlated lead VC characteristics explains the different performance gaps. I run my primary analyses using an orthogonalized measure of female lead GP presence and find nearly identical results, ruling out this explanation.

1 Related literature

This paper most directly contributes to a growing body of literature on the impact of gender on entrepreneurial firm financing. One of the papers in this literature, Gompers et al. (2014), for instance, focuses on the difference in the overall performance of individual GPs' portfolios by GP gender and the impact of female GPs on the performance gap between the portfolios of other female and male GPs in the same VC. It finds that, while female GPs' investments perform worse than male GPs' investments, this difference goes away if the VC has multiple female GPs. This paper also studies the effect of female GPs on performance gaps. However, the focus here is on the performance gap between female and male-led startups rather than on female and male GPs' portfolios. While GP gender-based differences in portfolio performance have import for VC financing, founder gender-based differences in startup performance have implications for entrepreneurship, as well.

A more recent paper in this literature, Ewens and Townsend (2020), using data from AngelList, an online angel investing platform, finds that female and male angel investors show different levels of interest and, ultimately, have different propensities to invest in startups led by female versus male founders.[8] The paper also documents that startups whose founders and angel investors are of the same gender are less likely to subsequently secure VC financing.[9] In two specific ways, Ewens and Townsend (2020) is useful for the research presented in this paper. First, it investigates the potential hurdles to entry into entrepreneurship for female-led startups posed by early-stage investors whereas this paper studies hurdles to exit from entrepreneurship for female-led startups posed by early-stage investors.[10] Therefore, the questions we study are complementary: it focuses on *entry into entrepreneurship*, naturally studying angels, who are early-stage investors, whereas this paper focuses on *exit*

[8] Gafni et al. (2020) shows similar evidence for crowdfunded projects using Kickstarter data, while Hebert (2019) finds differing preferences for financing female- and male-led startups among French investors.

[9] It also documents that IPOs and acquisitions are impacted but startups almost always also go through VC financing prior to IPO/acquisition, which makes this finding more difficult to interpret.

[10] Gornall and Strebulaev (2019) also studies potential hurdles to entry into entrepreneurship for female founders. Unlike Ewens and Townsend (2020), which uses AngelList platform data, it runs a field experiment on VCs and angels using pitch emails from fictitious startups.

from entrepreneurship, naturally studying venture capitalists, who are later-stage investors of entrepreneurial firms.

Second, its findings for angel investors help contextualize this paper's VC-focused findings. Ewens and Townsend (2020) finds that same-gender pairs of investors and founders are less likely to exit angel financing whereas this paper finds same-gender pairs of female-led investors and founders are more likely to exit VC financing. Differences in the source of capital and investment amounts between angels and VCs explain these opposing findings. As angel investors invest their own money whereas VCs are primarily investing money committed by a number of limited partners (LPs), VCs are accountable to outside investors and there are many more agents independently monitoring VCs' investment decisions than those of angel investors. Therefore, even if an angel and a GP share the same biases, the angel's investments are far more likely to reveal those biases than the investments of the GP's VC. Second, angels invest much less in each investment[11] than GPs do in each financing round.[12] By bringing these differences into focus, Ewens and Townsend (2020) helps to contextualize this paper's findings and highlights key characteristics of VC financing.

This paper also connects to the small business financing literature on the interaction of gender and firm financing. Alesina et al. (2013) finds that female small business owners seeking bank loans pay more for credit than do male owners. Bellucci et al. (2010) finds that female owners face tighter credit availability than male owners when seeking bank loans. That paper also reports that female loan officers require lower collateral from female owners for loans than from male owners. These papers look at the impact of business owner and financier gender on financing outcomes (cost of credit and credit availability, in particular), whereas I examine the interaction of entrepreneur and financier gender on overall

[11] The typical angel invested approximately $35,000 in 2015 according to the 2017 Angel Funder Report by the Angel Capital Association. See `https://www.angelcapitalassociation.org/data/Documents/TAAReport11-30-17.pdf?rev=DB68`.

[12] The typical VC invested approximately $13.5 million in 2015 according to the 2017 NVCA Yearbook published by the National Venture Capital Association (see `http://nvca.org/download/5080`). Even if a GP provides only the baseline 1% of the capital that the VC invests (as Preqin and a number of other industry sources state), the GP is investing $135,000 per investment, on average.

firm performance (e.g., IPO, acquisition, and exit from VC financing). Furthermore, these papers examine bank-financed small businesses, whereas I study venture capital-financed entrepreneurial firms, which are fundamentally different sorts of small businesses.[13]

This paper adds to the literature on entrepreneur and VC characteristics that affect entrepreneurial firm performance as well. Hochberg et al. (2007) shows that greater VC firm connectedness is associated with better exit outcomes for financed entrepreneurial firms. Lerner (1994) presents evidence that VC firms' experience helps them better time the exit of financed firms via IPO. Gompers et al. (2010) documents that previous entrepreneur success also predicts entrepreneurial firm success. There is also a large subliterature studying whether the project or the management team is more important for entrepreneurial firm success (see Kaplan et al., 2009; Gompers and Lerner, 2001; Gladstone and Gladstone, 2002). Another branch of this literature considers the role of VC firms' bargaining power in fund performance (see Hsu, 2004; Kaplan and Schoar, 2005; Hochberg et al., 2010). This paper offers evidence that gender-based pairing between lead GPs of VC syndicates and founders also helps determine the performance of entrepreneurial firms.

More generally, this paper relates to papers in other literatures that examine the role of gender pairings. Within finance, Huang and Kisgen (2013) provides evidence that male executives exhibit overconfidence in corporate decision-making relative to female executives, which suggests that the impact of female GPs may come from actions of the female GP herself. Adams and Ferreira (2009) and Ahern and Dittmar (2012) find that the gender composition of corporate boards has an impact on firm value. In a labor setting, Tate and Yang (2015) shows that female workers lose more in wages than male workers when they lose a job but that this difference is narrower if the workers are rehired by a firm with female leadership. In management, Athey et al. (2000) provides a model of organizational heirarchy focusing on the impact of gender (or ethnic) diversity on the diversity in upper- and lower-level employees. Tsui et al. (1989) finds that superior-subordinate gender dissimilarity is

[13] Levine and Rubinstein (2017) presents compelling evidence on the differences between entrepreneurial and non-entrepreneurial small businesses.

associated with lower effectiveness in corporate settings. In education, Lim and Meer (2017) and Paredes (2014) show that female students paired with female teachers perform better in testing whereas male students do not exhibit any change in performance due to teacher gender. Carrell et al. (2010) examines the pipeline to STEM employment and finds that gender gaps in grades and chosen majors disappear when female students are taught by female professors in the US Air Force Academy. My findings suggest that similar effects of gender pairings may exist in VC financing as well.

This paper draws some techniques and insights from the economics literature on discrimination. In labor economics, there is a great deal of research on discrimination based on gender, ethnic, and racial identities. Goldin and Rouse (2000), for instance, provides evidence of discrimination against females in symphony orchestra auditions. Bertrand and Mullainathan (2004) presents evidence of discrimination by race in employment interview callbacks. While such discrimination is not the principal focus of my study, the underlying frameworks of discrimination pioneered by Becker (1971) and Arrow (1973) help motivate the empirical analyses in this paper as well.

2 Empirical setting

Because most publicly available databases on VC financing lack biographical information, I construct a novel dataset that includes biographical information for the founders leading startups and the GPs of the VCs financing them. In this section, I (briefly) discuss the structure of the VC financing industry, present basic statistics detailing my dataset, and outline my data sources. For further information on how I construct the dataset, please refer to Internet Appendix A.

2.1 VC financing process

VC financing is a form of private equity financing for startups operating in markets where there is high information asymmetry between firm insiders and outsiders. VCs form a bridge between three parties: startups, early investors, and later investors. They evaluate potential startups and advise the startups they choose to finance. They interact with large investors (limited parters or LPs) who provide the bulk of the capital for this stage of entrepreneurial financing. These investors tend to be institutions such as pension funds and sovereign wealth funds but can also be wealthy individuals or family offices. Finally, VCs also manage the exits from VC financing of successful startups. In this role, they deal with the public equity markets and potential acquirers who provide subsequent financing for the now-matured, successful startups.

The two-sided matching between VCs and startups is highly informal.[14] As this paper focuses on the interaction between VCs and startups, it is important to understand this fact. First, information about startups seeking financing can come from a number of sources: GPs' personal connections, the VC's network of lawyers, investment bankers, accountants, et cetera, and, sometimes, even through formal channels put in place by the VC. Once the startup indicates that it is seeking financing from the VC, analysts at the VC study the startup and provide recommendations to the VC's leadership. The GPs then jointly decide on whether to finance the startup. While this is not always the case, the decision to finance a startup usually needs to be unanimous.[15] Generally, the VC also presents the investment to other VCs to form a syndicate of financiers for the startup. Syndicating the investment helps the VC to confirm its understanding of the investment by comparing its analysis to that of its peers. In such a syndicate, the sourcing VC is referred to as the lead VC.

VCs provide startups with capital in a series of financing rounds. At each financing round, existing and new investors assess the performance of the startup and decide whether

[14] This insight arises from discussions I had with VCs about how they source their portfolios.

[15] Additionally, while analysts provide quantitative analysis of the startups, there is no "cutoff" above which a startup is certain to receive financing or below which it is certain to be rejected.

and on what terms to invest in the startup.[16] The periodic reassessment of startups is one characteristic of VC financing that helps mitigate some of the problems associated with financing high uncertainty, early-stage businesses (Gompers and Lerner, 2004).

2.2 Data

I primarily use two data sources for this research project: VentureXpert and Crunchbase. As Crunchbase is not a well-known data source, I discuss it in some detail below before presenting the dataset I create using the two sources.

2.2.1 Data source: Crunchbase

The Crunchbase database provides data on high-tech startup activity. They aim to be the "master record of data on the world's most innovative companies."[17] A key feature of the database is that it allows anyone to update the database ("CrunchBase is a crowdsourced database, so anyone can edit any profile."[18]). This affords Crunchbase two substantial benefits.

First, Crunchbase's crowdsourcing greatly mitigates concerns of bias arising from a limited number of contributors. Most VC databases arise from data provided by a few sources or, sometimes, just one source (an LP). In 2014 alone, over 80,000 sources edited or contributed to Crunchbase.[19] Additionally, as of mid-2018, over 3,600 VCs, accelerators, and incubators provide up-to-date portfolio company information to Crunchbase directly.[20] These investors provide updates to Crunchbase on a monthly basis in exchange for access to Crunchbase data. Having a wide base of contributors reduces the likelihood of a bias tied to single

[16] This does not imply that VCs do not monitor and advise startups between disbursements. As Gorman and Sahlman (1989) shows, VCs spend a significant amount of time monitoring and advising their investments between financing rounds.

[17] See `https://about.crunchbase.com/about-us`. The webpage was accessed on 27 August 2018 but has been updated since then. Author can provide previous version of webpage upon request.

[18] See `http://info.crunchbase.com/about/faqs`. The webpage was accessed on 3 April 2015 but has been updated since then. Author can provide previous version of webpage upon request.

[19] See `https://about.crunchbase.com/blog/showcasing-our-contributors`.

[20] See `https://about.crunchbase.com/partners/venture-program`.

perspective or few perspectives.

Second, crowdsourcing mitigates issues tied to voluntary disclosure. Most of the existing data on VC-financed firms come from voluntarily disclosed information provided by their VC investors or their limited partners. These data are likely to be biased in a manner that favors the data provider. For instance, in Kaplan and Strömberg (2003), the authors point out that their sample of 119 portfolio companies may be "biased towards more successful investments," given that they find a 25% IPO rate. While this bias does not impact their findings, it highlights the potential issues with voluntary disclosure. Crunchbase data are not sourced solely from VCs, LPs, or portfolio firms. This mitigates concerns about biases stemming from voluntary disclosure by involved parties.

Incomplete observations were a substantial issue for Crunchbase in the past, but the situation has improved considerably in the last few years.[21] Much of the improvement arises from Crunchbase's partnerships with investors and network effects associated with being a leading data source for startup information. The incompleteness that remains arises primarily because personnel information was not added to Crunchbase for some startup or VC. However, as I discuss in Section 2.2.3, the problem is quite minimal at this point.

Furthermore, while crowdsourcing could lead to data quality issues, Crunchbase has a number of mechanisms in place to ensure data quality: proper sourcing of all database alterations, authentication of all data providers' identities, and algorithmic and manual verification of all database changes.[22] In Internet Appendix B, I compare Crunchbase data to two other data sources used in academic studies on entrepreneurial financing. For financing round activity, I compare to VentureXpert and find that, on average, Crunchbase has better early round coverage of startup financing activity than VentureXpert. I also compare IPO exits in Crunchbase to SEC data and find that Crunchbase data on IPOs within the US match

[21] For instance, in the earliest version of this paper, founder gender data was only available for 64% of initial financing rounds and GP gender data for 63% of initial financing rounds. With the most recent version, these statistics have improved to 95% and 96.5%, respectively.

[22] See `http://info.crunchbase.com/about/faqs`. The webpage was accessed on 3 April 2015 but has been updated since then. Author can provide previous version of webpage upon request.

SEC records perfectly. Additionally, Crunchbase also incorporates data on international IPOs. These comparisons, detailed in Internet Appendix B, attest to the high quality of Crunchbase data.

Finally, the reliability of Crunchbase's data is good enough that many well-established organizations frequently use it as a primary source for startup-related activity. For instance, in recent articles, both *The Wall Street Journal* and *The New York Times* employed Crunchbase to provide data on the VC sector (see Back, 2018; Griffith, 2018). Experienced VC investors such as 500 Startups, Accel Partners, a16z, and Draper Fisher Jurvetson partner with Crunchbase for access to its data.[23] Additionally, the database has been used as a data source for teaching startup valuation at respected business schools.[24] Based on this frequent usage by well-established VCs, news media, and business school academics, Crunchbase data are likely as good as proprietary data sources on VC financing, especially when examining early-stage financing.

2.2.2 Data cleanup

To ensure the quality of my sample from Crunchbase, I perform a series of operations that shrink my analysis sample to 2,682 startups. First, I limit my sample of startups to those that have at least one well-established VC as an investor. Proxying "being established" using portfolio size, I flag a VC as being well-established if it is one of the top fifty VCs in VentureXpert by number of financings (as of June 2018). This allows me to exclude hobbyists, garage projects, etc. that may be masquerading as legitimate startups on Crunchbase. In Table 1, we see that there are major differences between projects not financed by well-established VCs and those that are. First, on average, the hobbyist projects have less than half a financing round in the data, compared to over 3.5 financing rounds for startups with one or more well-established VC investors. Second, their rates of successful exit from VC financing are

[23] See `https://about.crunchbase.com/partners/venture-program`.

[24] For example, Jerry Neumann uses CrunchBase to collect financing data on Zipcar for his course at Columbia University. See `http://reactionwheel.net/2018/05/zipcar-fundraising-breakdown.html`.

nearly two-thirds lower than startups with one or more well-established investors. Both of these characteristics indicate that most of these hobbyist "startups" never go beyond the garage project stage. I also find that many of these garage projects do not provide much data, either. For instance, only 28% of them report any founders, as compared to over 80% for startups with well-established investors. Excluding such hobbyist projects reduces my sample to 5,232 startups but allows me to focus on projects that are more representative of high-tech VC-financed startups.

While these startups have financing rounds as far back as 1995, I further limit my analyses to startups with initial financing rounds from 2005 to 2013. I exclude pre-2005 startups because Crunchbase was established in 2005. Since it started in 2005, startups with financings before 2005 reported in Crunchbase may differ systematically from the rest of the startups in the data. As it was not possible to submit data before 2005, all financing rounds prior to that date are provided by contributors filling in historical information. This creates a systematic difference in the types of startups represented before and after 2005. In particular, they are much more likely to be successful in exiting VC financing. Table 2's information on exits (in the last panel) shows that, relative to the 2005 and later sample, the total sample has a much higher success rate (35.8% instead of 27.8%). This implies that the pre-2005 sample has an exit rate of 62%, which is evidence of this backfill bias. By excluding startups initially financed prior to 2005 from my analyses, I avoid problems associated with this bias. As we see in the second column of Table 2's first panel, out of the grand total of 5,232 startups, 1,215 were initially financed prior 2005, and excluding them reduces my sample by 23% to 4,017 startups.

As mentioned above, I also exclude startups initially financed after 2013 from my data because, at the point that I put together the data, startups initially financed after 2013 have not had sufficient time to exit, which makes exits a poor measure of performance for those startups. Comparing pre-2013 (inclusive) and post-2013 startups in the bottom panel of Table 2, we see that the 2005 to 2013 sample has an exit rate of 37.7%. Startups financed

post-2013 have a far lower exit rate of 7.9% (calculated using data from the table). We can also observe the overall downward trend in exit rates over time in Figure 1. Earlier "vintages" of startups have greater likelihoods of exit simply because they have had more time to do so. Therefore, exit is a coarse and noisy measure of performance for late entrants, since it may not pick up "good" startups that simply require more time to exit VC financing. Anecdotally, both Facebook and Google took six years from their initial financing round to their IPO. Four years after their initial financing, neither Facebook nor Google would be considered "good" startups. Excluding the post-2013 startups reduces my sample to 2,682 startups.

While substantially smaller than the Crunchbase universe, this set of startups is the right set to analyze, given the vast number of hobbyist projects masquerading as startups and the data limitations for actual startups initially financed prior to 2005 and after 2013. Note that from here onwards, I provide statistics and analyses on these 2,682 startups, unless I explicitly note otherwise.

2.2.3 Data description

The data I use are summarized in the last column of Table 2. I possess information on each startup's financing rounds, founders, and whether and how the startup eventually exits VC financing. For the startups' 11,311 financing rounds, I know when the financing round was announced, the VCs that were involved in the round, and the GPs of the involved VCs. For founders and GPs, the dataset includes full name and gender. And, for exits, I know the type of exit (IPO or acquisition) and the date of exit announcement.

While all of the startups in the data belong to the high-tech sector, they operate in a number of product markets. Startups report their product markets to Crunchbase and I use these self-reported data to identify the most common product market that each startup reports and use this as the main market in which the startup operates.[25] In Figure 2, we

[25] In identifying their main product markets, I intentionally exclude the "Software" product market category because over half of the startups report that product market, making it a nearly meaningless categorization

can see that nearly one-third of startups operate in the "Internet Services" market. The next biggest market is "Information Technology" at 10%, followed closely by "Health Care" and "Media and Entertainment" at just over 9%. "Commerce and Shopping", "Hardware", and "Financial Services" are all reported by 7% of startups, each. I aggregate the smaller markets into "Other", which include a little over 9.5% of the startups. From this figure, we can observe that most startups in the data are focused on computing and internet, some on pharmaceuticals, and some on manufacturing.

I focus primarily on initial financing rounds involving VCs and, for some analyses, on second VC rounds. We see in Table 2 that initial and second financing rounds are quite similar. There are 1,995 total initial VC financing rounds in 2005 through 2013 and 1,964 second rounds for the same set of startups. Approximately 89% of initial rounds have founder data and 97% have GP data, with 86% having both founder and GP data. For second rounds, gender data is more prevalent, with 94% of rounds having founder data and 98% having GP data (93% have both). The table also shows that there are slightly more VCs in each second round, 2.5 compared to 2.0 in the first round.

Looking at the presence of men and women in the data, it becomes obvious that far fewer women participate in VC-financed entrepreneurship than men. For instance, in Table 3, we observe that there are almost no financing rounds led entirely be female lead GPs (GPs in lead VCs). Approximately 0.2% of VC financing rounds have all female lead GPs. Similarly, only about 3.4% of startups have all female founders. There are far more mixed-gender syndicates: 67% (62%) of initial (second) financing round syndicates have both female and male lead GPs. Gender of startup founders is skewed far more towards all male founders: while 3% of startups have all female founders, under 9% of startups have both female and male founders. The vast majority of startups (nearly 88%) have all male founders.[26]

These gender distributions bear out at the individual level, as well. In Table 4, we observe that there are 3,801 founders in the data. Of these, 243 are female (6.4%) and the rest are

for startups.

[26]This skewness informs this paper's avoidance of linear models in regression analyses, as well.

male. Per startup, on average, there are 0.12 female founders and 1.78 male founders. On the investor side, out of 49,274 GPs in initial financing rounds, 7,106 are female (14.4%). While this is a higher female percentage than we see among founders, as we get closer to the "important" set of GPs, the ratios begin widening. For instance, among lead GPs of initial financing round syndicates, 2,848 out of 25,779 GPs are female (11.0%). Among GPs that are appointed to startups' boards at the initial round, only 30 out of 1,010 appointees (3.0%) are female.[27]. For second VC financing rounds, the disparities are smaller but still large for "important" GPs in each financing round.[28]

3 Overall startup performance

I measure VC-financed startups' performance using exit from VC financing via initial public offering (IPO) or acquisition. The last panel of Table 2 presents overall exit rates for startups based on initial financing year. The last column shows exit statistics for startups initially financed between 2005 and 2013, including both years. These startups have an overall exit rate of 37.7%, with slightly under one-sixth exiting via IPO (5.9%) and the rest exiting via acquisition (31.8%). This five-to-one ratio of acquisition-to-IPO exits is roughly consistent with overall high-tech startup exits reported by the National Venture Capital Association (NVCA). In its 2017 Pitchbook, NVCA reported that there were 446 IPOs and 1,949 acquisitions of VC-financed startups between 2005 and 2013[29], which is quite similar to the ratio I observe.[30]

Looking at trends in exits over time, I find that older startups are more likely to have exited and that there is an upward trend in exits per year at the start of the analysis period

[27] As I point out in the analysis involving board members discussed in Section 6, the low number of female appointees reduces the power of any test that employs it.

[28] While there are more female GPs per round (4.9 versus 3.6), because there are more GPs in total (32 versus 24.7), there are similar proportions of female GPs in the first and second rounds (15.0% versus 14.4%). There is a higher proportion of female GPs in lead VCs in the second round than in the first round, however (15.1% versus 11.0%).

[29] See `http://nvca.org/download/5080/`.

[30] This also confirms that the procedure I employ to gather data does not bias the startup sample.

and a downward trend near the end. We can see this in Figure 1, which shows the percentage of startups that have exited, overall and via IPO and acquisition, for each "vintage" year of initial financing from 2005 to 2018. The overall downward trend in exits is because later vintages of startups have less time to exit (as discussed earlier). Examining trends in exits year-by-year in Figure 3, we see that, from 2005 to 2014, the number of exits is almost monotonically increasing for overall exits and exits via IPO and acquisition. This is primarily because I exclude startups with initial financing years prior to 2005, so the startups in the data slowly begin exiting in this period. There is a slight drop in 2011 to 2013, but it is quite small, especially in comparison to the general trend in the period. The slight dip coincides with the passing of the Jumpstart Our Business Startups Act (JOBS Act) in September 2012, which had implications for private financing of businesses.[31] In the latter part, 2014 to 2017, there seems to be a sharp drop in exits, but this is driven primarily by the spike in exits in 2014. Excluding 2014, we see that exits are relative stable between 60 and 90 per year. Again, we observe that acquisitions are far more prevalent than IPOs.[32]

While exit from VC financing is often used as a measure of performance in the VC literature[33], it cannot distinguish between exits that provide large versus small returns on VC investment. Returns cannot be calculated for startups in the data because of a lack of information about the VC financing contracts offered to startups.[34] Hochberg et al. (2007) provides some assurance that, at the fund level, exit rates are positively correlated

[31] Note, however, that the SEC began enforcing the relevant parts of the JOBS Act in 2016, not 2012. For more information, refer to the SEC's press release on 30 October 2015, 2015-249, available at `https://www.sec.gov/news/pressrelease/2015-249.html`.

[32] The greater prevalence of acquisitions is also consistent with IPOs only being available as a form of exit for exceptionally high quality startups.

[33] For instance, Hochberg et al. (2007) uses portfolio firm exits via IPO or acquisition to measure fund performance. Gompers et al. (2010) uses exits via IPO to measure entrepreneur success (and find that results are similar if they include acquisition as a success). Nanda et al. (2020) uses exits via IPO to measure VC performance. Phillips and Zhdanov (2017) provides evidence that VCs depend on active M&A markets to facilitate successful exits.

[34] In order to calculate returns for the initial financiers' investment, the empiricist needs to know not only the contract details for the initial financing but also for all intermediate investments in the startup (i.e., the entire term sheet for the startup), as each of those investments may dilute the stake of the initial financier in the company. This makes it even harder to calculate returns on investment for the VC financiers of these startups.

with returns: based on Freedom of Information Act requests, they find a correlation of 0.42 between exit rates (via IPO or acquisition) and funds' IRRs. Given the lack of data necessary to calculate returns at the startup level, exits are the best measure of startup performance available.

4 Founder gender-based performance gap

Splitting startups by founder gender, I find that there is a substantial difference in the average performance of female- and male-led startups. As we see in Table 5, 33% of female-led startups (i.e., startups with one or more female founders) successfully exit VC financing whereas nearly 41% of male-led startups have successful exits.[35] This performance gender gap of 8 percentage points is large, indicating a 20% lower exit rate for female-led startups, and statistically significant with a p-value of 0.028.

I confirm this performance gap between female- and male-led startups using logistic regression analysis. In the first two columns of Table 6, I examine likelihood of success, in column (1), without any additional controls or fixed effects and, in column (2), with initial financing year fixed effects, product market fixed effects, and controlling for the amount raised in the initial financing round. Across both specifications, I find consistent evidence that female-led startups are approximately 40% less likely to successfully exit VC financing than male-led startups. To my knowledge, this is the first study to document this performance gap between female- and male-led VC-financed startups.[36]

Examining the performance gender gap further, I find that the gap persists across most financing years, with the exception of 2009. In Figure 4, I plot the likelihood of success for female- and male-led startups against the startups' initial financing year. I find that

[35] If I define female-led startups as startups with *only* female founders, I am left with only 3% of my sample (82 startups), as I document in Table 3. As my focus is on the effect of female presence on founder (and, later, financier) teams, my current definition of "female-led startups" is appropriate and provides greater statistical power for empirical tests.

[36] In a research-based setting in the life sciences, Ding et al. (2006) documents a similar patenting gap between female and male scientists.

female-led startups have worse performance in every initial financing year except 2009. The 2009 cohort of female-led startups perform remarkably better than the male-led startups and almost better than every other cohort in the figure.[37]

I find that the gap is present in almost all product markets. In Figure 5, I plot the performance of female- and male-led startups for each product market. Overall, the gap is clearly present in most product markets. It is particularly large in "Biotechnology" and "Internet Services" product markets. The gap reverses for two product markets: "Commerce and Shopping" and "Financial Services". Aside from these two exceptions, we see strong evidence that the peformance gender gap exists in most product markets.[38]

There are a number of potential reasons that female-led startups perform worse than male-led startups. Given the technical nature of the high-technology sector, the large gap in the far right tail of quantitative ability posed by Ellison and Swanson (2010) may explain the performance gap we observe. That paper documents that there are 2.1 males for every female who achieves a perfect score on the math SAT. The same paper also shows that the ratio of males to females is 9:1 in the top 1% of scores in the American Mathematics Competition. Another potential reason for the gap is differing reactions to competition among men and women, as discussed in Croson and Gneezy (2009). That survey paper discusses experiments and field studies that show that men increase effort in competitive environments while females do not do so. If men respond with greater effort to competition whereas women do not, the performance gap documented here could be explained by this difference, given competition is ever-present in the VC-financed startup ecosystem. Besides these, there may be a number of other reasons. In the following analyses, I study whether, putting aside potential intrinsic differences between females and males, VC financing may

[37] Many of the startup cohorts in this figure are small in size, so determining statistical difference between cohorts is difficult.

[38] In unreported analysis, I test for any variation in the presence of female lead GPs in initial financing rounds across these product markets in order to test whether they correlate with the performance gaps reported here. However, I find no statistical difference in the presence of female lead GPs. The "Hardware" and "Mobile" sectors have slightly lower proportions of lead VCs with female GPs, but these differences are not statistically significant.

also affect the performance gap in VC-financed startups.

5 VC effect on performance gap

VCs could influence the performance gender gap both in their evaluative and advisory roles within the startup ecosystem. In their evaluative role, if some VCs choose to invest in worse female-led startups, they could give rise to the observed gap by reducing the quality of the set of financed female-led startups. In their advisory role, if some VCs do not (or are unable to) guide female-led startups towards success as well as male-led startups, they could create (or widen) a gap in the performance of the two groups of startups.

To study the potential influence of VC financing on the performance gap, I separate syndicates based on whether they have female general partners (GPs) in the lead VC. I separate syndicates based on lead GP gender composition because syndicates with female lead GPs and those with all male lead GPs likely have heterogeneous effects on the performance gap. If VCs have difficulty choosing high quality female-led startups, female GPs may have less difficulty choosing them. For instance, female GPs may be better able to evaluate projects led by female entrepreneurs or information may transfer more easily between founders and GPs of the same gender. Such effects, termed gender homophily, have been documented within larger organizations (e.g., Ibarra, 1992). Alternatively, female GPs may be partial towards female founders and preferentially finance female-led startups. If VCs, generally, have difficulty advising female-led startups, VCs with female GPs may experience such difficulties less intensely. For instance, founders may be more amenable to advice coming from a GP of the same gender as them. Female GPs may better understand the difficulties that female founders face. Or female GPs may offer more useful connections to female founders. For all these potential reasons, if financing affects the performance gap, we should expect differing impacts across syndicates with and without female lead GPs.

I focus on lead VCs because the lead VC is always involved in both roles of the VC

syndicate. Other VCs may not be involved in evaluating or advising the startup. I could further narrow the focus of the analysis to the gender of GPs appointed to a startup's board. However, by focusing exclusively on board appointees, I would exclude non-board appointees within the lead VC who may have played a role in evaluating which startups to finance. Having talked to some GPs, I have learned that the decision to invest in a startup is almost always taken jointly by all GPs of a VC. [39] Additionally, board members may be appointed not because of their ability to advise financed startups but for lending credibility to a startup or for their business contacts. Given the shortcomings of using all GPs and using board appointees only, I focus my analyses on lead GPs.

Using logistic regressions, I find strong evidence of a difference in the founder gender-based performance gap based on whether the initial financing syndicate has a female lead GP. The last five columns of Table 6 present the results of logistic regressions of the likelihood of successful exit on indicators of female founder presence and female lead GP presence in the syndicate, as well as the interaction of the two indicators. The five columns include different sets of controls and fixed effects: no fixed effects or controls, initial financing year fixed effects, product market fixed effects, amount raised in the initial financing round, and both fixed effects and a raised amount control. The exact specification of the regression, excluding fixed effects and controls, is

$$\Pr\left(\text{exit}_i = 1\right) = F\left(\gamma_1 fem_i^f + \gamma_2 fem_{i,r}^v + \beta\left(fem_i^f \times fem_{i,r}^v\right)\right), \tag{1}$$

where exit_i is exit from VC financing for startup i, $F(\cdot)$ is the logistic function, fem_i^f is an indicator for startup i having 1 or more female founders, and $fem_{i,r}^v$ is an indicator for startup i's initial financing round r syndicate having 1 or more female lead GPs. I present and discuss the coefficients for these regressions (and all other logistic regressions in the paper) as odds ratios, wherein the coefficient states the multiplicative change in the likelihood of success for

[39] While I do not use board appointees in the primary analysis for the stated reasons, I do employ board appointee data in Section 6 to explore reasons for the performance gender gap differences I discover.

every unit increase in the explanatory variable. In the first row of the top panel of columns 3 through 7 of Table 6, we see that female-led startups initially financed by syndicates with no female lead GPs are 62 to 70% less likely to successfully exit VC financing. This is not only statistically significant (with p-values below 0.01 in three of the specifications), but also an economically meaningful gap. It implies that female-led startups financed by syndicates with all male lead GPs succeed at one-third the rate of male-led startups. As we observe in the first row of the second panel of the table, female-led startups' performance is statistically indistinguishable from that of their male-led counterparts when financed by syndicates with female lead GPs. There is no performance gap among startups initially financed by syndicates with female lead GPs. These two results of Table 6 are illustrated in Figure 6, which confirms that the performance gap is virtually non-existent among startups initially financed by syndicates with female lead GPs whereas it is large among startups financed by syndicates will all male lead GPs.

The regression results also indicate that the performance gap difference arises from better performance among female-led startups rather than worse performance among male-led startups. In the bottom row of the second panel of Table 6, I show that female-led startups are 2.1 to 2.5 times more likely to successfully exit when initially financed by syndicates with female lead GPs. This improvement across the financing syndicates is, again, economically large and statistically significant in all specifications. Additionally, the second coefficient of the top panel shows that male-led startups have similar performance in both groups of syndicates. Again, Figure 6 illustrates these points, showing that the relative performance of female-led startups is dramatically better among syndicates with female lead GPs whereas male-led startups' performance is essentially unchanged.

5.1 Alternative hypotheses

While I ascribe the performance gap to VC actions above, there are two competing hypotheses that could drive the observed gap in female- and male-led startups performance. First,

high quality female-led startups may preferentially seek financing from syndicates with female lead GPs. Second, presence of female lead GPs may be correlated with something else about VCs that drives differences in the performance gap. In this section, I study these two alternative hypotheses and provide evidence that they do not, by themselves, explain the difference in performance gaps between syndicates with and without female lead VC GPs and, therefore, cannot drive the performance gap alone.

5.1.1 Founder preferences

The better performance of female-led startups financed by syndicates with female lead GPs may be completely driven by higher quality female-led startups preferentially applying to them for financing rather than being the result of differences in VCs' ability to evaluate and/or advise female-led startups. If more of the better female-led startups seek financing from syndicates with female lead GPs, the overall likelihood of success for these female-led startups will be higher than for female-led startups financed by syndicates without female lead GPs, which, in turn, would show up as a narrower performance gap among startups financed by syndicates with female lead GPs. This is what I refer to as the "founder preference" hypothesis and it may completely explain the performance gap differences I present in this paper.

To study whether founder preference drives the aforementioned findings in this paper, I exploit the different timings of startup and VC actions immediately prior to a financing round. After startups request financing (and before the VC decides to finance it or not), founders are effectively "locked in" and can no longer adjust their choices if the VC's leadership changes. For instance, if VCs require 90 days to assess a startup, then startups submit their financing requests 90 days before a potential financing round announcement. As a result, any lead VCs' GP entries or departures in those 90 days *cannot* affect the startup's choice of VC financier, as they occur during the founders' "locked in" period. On the other hand, GP entries and departures in that period change the leadership of the VC and *will*

affect its decision-making. In Figure 8, I present the timeline visually, with T referring to the announcement date for the financing round and t_a referring to the amount of time VCs require to assess a startup (e.g., 90 days). In the interval between $T - t_a$ and T, founders are "locked in" in terms of their VC choice whereas lead VCs assess the startup requesting capital.[40]

To test if founder preferences drive this paper's findings, I compare the performance gap between startups financed by syndicates where female lead GP presence does not change in the "locked in" period before the round and startups financed by syndicates where female lead GP presence either increases or decreases in the "locked in" period.[41] As startups are unable to change their choices in the "locked in" period, if founders' preferences entirely determine the performance gap difference, changes in the lead VC's gender composition during the "locked in" period should not affect the the performance gap between these two sets of startups. On the other hand, if the performance gap differences are affected by VC actions, we should find a difference in the gap between the two sets of startups. The formal specification for this logistic regression analysis is:

$$\begin{aligned}\Pr\left(\text{exit}_i = 1\right) = F\Bigg(&\gamma_1 fem_i^f + \gamma_2 dfem_i^{v-} + \gamma_3 dfem_i^{v+} + \\ &\beta_1\left(fem_i^f \times dfem_i^{v-}\right) + \beta_2\left(fem_i^f \times dfem_i^{v+}\right)\Bigg),\end{aligned} \tag{2}$$

where all previously defined variables retain their definitions and $dfem_i^{v-}$ ($dfem_i^{v+}$) is an indicator for whether the proportional representation of female lead GPs in syndicate v reduced (increased) in the 90 days prior to startup i's initial financing round. In the above regression, if founder preference is solely responsible for the performance gap difference, β_1 and β_2 should both be 1. Alternatively, if VCs play a role in the performance gap difference,

[40] In the period prior to $T - t_a$, startups are still shopping around for the best VC to approach for capital. In that period, founders' preferences likely matter tremendously.

[41] In the results provided here, I run the analysis assuming a "locked in" period of 90 days (i.e., $t_a = 90$). However, I perform the same test with $t_a \in \{30, 45, 60\}$, as well, and find no substantive differences in the results.

a decrease in female lead GP presence should widen the performance gap (i.e., β_1 should be less than 1) and/or an increase in female lead GP presence should narrow the performance gap (β_2 should be greater than 1).[42]

In Table 7, I show that my empirical test should have sufficient statistical power as there is substantial entry and departure of lead GPs in the "locked in" period. Focusing on the analysis subgroup (syndicates with female lead GPs at the start of the period), we observe that about two-thirds (575) of the syndicates experience no change in female lead GP presence in the "locked in" period, approximately 22% (191) have a net loss of female lead GPs in that period, and approximately 10% (88) increase their female lead GP representation. These numbers indicate that my empirical test should have sufficient power to identify differences in the performance gap, if they exist.

As I show in Table 8, startups and financing syndicates in the three groups of financing rounds are similar on key observable dimensions. Startups financed by syndicates with no changes, increases, or decreases in female lead GP representation have similar overall likelihoods of success and presence of female founders. Similarly, VCs in those three syndicate groups have similar likelihoods of having female lead GPs at the start of the "locked in" period. These comparisons indicate that there are no major observable differences between the three groups of financing rounds that may give rise to endogeneity issues for the analysis.

In Table 9, I present the results of the regression detailed in Equation 2. The first column results are without any fixed effects or controls whereas the second column has initial financing year and product market fixed effects and controls for the amount raised in the financing round. Both columns include all startups financed by syndicates with female lead GPs at the start of the "locked in" period. Focusing on the second column, in the top row, we see that there is no performance gap for startups financed by syndicates (with female lead GPs) that experience no change in lead GP gender composition. Among syndicates where female lead GP presence reduces, we observe, in the fourth row, that the performance gap

[42] Note that this test necessarily excludes startups financed by syndicates with all male lead GPs at the start of the "locked in" period, as those syndicates cannot reduce their female lead GP presence.

between female- and male-led startups widens by 78 to 83%. The first row of the second panel shows that female-led startups financed by syndicates that lose female lead GPs perform 77 to 81% worse than female-led startups financed by syndicates with no change. Both of these findings are statistically significant. The wider performance gender gap and worse female-led startups' performance when female lead GPs' presence in the syndicate declines implies that VCs play a role in the performance gender gap. Founder preferences do not, on their own, explain the difference in performance gender gap between syndicates with and without female lead GPs.

Among syndicates where female lead GP presence increases, we observe, in the fifth row of the first panel of Table 9 that the performance gender gap does not narrow further. Similarly, the second row of the second panel shows that female-led startups' performance does not improve with greater female lead GP presence. This asymmetry between increases and decreases in female lead GP representation is likely driven by the different implications of gaining versus losing a female lead GP. When a female lead GP departs a syndicate, it often means the syndicate no longer has any female lead GPs at all[43], whereas when a new female GP is brought on by the lead VC, it adds on to an already-existing base of female lead GPs. The stronger findings for reduced female lead GP presence is consistent with the much larger marginal effect of losing the only female perspective when assessing startups than of adding to already-present female perspectives.[44] Overall, these findings imply that the performance gap difference between syndicates with and without female lead GPs cannot be explained by founder preference alone.

5.1.2 Lead GP gender covariates

VC size, experience, and age all correlate with female lead GP presence, with larger, more experienced, and older VCs being more likely to have female GPs. Figure 7 presents the

[43] In Table 4, I report that there are 2.2 female lead GPs in a typical initial VC financing round.

[44] This could also be interpreted as evidence of the declining marginal impact of female lead GPs on female-led startups' performance.

(standardized) distributions of these characteristics for initial financing rounds with and without female lead GPs.[45] The overall lack of female GPs in VCs (Table 2 reports that 2.2 out of 20.2 GPs in lead VCs are female in initial VC financing rounds) tells us that the large difference in the number of GPs for lead VCs with and without female GPs is mechanical. Also, as VCs tend to add GPs over time[46], the differences in lead VCs' experience and age across female lead GP presence can also be explained by this mechanical relationship.

Given these strong correlations, it is possible that experience, age, or size drive the narrower performance gender gap for startups with female lead GPs that we observe in Table 6. For instance, it could be argued that more experienced VCs are better at evaluating or advising female-led startups simply because they have prior experience with female-led startups and already know and can avoid potential pitfalls when financing them.

To test whether lead VC age, size, and experience covariates explain the difference in the performance gender gap between startups financed by syndicates with and without female lead GPs, I execute the performance gap difference analysis using an orthogonalized version of the female lead GP presence variable. I build the orthogonalized measure of female lead GP presence in two steps. First, I regress the number of female lead GPs in an initial financing round on lead VC age, size, and experience and extract the residual from that regression.[47] Next, I use this residual to build an indicator variable for whether a financing syndicate has 1 or more female lead GPs, independently of VC age, size, and experience. I then repeat my primary analyses, replacing the female lead GP explanatory variable with this residual, and present the results in Table 11. Comparing Table 11 to Table 6, I find that, although there is slightly less narrowing of the gender gap when startups are financed by syndicates with female GPs (as measured by the new variable), the narrowing is still quite economically

[45] Other syndicate characteristics do not correlate strongly with female GP presence in the lead VC, so I omit them from the figure (e.g., financed startup female founder presence, financed startup product market, growth of startups financed per year, etc.).

[46] The correlations between these three characteristics – size, experience, and age – range between 0.45 and 0.69 among lead VCs of initial financing rounds in the data.

[47] In formal notation, I extract the residual of the following regression: $\#\text{ fem lead GPs}_{i,r} = a + b_1 \times \text{lead VC age}_{i,r} + b_2 \times \text{lead VC size}_{i,r} + b_3 \times \text{lead VC experience}_{i,r} + \epsilon_{i,r}$.

large (the gap is between 2.2 and 2.5 times narrower for startups financed by syndicates with female lead GPs) and statistically significant. There is, again, no performance gap among startups financed by syndicates with female lead GPs and female-led startups generally perform better when financed by syndicates with female lead GPs. These findings imply that the observed difference in the performance gap is not due to a correlation of lead VC age, size, or experience with female lead GP presence.

5.2 Time and industry-based patterns

The difference in the performance gap seems to narrow a bit over time. Splitting the financed startups in two by the year of initial financing, 2005-2008 and 2009-2013, Figure 9 depicts the performance of female- and male-led startups when financed by syndicates with female lead GPs, relative to female- and male-led startups, respectively, financed by syndicates without female lead GPs. The figure shows that there is a dramatic improvement in female-led startups' performance when financed by syndicates with female lead GPs in 2005-2008 (they are three times more likely to exit) whereas there is nearly no difference in the performance of male-led startups in the same period. The period 2009-2013 is similar, except that the improvement of female-led startups' performance is a bit smaller (they are two times more likely to exit with female lead GPs). While the data in Figure 9 are point estimates, they suggest that the difference in the performance gap has narrowed somewhat over time.

The narrower difference in the performance gap in the second half of the period could arise because startups from later years have shorter exit windows. A narrower gap provides a smaller scope for improvement, which would explain the smaller improvement for female-led startups in the latter period in Figure 9. While there is no evidence of a narrower performance gap for younger startups in Figure 4, it may simply not be visible in an 8-year period. It is tempting to assign the narrowing difference to an erosion of financing inefficiency over time, but there is insufficient evidence to support such a hypothesis over a mechanical explanation, such as an attenuation of the gap due to shorter exit windows for second half

startups.

The difference in the performance gap between the two groups of syndicates varies somewhat across product markets. Figure 10 depicts the performance of female- and male-led startups financed by syndicates with female lead GPs relative to startups financed by all-male VC syndicates for each product market. We see that startups in the "Commerce and Shopping" and "Financial Services" markets show a dramatic improvement of female-led startups' performance (3 to 4 times more likely to succeed with female lead GPs). Recall that these two markets were also the ones with reversed performance gaps overall, which suggests that the female lead GP impact may be heavily impacting the aggregate performance gap in these markets. "Health Care" tells a different story: male-led startups perform worse with financing from syndicates with female lead GPs (half as likely to succeed) whereas female-led startups perform similarly with both types of syndicates. These markets were the only ones sufficiently large to provide disaggregated performance comparisons. For all other startups, which are grouped together to allow for statistical analysis, I find that the relative performance of female-led startups improves (4 times more likely) and that of male-led startups is unchanged when they are financed by syndicates with female lead GPs. Overall, the difference in the performance gap varies somewhat, depending on the startup's product market but the overall impact of female GPs is similar.

6 Reasons for the VC effect

In this section, I compare the importance of female GPs' ability in evaluating and advising female-led startups via four sets of analyses. Together, these four tests' findings are consistent with the hypothesis that female GPs are better at evaluating good female-led startups.

6.1 Evaluation versus advising

VCs have two main roles as financiers of entrepreneurial projects: evaluating prospective investments in startups and advising startups they invest in. In which of these roles do VCs actions impact the performance gender gap? In the tests I present below, I find that female GPs possess an advantage in evaluating female-led startups. On the basis of these findings, I conclude that VCs' ability to evaluate female-led startups impacts the performance gender gap among startups.

6.1.1 Initial versus second rounds

I compare initial and second financing rounds' founder and GP genders' impact on success to take advantage of the differing importance of VCs' evaluative role between them. When investing in an initial financing round, lead VCs expend substantial effort in evaluating the financed startup. By contrast, in a startup's second round, there is far less effort required to evaluate the startup. The syndicate (in particular, the lead VC) must still perform its due diligence in making the investment, but the startup has already been vetted carefully by VCs once before and received financing, which is a strong signal of quality and reduces the effort required to evaluate the startup. The advising role, on the other hand, requires similar effort levels for initial and second round financiers. By exploiting this difference in the relative importance of evaluation and advising across the two rounds, I can assess how female GPs narrow the performance gap. In my analysis, I compare initial and second round impact differences using a logistic regression of success on indicators for female presence as a startup founder, female presence as a lead GP in the financing syndicate, and second VC-financed round, along with their interactions (including a triple-interaction of all three

indicators). The regression specification, without controls or fixed effects, is:

$$\Pr\left(\text{exit}_i = 1\right) = F\Bigg(\gamma_1 fem_i^f + \gamma_2 fem_{i,r}^v + \gamma_3 rnd2_{i,r} + \beta_1\left(fem_i^f \times fem_{i,r}^v\right) + \beta_2\left(fem_i^f \times rnd2_{i,r}\right) + \beta_3\left(fem_{i,r}^v \times rnd2_{i,r}\right) + \delta\left(fem_i^f \times fem_{i,r}^v \times rnd2_{i,r}\right)\Bigg), \tag{3}$$

where all variables previously defined in Equation 1 retain their previous definitions and $rnd2_{i,r}$ is an indicator for whether financing round r for startup i is a second round. If the difference in the performance gap between the two sets of syndicates widens further in subsequent rounds for syndicates with female lead GPs (i.e., the odds ratio for δ is larger than one), female GPs narrow the performance gap by improving VC advising of female-led startups. Alternatively, if the difference is the same or narrower in subsequent rounds (i.e., the odds ratio for δ is less than or equal to one), female GPs narrow the performance gap by improving VC evaluation of female-led startups.

The regression analysis indicates that female lead GPs evaluate female-led startups better.[48] I show the results of the analysis, with standard errors clustered by startup, in Table 12. The coefficient on the triple interaction of the three indicator variables (the last row of the first panel of the table) presents the change between the first and the second financing round in the performance gap difference between syndicates with and without female lead GPs. The coefficient indicates that the performance gap difference shrinks by 71% from the first round to the second round and that the change is statistically significant. The smaller performance gap difference in the second round tells us that syndicates with female lead GPs improve female-led startups' performance primarily in the initial financing round. Given the greater emphasis on evaluation in the first round, this indicates that syndicates with female lead GPs narrow the performance gender gap by evaluating female-led startups better.

[48] As discussed in Section 2.2.3, initial and second financing rounds are fairly similar in terms of observable characteristics like female GP presence, syndicate size, etc.

The regression also shows that the shrinking of the performance gap difference in the second round arises from startups financed by all-male lead GP syndicates. In the first row of the second panel of Table 12, we see that the performance gap for such syndicates is 69% narrower in the second round than in the first round. This narrowing is statistically significant and tells us that all-male lead GP syndicates' performance gap is much narrower when evaluation does not matter as much. Figure 11 presents the same finding visually. The dark-hued bars in that figure show a large performance gender gap among startups financed by all-male lead GP syndicates in the first round and a negative performance gap in the second round for these startups.

Finally, the regression also shows that the performance gender gap among startups financed by syndicates with female lead GPs does not narrow further in the second round. The bottom row of the second panel of Table 12 shows that there is no statistically significant change between rounds in the performance gender gap among startups financed by syndicates with female lead GPs. The light-hued bars in Figure 11 illustrate this lack of change of the performance gap, as well.

Jointly, these findings imply that VCs' ability to evaluate female- and male-led startups influences the performance gap. Most importantly, overall, we see a narrower performance gap difference in the second round, where evaluation is relatively less important than advising. Additionally, there is no difference (improvement) in the performance gap for startups financed by syndicates with female lead GPs from the first to the second round. As advising is relatively more important in the second round, this suggests that female GPs' main advantage is in evaluation rather than advising. All of these findings are consistent with the interpretation that female lead GPs are better at evaluating female-led startups, which implies that VCs' evaluative abilities influence the performance gender gap.

6.1.2 Founder gender-based differences in financing

I find that syndicates with female lead GPs finance lower proportions of female-led startups, which, again, suggests that they are better at evaluating female-led startups. We see this in Table 13, which shows the number of female- and male-led startups financed by syndicates with and without female lead GPs, as well as the percent of financed startups that are female-led for both groups of syndicates. Female-led startups compose 11.7% of the portfolio of syndicates with female lead GPs and 15.8% of the portfolio of syndicates without female lead GPs. This difference is economically large (all-male lead VC syndicates have 30% more female-led startups in their portfolios) and statistically significant. Under some reasonable assumptions about VC rationality and deal flow to VCs[49], this impliess that syndicates with female lead GPs are more selective in the female-led startups they choose to finance, which would suggest that they are better at evaluating female-led startups than syndicates without female lead GPs. But this is only suggestive, as there could be other reasons for the difference in the portfolio composition of the two groups of syndicates.[50] While these differences in portfolio composition only suggest that syndicates with female lead GPs are better at evaluating female-led startups, they are consistent with the much more impactful findings of the previous analysis.

6.1.3 Board member advising impact

I examine the interacted impact of founder and VCs' board appointees' gender on exit to study VCs' advising role more directly. Board appointees are directly tasked with advising startups. Therefore, I use this greater focus of board appointees on advising to test whether

[49] We must assume that investors choose to finance projects in decreasing NPV order and projects that arrive to the two sets of syndicates are not systematically different in quality.

[50] For instance, all-male lead VCs may be more concerned about the optics of a portfolio dominated by male-led startups. Or, as has been reported in the media, male GPs may extract non-pecuniary benefits from financing female-led startups. The 2018 survey of female founders conducted by YCombinator on sexual coercion and assault by angels and investors provides some insight into this issue. See `https://blog.ycombinator.com/survey-of-yc-female-founders-on-sexual-harassment-and-coercion-by-angel-and-vc-investors` for details.

female financiers' advising plays a role in the performance gender gap difference.[51] Using the framework from Equation 1, but defining $fem^v_{i,r}$ as the presence of a female board appointee for startup i in the initial financing round r, I test the interacted impact of founder and VCs' appointees' gender on exits.

Before presenting the results, it is important to note that this test has low statistical power. As we observe in Table 4, only 30 of the board appointees I observe are female. Even though my sample is large, the low proportion of appointees that are female weakens the statistical power of the following tests.

I present the results of my board appointee regression in Table 14. Based on the first row of the first panel of the table, we see that female-led startups do not perform significantly worse than male-led startups when their initial financing syndicates place male GPs on their boards. Second, when a female GP is placed on their board, female-led startups do not perform worse than male-led startups either.[52] This suggests there is no difference in the performance gaps of startups based on board appointees' gender. As board appointees are crucial as advisors for financed startups, these findings suggest that advising female-led startups better is not female GPs' advantage and VCs' advising does not impact the narrower performance gender gap. This test is likely lacking in statistical power but, again, is consistent with the findings of the previous analyses indicating the primacy of VCs' evaluation role in their effect on the performance gender gap.

6.1.4 Improved connections through female GPs

As part of their advising role, VCs provide startups with connections to useful people and organizations (e.g., other investors, lawyers, investment bankers, etc.). Some surveys suggest

[51] Note that board appointees also play a role in evaluating the startup. But, by excluding the vast majority of lead GPs, who are all involved in evaluation, I remove much of the impact GP gender could have on evaluation in this test.

[52] Moreover, although neither estimate is statistically significant, we find that the gap with female board appointees is much larger (77% worse performance) than among startups with all male board appointees (15% worse). While this is not conclusive, it suggests that, given sufficient statistical power, we may find that female board appointees are detrimental to female-led startups' success.

that one of the weaknesses of the VC pipeline for female founders is that they do not benefit as much from these connections as male founders.[53] One reason that the performance gender gap may be narrower for syndicates with female lead GPs is that female GPs provide female founders with greater access to female mentors in the future. I am able to test whether female-led startups financed by syndicates with female lead GPs are more likely to be subsequently financed by syndicates with female lead GPs as well. A positive finding would suggest that female GPs help female founders secure financing from other female financiers in the future, who ease the mentoring issues for these founders and improve the performance of the startup.

Female GPs do not provide female founders with additional connections to other female GPs. Table 15 shows the results of logistic regressions where I regress the likelihood of being financed in a subsequent round by a syndicate with female lead GPs on indicators for the presence of a female founder and presence of a female lead GP in the initial financing syndicate as well as the interaction of the two indicators. The third row of coefficients shows that female-led startups are no more likely to receive subsequent financing from syndicates with female GPs than male-led startups financed by syndicates with female lead GPs. This indicates that female founders paired with female GPs do not have additional female investors moving forward, suggesting that the performance gap difference is not driven by more useful connections. Overall, the findings in this section, especially the test comparing performance gap differences between the initial and second financing rounds, indicate that female lead GPs are better at evaluating female-led startups. This, in turn, implies that VCs' evaluative abilities impact the observed performance gender gap.

[53]For instance, female founders often report a lack of mentors (Robb et al., 2014).

7 Conclusion

In this paper, I explore the effect of gender on the performance of VC-financed entrepreneurship. I find that there is a large performance difference by entrepreneur gender: male-led startups perform 24% better than female-led startups. I study whether VC financiers may be responsible for this performance gap by comparing the gap between startups financed by syndicates with and without female lead GPs. I find that startups financed by syndicates with all male lead GPs have a large performance gap whereas startups financed by syndicates with female lead GPs have no performance gap at all. Furthermore, exploiting the timing of founder and VC actions, I am able to rule out alternative explanations for the performance gap differences tied to female founder financing preferences. Finally, through a series of tests, I find that syndicates with female lead GPs are better able to evaluate female-led startups, which directly impacts the difference in the performance gap between the two sets of syndicates. Overall, these findings imply that VC financing influences the performance gap between female- and male-led startups, primarily through differing abilities of VCs to evaluate female-led startups.

These findings are important for at least two reasons. First, a VC contribution to the performance gap means that some intrinsically valuable female-led startups do not succeed because of VC financing. If LPs choose to reduce their investment in VC as a result, this may have large negative externalities for the VC sector. Second, if some VCs hurt female-led startups' performance, women may be less likely to lead VC-financed projects. This, in turn, would mean that some valuable projects are never undertaken due to the possibility of VC-induced failure.

Such reduced female participation in entrepreneurship and business is the focus of an important debate in policy circles. Most of these debates focus on increasing the appeal of entrepreneurship for women.[54] This paper's findings suggest a complementary strat-

[54]See, for instance, the 2015 Issue Brief by the White House, "Expanding Opportunities for Women in Business" (`https://obamawhitehouse.archives.gov/sites/default/files/docs/women_in_business_issue_brief_final_nonembargoed.pdf`).

egy for increasing female participation: increase female participation as VC partners, especially in early financing rounds, where their advantage in evaluating female entrepreneurs' projects plays a larger role. This strategy may improve not only women's participation in entrepreneurship, but also their success.

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Tables and Figures

Table 1. Differences between startups with and without financing from major VCs. This table presents differences between startups that have received capital from one of the top 50 VCs (by total financing amount) in at least one financing round to those that have not received any capital from those VCs. The first and second columns present statistics for startups with and without one or ore financing rounds with top 50 VCs, respectively, with standard deviation presented below each statistic in parentheses. The last column of the table compares the statistics presented using a t-test on the difference in means, with standard errors presented in parentheses below.

	Fin'd by a top 50 VC		
	Yes	No	Diff.
Num funding rounds	3.669	0.325	3.344***
	(2.496)	(0.912)	(0.013)
% successful exits	36.015	13.449	22.566***
	(48.009)	(34.118)	(0.475)
% with 1+ founders	81.316	28.431	52.885***
	(38.982)	(45.108)	(0.625)
Num founders	1.734	0.459	1.275***
	(1.339)	(0.870)	(0.012)

Table 2. Data summary. This table presents useful statistics for the data used in this paper. The three columns of data refer to the subset of observations over which the statistic is calculated: "All" refers to the complete sample, "2005 on" refers to startups with initial financing rounds in or after 2005, and "2005 to 2013" refers to startups with initial financing rounds between 2005 and 2013, including both end years.

	All	2005 on	2005 to 2013
Startups	5,232	4,017	2,682
with founder data	80.4%	90.4%	89.9%
with female founders	9.7%	11.7%	11.0%
Financing rounds	19,076	14,595	11,311
VC financing rounds	14,720	11,318	8,647
with founder data	86.9%	95.1%	94.9%
with GP data	96.6%	96.5%	96.5%
with founder & GP data	84.0%	91.8%	91.7%
Initial VC financing rounds	3,964	3,036	1,994
with founder data	79.6%	90.3%	88.8%
with GP data	96.7%	96.6%	96.9%
with founder & GP data	77.1%	87.3%	86.2%
Second VC financing rounds	3,583	2,781	1,968
with founder data	85.8%	95.0%	94.4%
with GP data	97.5%	97.7%	98.1%
with founder & GP data	83.8%	93.0%	92.7%
VCs per VC financing round	2.718	2.731	2.707
initial round	2.074	2.096	1.970
second round	2.625	2.633	2.490
% of startups successfully exited	35.8%	27.8%	37.7%
via IPO	4.9%	4.5%	5.9%
via acquisition	30.9%	23.4%	31.8%
Duration of VC financing	6.04y	4.99y	5.30y
for IPO startups	5.82y	5.21y	5.91y
for acquired startups	6.08y	4.95y	5.18y
USD raised in initial round	25.42M	27.08M	22.53M

Table 3. Startup and financing round female leadership distribution. This table presents the number and percentage of startups and financing rounds that have all female founders or lead GPs (GPs in lead VCs of a syndicate), some female and some male founders or lead GPs, and all male founders or lead GPs. The startups are restricted to those whose initial financing occurred in 2005 to 2013 and the financing rounds are limited to those of startups with initial financing rounds in 2005 to 2013, as well.

	All female	Female & male	All male
Startups' founders	82	211	2,116
	3.40%	8.76%	87.84%
VC financing rounds' lead GPs	11	2,817	1,725
	0.24%	61.87%	37.89%
Initial financing rounds' lead GPs	2	884	432
	0.15%	67.07%	32.78%
Second financing rounds' lead GPs	3	807	486
	0.23%	62.27%	37.50%

Table 4. Founder and GP presence by gender. This table presents statistics on the presence of founders and GPs, overall as well as separated by gender. For GPs, it presents data on presence in initial and in second financing rounds for all GPs,lead GPs (GPs in lead VCs of a syndicate), and appointees to a startup's board. The three columns of data present statistics on the overall sample, the sample for females, and the sample for males. The overall sample includes all startups initially VC financed between 2005 and 2013, including both end years.

	All	Female	Male
For startup			
Founders	3,804	242	3,562
per startup	1.91	0.12	1.79
For initial VC rounds			
GPs	49,255	7,104	42,151
per round	24.73	3.57	21.16
Lead GPs	25,758	2,846	22,912
per round	20.22	2.23	17.98
Appointed board members	1,009	30	979
per round	1.37	0.04	1.33
For second VC rounds			
GPs	62,977	9,543	53,434
per round	31.97	4.84	27.12
Lead GPs	28,175	4,245	23,930
per round	19.46	2.93	16.53
Appointed board members	862	45	817
per round	1.28	0.07	1.21

Table 5. Performance differences by founder gender. This table presents performance measured by exit from VC financing for startups led by one or more female founders ("female-led startups") and startups led by all male founders ("male-led startups") as well as the difference in performance between the two groups. All the startups in this sample have initial financing rounds between 2005 and 2013, inclusive. The top row in each cell shows the proportion of startups in that column that have exited. The bottom row shows the count of exits. The difference column reports the difference in proportions exited in the top row and the p-value for the χ^2-statistic (with $df = 1$) reported for a Pearson test of the equality of proportions across the two groups.

	Female-led startups	Male-led startups	Diff. p-val
Exits	33.2%	40.6%	-7.4%
	71	631	0.037

Table 6. Founder and lead VC GP gender impact on performance. This table presents logistic regressions of the impact of founder gender and lead VC GP gender on startup performance measured by exit via IPO or acquisition. All the startups in this sample have initial financing rounds between 2005 and 2013, inclusive. The R^2 reported is a goodness-of-fit measure based on the maximum likelihood function used to estimate logistic regressions.

	Likelihood of success						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Fem-led startup	0.585***	0.635**	0.322***	0.384**	0.300***	0.327***	0.369**
	[2.71]	[2.17]	[3.03]	[2.51]	[3.20]	[2.99]	[2.56]
Fem GP in lead VC			1.010	0.985	1.017	0.950	0.937
			[0.07]	[0.10]	[0.11]	[0.34]	[0.42]
Fem-led startup × fem GP in lead VC			2.438**	2.245*	2.442**	2.465**	2.220*
			[2.01]	[1.78]	[2.00]	[2.03]	[1.73]
Fem- vs. male-led startups			0.786	0.862	0.732	0.805	0.819
with fem GP in lead VCs			[1.01]	[0.61]	[1.29]	[0.90]	[0.80]
Fem vs. all-male lead VCs			2.462**	2.212*	2.483**	2.343**	2.080*
for fem-led startups			[2.15]	[1.85]	[2.16]	[2.02]	[1.68]
Init. fin. year FEs		X		X			X
Prod. mkt. FEs		X			X		X
Amt. raised		X				X	X
R^2	0.0073	0.0867	0.0121	0.0606	0.0281	0.0248	0.0895
Observations	1044	1044	1044	1044	1044	1044	1044

Absolute t statistics in brackets
* p<0.1, ** p<0.05, *** p<0.01

Table 7. Pre-round change in female lead GP, differences by female lead GP presence pre-round. This table presents the proportions of initial VC financing rounds that experience no change in female lead GP proportion, a negative change, and a positive change for three sets of syndicates: all syndicates, syndicates with female lead GPs 90 days prior to the round, and syndicates without female lead GPs 90 days prior to the round. For each cell in the first three rows, the top row provides the percentage of financing rounds in that group to experience that change and the bottom row provides the number of rounds. All startups in this sample have initial financing rounds between 2005 and 2013, inclusive.

Δ in fem lead GP prop. in 90 days before round	All initial rounds	1+ fem GPs pre-round	No fem GPs pre-round
No Δ	73.6%	67.3%	86.4%
	938	575	363
$\Delta < 0$	15.0%	22.4%	0.0%
	191	191	0
$\Delta > 0$	8.2%	10.3%	4.0%
	105	88	17
Total	1,274	854	420

Table 8. Startup and syndicate characteristics by pre-round change in female lead GP. This table presents differences between startups and syndicates that lose, gain, or experience no change in female lead GP representation in the 90 days before the financing round. The first three columns present statistics for startups and characteristics that lose, experience no change in, and gain female lead GP representation, respectively, with standard deviations presented below each statistic, in parentheses. The fourth (fifth) column presents the difference between startups and syndicates that lose (gain) female lead GP representation and those that experience no change, with standard errors for the differences presented below each statistic, in parentheses. All startups in this analysis have at least one female lead GP in the syndicate 90 days before the financing round and have initial financing rounds between 2005 and 2013.

	Δ F GP < 0	Δ F GP $= 0$	Δ F GP > 0	Diff.	
	(1)	(2)	(3)	(1) - (2)	(3) - (2)
% startups exited	41.361	43.478	37.500	-2.117	-5.978
	(49.377)	(49.616)	(48.690)	(4.139)	(5.666)
Any female founders (%)	11.585	11.850	10.127	-0.265	-1.724
	(32.103)	(32.354)	(30.361)	(2.920)	(3.895)
% female founders	7.083	6.731	5.485	0.353	-1.246
	(22.348)	(21.054)	(17.444)	(1.934)	(2.499)
Any female lead GPs	100.000	100.000	100.000	0.000	0.000.
90 days before round (%)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
% female lead GPs	13.547	12.089	10.437	1.458	-1.651
90 days before round	(13.577)	(10.287)	(8.237)	(0.935)	(1.149)

Table 9. Pre-round change in female lead GP impact on performance gender gap. This table presents logistic regressions of the impact of founder gender and of changes in representation of females as GPs of lead VCs in the 90 days before initial financing rounds on startup performance measured by exit. All startups in this analysis have at least one female lead GP in the syndicate 90 days before the financing round and have initial financing rounds between 2005 and 2013. The R^2 reported is a goodness-of-fit measure based on the maximum likelihood function used to estimate logistic regressions.

	Likelihood of success	
	(1)	(2)
Fem-led startup	1.011	1.109
	[0.04]	[0.34]
Fem lead GP prop drop	1.042	1.020
	[0.21]	[0.10]
Fem lead GP prop rise	0.770	0.813
	[0.99]	[0.73]
Fem-led startup × fem lead GP prop drop	0.223**	0.172**
	[2.11]	[2.38]
Fem-led startup × fem lead GP prop rise	1.611	1.657
	[0.60]	[0.61]
Lead GP fem proportion drop vs. no change diff in fem-led startups' success	0.226**	0.190**
	[2.29]	[2.45]
Lead GP fem proportion rise vs. no change diff in fem-led startups' success	1.630	1.837
	[0.65]	[0.79]
Init. fin. year FEs		X
Prod. mkt. FEs		X
Amt. raised		X
R^2	0.0112	0.0975
Observations	712	712

Absolute t statistics in brackets

* p<0.1, ** p<0.05, *** p<0.01

Table 10. Financier gender by founder gender. This table presents details on the differences in financiers' gender in initial financing rounds for female- and male-led startups. The top two panels use lead GPs' gender to examine financier gender and the bottom two panels study board members' gender. For each measure of financier gender, the first panel presents the distribution of startups based on whether the startup has a female founder and whether the initial financing syndicate has a female financier. The second panel presents the percent of initial financing syndicates with female financiers for startups with and without female founders. The last column presents the difference in female financier representation in the two sets of startups and the p-value for the χ^2-statistic (with $df = 1$) reported for a Pearson test of the equality of proportions across the two dimensions.

	Female-led startups	Male-led startups	Diff.
Initial round syndicate with			
no female lead GPs	52	278	
1+ female lead GPs	85	644	
% financed by female lead GPs	62.0%	69.8%	-7.8%*
Board appointees			
no female appointees	87	589	
1+ female appointees	5	22	
% appointing female board members	5.4%	3.6%	1.8%

Table 11. Founder and 'residual' lead VC GP gender impact on performance. This table presents logistic regressions of the impact of founder gender and 'residual' lead VC GP gender on startup performance measured by exit via IPO or acquisition. 'Residual' lead VC GP gender is estimated by taking the residual of an OLS regression of the number of female lead GPs on lead VC size, experience, and age and using the residual number of female GPs to calculate female lead GP presence. All the startups in this sample have initial financing rounds between 2005 and 2013, inclusive. The R^2 reported is a goodness-of-fit measure based on the maximum likelihood function used to estimate logistic regressions.

	Likelihood of success				
	(1)	(2)	(3)	(4)	(5)
Fem-led startup	0.322***	0.384**	0.300***	0.327***	0.369**
	[3.03]	[2.51]	[3.20]	[2.99]	[2.56]
Resid. fem GP in lead VC	1.010	0.985	1.017	0.950	0.937
	[0.07]	[0.10]	[0.11]	[0.34]	[0.42]
Fem-led startup × resid. fem GP in lead VC	2.438**	2.245*	2.442**	2.465**	2.220*
	[2.01]	[1.78]	[2.00]	[2.03]	[1.73]
Fem- vs. male-led startups	0.786	0.862	0.732	0.805	0.819
with fem GP in lead VCs	[1.01]	[0.61]	[1.29]	[0.90]	[0.80]
Fem vs. all-male lead VCs	2.462**	2.212*	2.483**	2.343**	2.080*
for fem-led startups	[2.15]	[1.85]	[2.16]	[2.02]	[1.68]
Init. fin. year FEs		X			X
Prod. mkt. FEs			X		X
Amt. raised				X	X
R^2	0.0121	0.0606	0.0281	0.0248	0.0895
Observations	1044	1044	1044	1044	1044

Absolute t statistics in brackets
* p<0.1, ** p<0.05, *** p<0.01

Table 12. Founder and lead VC GP gender impact on performance by financing round. This table presents logistic regressions of the impact of founder gender and lead VC GP gender across initial and second financing rounds on startup performance measured by exit via IPO or acquisition. All the startups in this sample have initial financing rounds between 2005 and 2013, inclusive. The R^2 reported is a goodness-of-fit measure based on the maximum likelihood function used to estimate logistic regressions. Standard errors are clustered at the startup level.

	Likelihood of success (1)
Fem-led startup	0.386** [2.41]
Fem GP in lead VC	0.944 [0.37]
Second round	0.768* [1.80]
Fem-led startup × fem GP in lead VC	2.200* [1.68]
Fem-led startup × second round	3.182*** [2.74]
Fem GP in lead VC × second round	1.034 [0.17]
Fem-led startup × fem GP in lead VC × second round	0.294** [2.24]
First vs. second round founder gender gap with no fem GP in lead VCs	0.314*** [2.74]
First vs. second round founder gender gap with fem GP in lead VCs	1.071 [0.26]
Init. fin. year FEs	X
Prod. mkt. FEs	X
Amt. raised	X
R^2	0.0925
Observations	2338

Absolute t statistics in brackets

* p<0.1, ** p<0.05, *** p<0.01

Table 13. Founder gender by lead GP gender. This table presents details on the initial financing of female- and male-led startups by syndicates with and without female lead GPs. The top panel presents the distribution of startups based on whether the startup has a female founder and whether the initial financing syndicate has a female lead GP. The second panel presents the percent of initial financings with female founders for syndicates with or without female lead GPs. The last column presents the difference in female-led startup representation in the two portfolios and the p-value for the χ^2-statistic (with $df = 1$) reported for a Pearson test of the equality of proportions across the two dimensions.

	Lead VC in syndicate has		Diff.
	1+ female GPs	no female GPs	p-val
Female-led startups	85	52	
Male-led startups	644	278	
% female-led startups	11.7%	15.8%	-4.1%*
N	729	330	0.066

Table 14. Founder and VC board appointee gender impact on performance. This table presents logistic regressions of the impact of founder gender and initial VC financing round board appointee gender on startup performance measured by exit via IPO or acquisition. All the startups in this sample have initial financing rounds between 2005 and 2013, inclusive. The R^2 reported is a goodness-of-fit measure based on the maximum likelihood function used to estimate logistic regressions.

	Likelihood of success
	(1)
Fem-led startup	0.850
	[0.59]
Fem board appointee	2.653*
	[1.94]
Fem-led startup × fem board appointee	0.270
	[1.16]
Fem- vs. male-led startups	0.230
with fem board appointees	[1.34]
Fem vs. all-male board appointees	0.717
for fem-led startups	[0.33]
Init. fin. year FEs	X
Prod. mkt. FEs	X
Amt. raised	X
R^2	0.1352
Observations	695

Absolute t statistics in brackets

* p<0.1, ** p<0.05, *** p<0.01

Table 15. Lead VC GP gender impact on subsequent round lead VC GP gender. This table presents logistic regressions of the impact of initial financing round lead VC GP gender on following round lead VC GP gender, along with its interaction with founder gender. All startups in this sample have initial financing rounds between 2005 and 2013, inclusive. The R^2 reported is a goodness-of-fit measure based on the maximum likelihood function used to estimate logistic regressions.

	Next round likelihood of fem GP in lead VC		
	(1)	(2)	(3)
Fem GP in lead VC	2.384***	2.375***	2.292***
	[4.79]	[4.46]	[3.95]
Fem-led startup			1.505
			[0.99]
Fem-led startup × fem GP in lead VC			1.500
			[0.74]
Init. fin. year FEs		X	X
Prod. mkt. FEs		X	X
Amt. raised		X	X
R^2	0.0400	0.0784	0.0888
Observations	570	556	556

Absolute t statistics in brackets

* p<0.1, ** p<0.05, *** p<0.01

Figure 1. Performance across initial financing years. This figure presents startup performance measured by overall exit, IPO, and acquisition for each initial financing year, from 2005 to 2018.

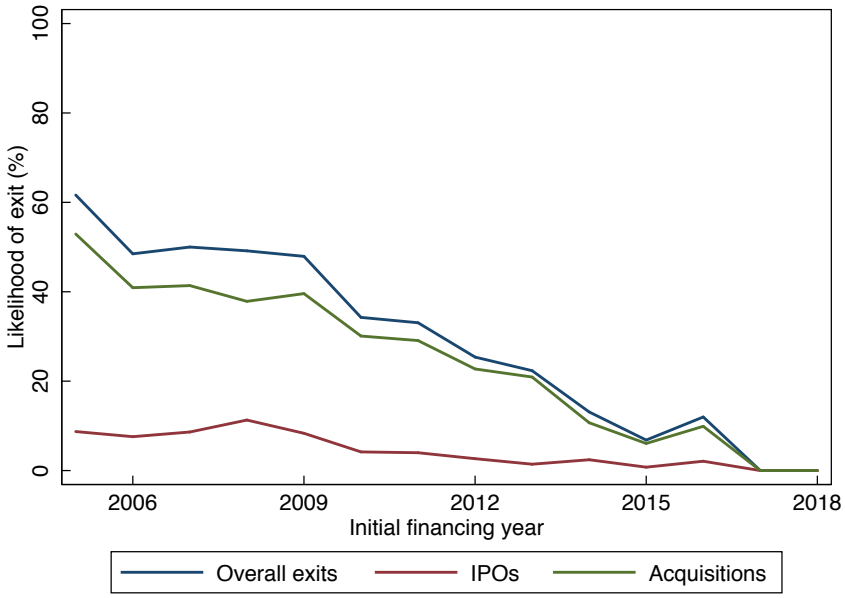


Figure 2. Startup product markets. This figure graphs the most common product market reported by each startup to CrunchBase, except "Software".

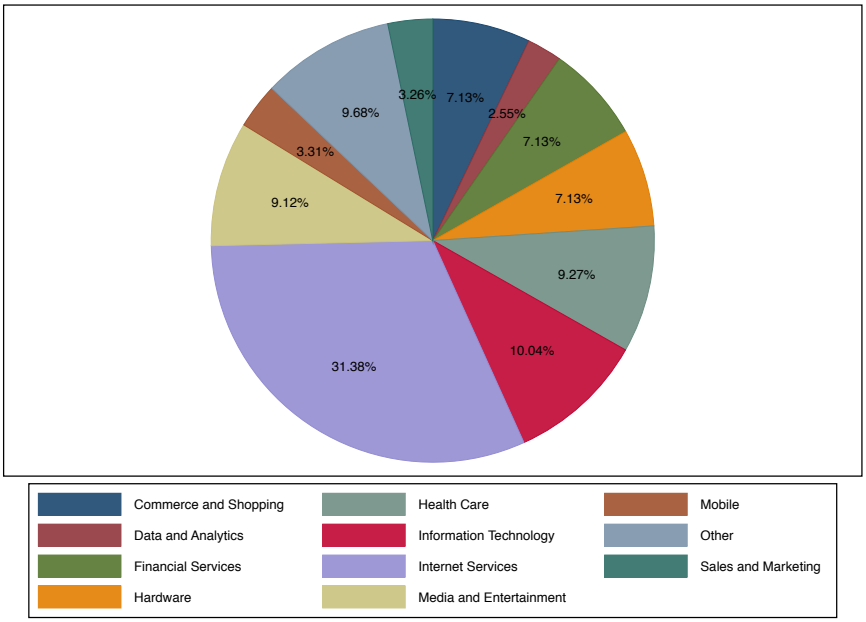


Figure 3. Performance across exit years. This figure presents startup performance measured by overall exit, IPO, and acquisition for each exit year, from 2005 to 2018. The sample is all startups initially financed by VCs in 2005 to 2013.

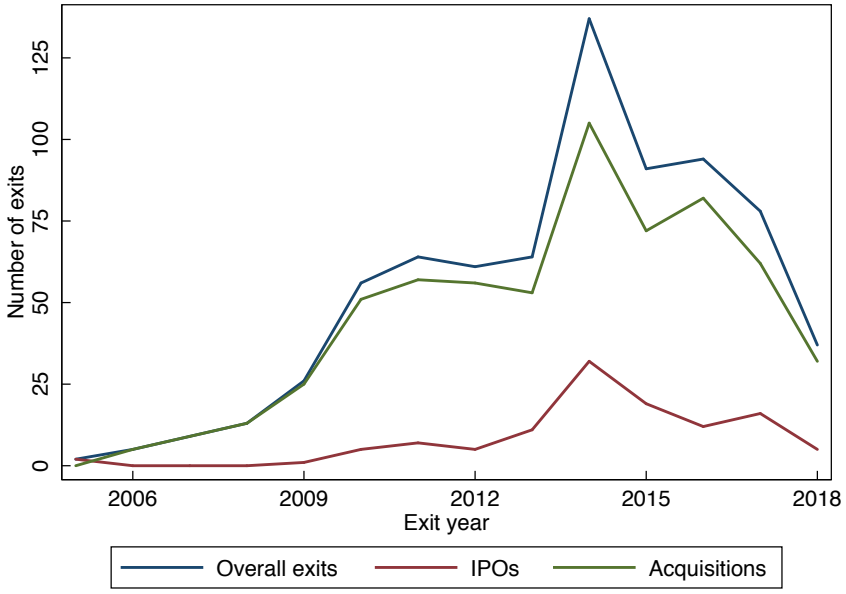


Figure 4. Performance by founder gender across initial financing year. This figure compares performance measured by overall exit for startups led by one or more female founders to startups led by all male founders within each initial financing year, from 2005 to 2013.

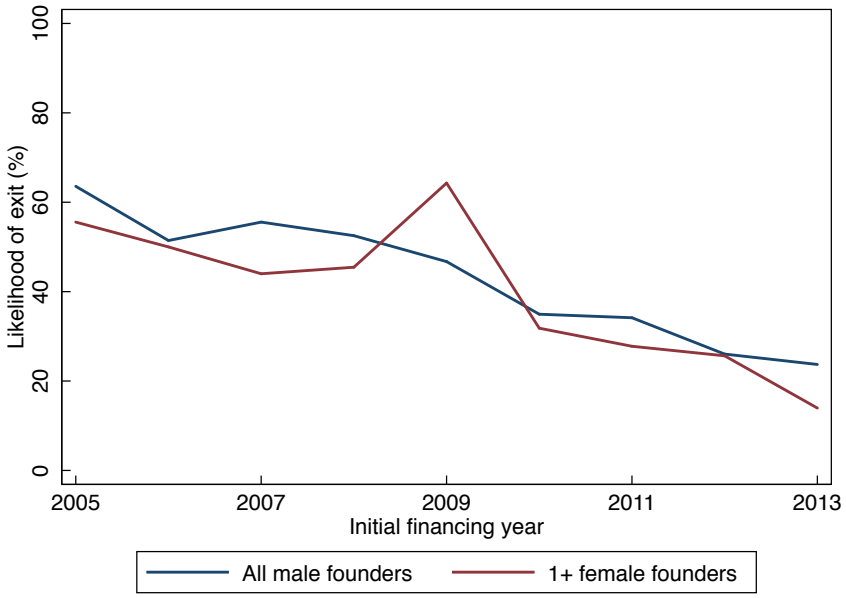


Figure 5. Performance by founder gender across product markets. This figure compares performance measured by overall exit for startups led by one or more female founders to startups led by all male founders across product markets. All startups in this sample have initial financing rounds between 2005 and 2013, inclusive.

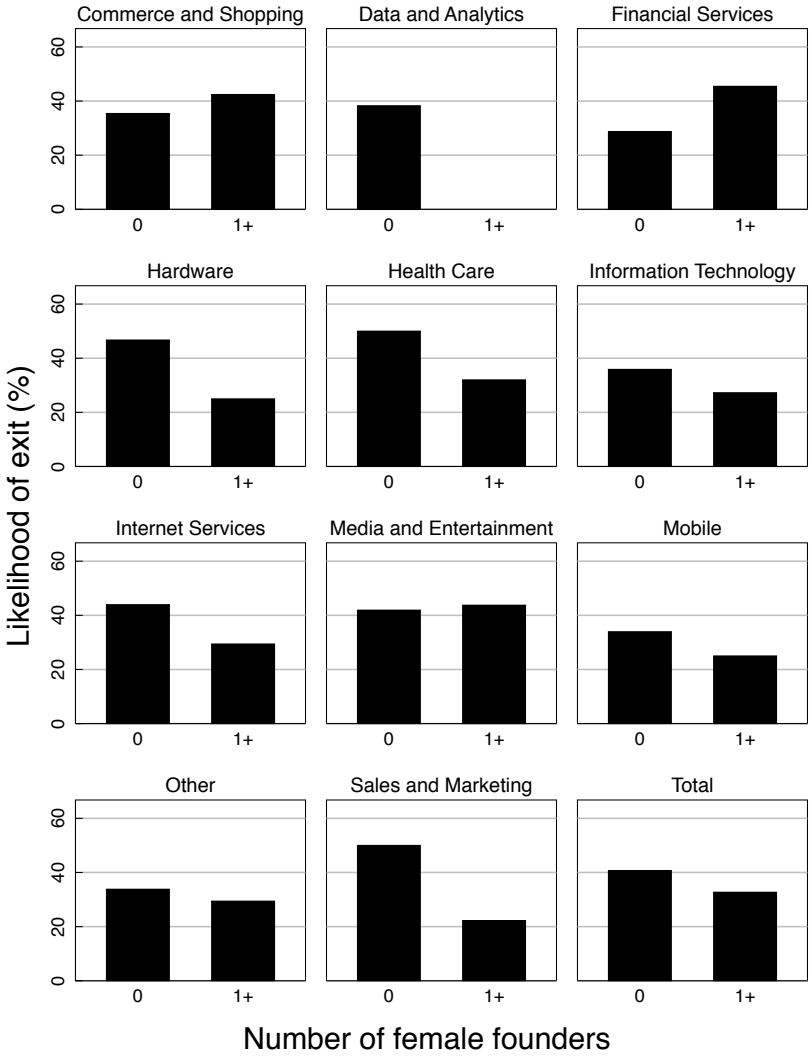


Figure 6. Performance by founder and lead VC GP gender. This figure compares performance measured by overall exit for startups led by one or more female founders to startups led by all male founders across startups initially financed by syndicates with no female general partners (GPs) in the lead investor and syndicates with female GPs in the lead investor. All startups have initial financing rounds between 2005 and 2013, inclusive.

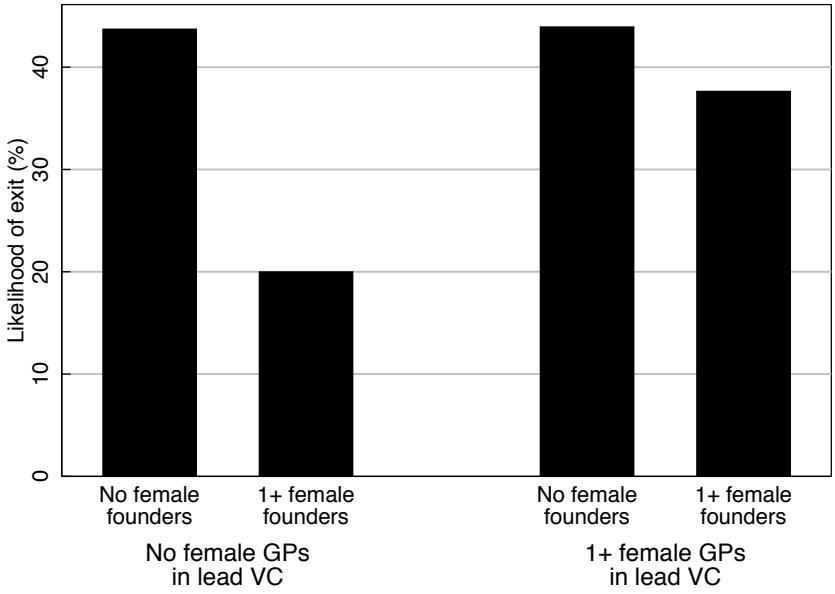


Figure 7. Distribution of lead VC characteristics by lead VC GP gender. This figure presents the distributions of three lead VC characteristics for initial financing rounds with and without female lead GPs. The distributions are presented as box and whisker plots. All startups have initial financing rounds between 2005 and 2013, inclusive.

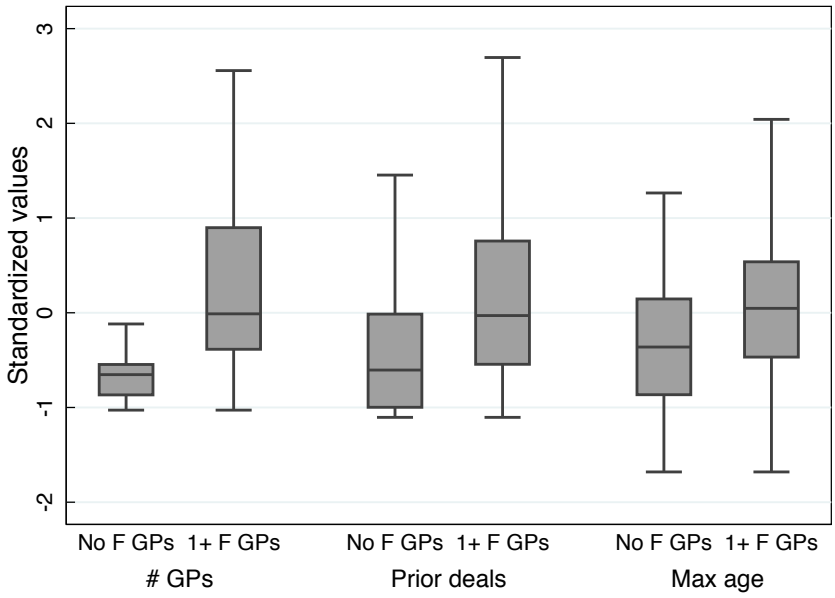


Figure 8. Pre-financing round timeline. This figure presents the timing (in days) of events occurring prior to a financing round. T refers to the day that the financing round is announced and t_a refers to the amount of time required by VCs to assess a startup.

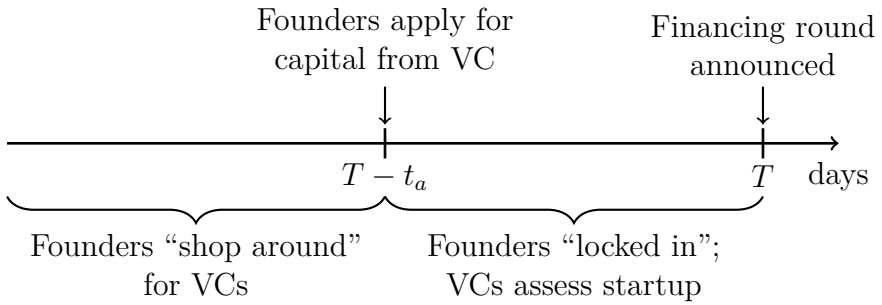


Figure 9. Impact of female GPs in lead VC on startup performance over time. This figure presents the ratio of exit likelihood for female- and male-led startups financed by syndicates with female GPs in the lead VCs relative to those financed by syndicates with all male lead VCs for two time intervals: 2005 to 2008 and 2009 to 2013. The ratios are estimated using the marginal effect of syndicates with female GPs in the lead VC on the likelihood of exit for female- and male-led startups. The red dashed horizontal line at 1 indicates if the likelihood of exit for startups is the same for the two sets of syndicates. All startups have initial financing rounds between 2005 and 2013, inclusive.

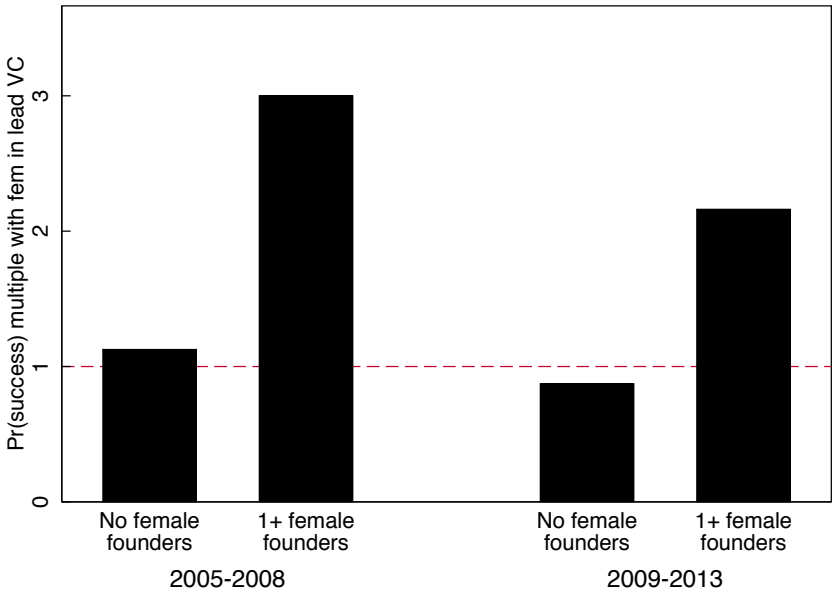


Figure 10. Impact of female GPs in lead VC on startup performance across product markets. This figure presents the ratio of exit likelihood for female- and male-led startups financed by syndicates with female GPs in the lead VCs relative to those financed by syndicates with all male lead VCs for different product markets. The ratios are estimated using the marginal effect of syndicates with female GPs in the lead VC on the likelihood of exit for female- and male-led startups. I omit product markets for which there are insufficient data to estimate these marginal effects (Biotechnology, Financial Services, Hardware, and Information Technology). The red dashed horizontal line at 1 indicates if the likelihood of exit for startups is the same for the two sets of syndicates. All startups have initial financing rounds between 2005 and 2013, inclusive.

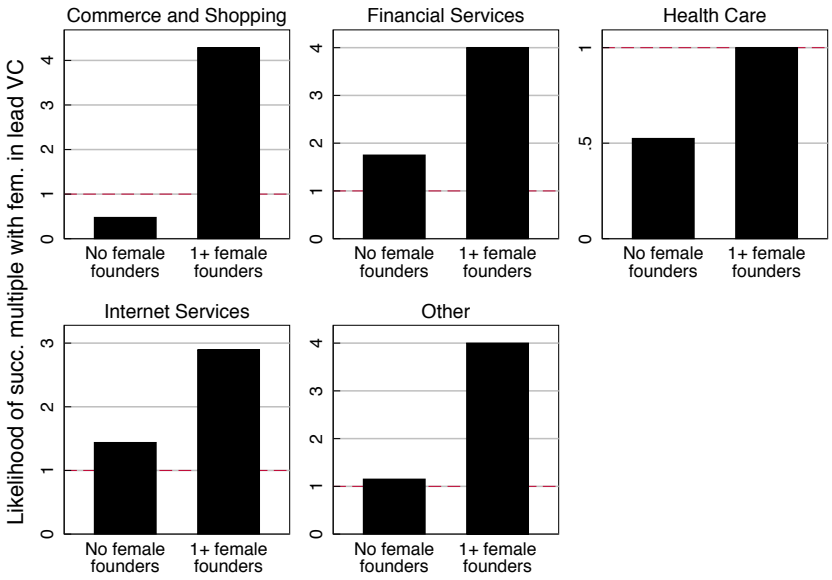
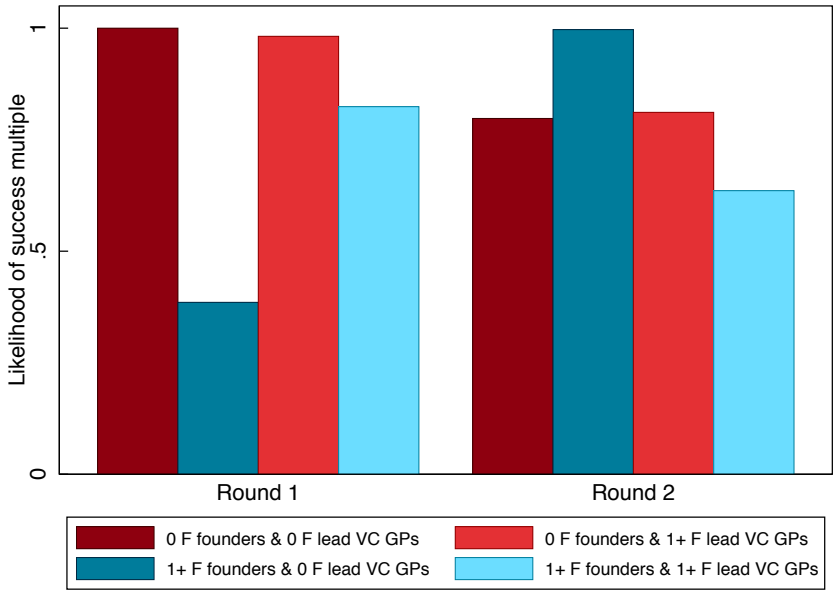


Figure 11. Performance by founder and lead VC GP gender in initial and second financing rounds. This figure presents the likelihood of successful exit multiple for startups based on founders' gender, lead VC GPs' gender, and round of financing. The baseline startup relative to which the multiple is defined is a startup with no female founders and no female GPs in the lead VC of the syndicate in its initial financing round. The multiples are estimated using the logistic regression used for Table 12. All startups have initial financing rounds between 2005 and 2013, inclusive.



Internet Appendix A Dataset construction

In this appendix, I explain the process used to build my dataset. A major hurdle in building a dataset for this project was that, for detailed information on startup activity, API access to Crunchbase is the only viable option.[55]. As the API access does not allow one to download the complete Crunchbase database, one has to specify a sample to the API service. I handled this obstacle by specifying a sample for the API consisting of all startups financed at least once by the fifty VCs with the greatest number of financings (as of June 2018), according to SDC's VentureXpert. This approach solves two problems at once. First, it reduces the likelihood of including errant organizations masquerading as startups. As the definition of early entrepreneurship may be vague, many "startups" in CrunchBase may be nothing more than a hobby of an "entrepreneur." Focusing on firms that receive financing at some point by a well-established VC removes such hobbyist projects from the sample. Second, it provides a systematic rule, devoid of subjective biases, that I can reliably use to collect data.

For each of the startups in my sample, I programmatically download information on founders and financing rounds, again using the API. For each financing round, I download information on all participating investors and, to complete my dataset, I download information on all participating investors from the API as well. I download these data using a number of Python programs that first download the relevant data using Crunchbase's API endpoints and then convert the downloaded information from heirarchical text files into usable form. For an example of one of these heirarchical text files, please refer to Figure A1, which shows the text file I downloaded for a startup, Cloudera.

For each startup, if it exited VC financing via IPO or acquisition, Crunchbase possesses data on the exit. For me, the most important aspect of the exit is the date, which is reported for nearly all exits.

I determine whether each person associated with a given VC or startup is important for

[55] Crunchbase has spreadsheet snapshots of their database updated daily, as well, but these snapshots do not contain all the information I need for this paper. For instance, in the snapshots, we get incomplete information on investors involved in financing rounds.

the analysis based on the role reported for the person in the database. For founders, I collect information on all individuals who have a 'founder' relationship with a startup. For GPs, I collect information on all individuals who have a 'job' relationship with a VC where the job description contains either 'partner' or 'founder.' The Crunchbase API has nearly complete data on the genders of both of these sets of individuals.

As GP status at VCs changes over time, my next step is to determine which GPs were associated with a VC at the time of the financing round. To do this, I compare the date of the financing round to the start and end dates of the job relationship between the GP and the VC. If the financing round occurs during the GP's tenure at the VC, I include the GP as part of the VC for the financing round.

API access is very useful for identifying lead VCs of a syndicate. The snapshots provided by Crunchbase do not properly identify them but the relationship between an investor and a financing round includes a descriptor for whether the investor led the financing round. I use this descriptor to identify lead VCs for each round.

I identified VC appointees to boards of financed startups by matching board members of startups to GPs of VCs and confirming that they became board members of the startup while they were GPs of the VC. To match board members and GPs, I used a person identifier provided by Crunchbase (UUID) and matched a list of all board members and a list of all GPs based on financed startup and potential board member. I kept the matches as potential VC appointees. For the next step, I compared the date at which the person was appointed to the startup board against the interval during which the person was a GP at the VC, keeping only those that matched. Finally, to determine at which financing round the GP was appointed to the board, I flagged earliest financing round at which the GP was a board member of the startup.

With these data in hand, I am able to execute all the analyses included in this project.

Internet Appendix B Crunchbase data comparison

In this section, I compare Crunchbase to other data sources for startup activity. First, I compare its financing round coverage to that of VentureXpert and find that it has better coverage than VentureXpert. Next, I compare its information on IPOs to SEC data and acquisitions to SDC's M&A database and find the coverage of IPOs equivalent to EDGAR data in the US while also possessing international IPO data.

Relative to Thomson Reuters's VentureXpert, a leading data source in VC-related research, Crunchbase has better coverage for the aspects of startup activity that are important for this study. As Table A1 shows, only about 52% of the startups I study can be found in VentureXpert. For the startups in both databases, Crunchbase has 0.123 more financing rounds available per startup, on average, than VenturExpert. For the startups with greater financing round coverage in VentureXpert, the difference is large (2.355) but similar in magnitude to startups with better Crunchbase round coverage. And Crunchbase also has better coverage of early rounds. Crunchbase's earliest reported financing round is approximately 3 months before that of VentureXpert. Therefore, for startups' financing rounds, especially early rounds, Crunchbase has better and more information available than VentureXpert.

To assess Crunchbase data quality for startup exits, I compare Crunchbase IPO information to that collected from SEC's Electronic Data Gathering, Analysis, and Retrieval (EDGAR) system and find that the coverage is equivalent in the US and Crunchbase has the additional advantage of possessing international IPOs as well. I match all the sampled startups to IPOs in the data collected by Kenney and Patton (2017) from the SEC by ticker or company name. First, obviously, SEC data do not include international IPOs. We can see that this is not a trivial advantage for Crunchbase in Table A2, which shows that Crunchbase provides 59 non-US IPOs that EDGAR lacks. Second, there are 201 IPOs in Crunchbase on US exchanges and 179 IPOs from the EDGAR-collected data. I checked the 22 IPOs in Crunchbase not in the EDGAR-collected data and confirmed that they are, in fact, on

EDGAR but excluded from the list provided in Kenney and Patton (2017).[56] Moreover, there were no startups for whom the EDGAR-collected data showed IPOs that Crunchbase did not provide. Therefore, Crunchbase data are equivalent to SEC data for US firms and superior to EDGAR data in the case of international IPOs. These findings verify the quality of Crunchbase exits data.

Internet Appendix Tables and Figures

Table A1. Comparison of Crunchbase and VentureXpert financing rounds data. This table compares the extent to which data are available in Crunchbase (CB) and VentureXpert (VX) for the startups studied in this paper. In particular, it shows the sample firms available in VX, the difference between VX and CB in the number of rounds of financing captured, and the difference in the number of years between initial financing rounds reported in VX and CB.

	Value
% startups with rounds in VX	26.5%
initial CB rounds in 2005-2013	51.7%
Diff. in number of financing rounds, VX - CB	-0.123
VX - CB | CB > VX	-2.208
VX - CB | CB < VX	2.355
# startups with same number of rounds	360
Years between initial VX and CB rounds	-0.238
# startups with earlier CB round	612
# startups with earlier VX round	503
# startups with same init. round date in CB & VX	271

[56] Many of the 22 "extra" IPOs are pharmaceutical companies that were immediately acquired by another firm. This seems to be the reason that Kenney and Patton (2017) excludes them. As acquisitions and IPOs are both considered successful exits in this paper, this distinction is not an issue.

Table A2. Comparison of Crunchbase and SEC EDGAR IPO data. This table compares initial public offerings reported in Crunchbase and in SEC's EDGAR, as collected by Kenney and Patton (2017). The first column reports information based on IPO data from Crunchbase and the second column based on EDGAR. EDGAR has data on initial equity raised on US exchanges and ends in 2015 while Crunchbase has reliable data from 2005 onwards, so the sample of compared startups is limited to those based in the US with initial financing rounds in Crunchbase in 2005 through 2015.

	Crunchbase	SEC EDGAR
Number of IPOs, ex-US	59	0
as % of total	5.5%	0.0%
Number of IPOs, US	201	179
as % of total	4.8%	4.3%


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Figure A1. *Cloudera* (entrepreneurial firm) information on CrunchBase.
This figure provides an example of the JSON file provided by CrunchBase for an entrepreneurial firm query. The data are organized into subparts in the JSON file using brackets and braces. Early stage firm data include entrepreneur and financing round information.