VCs, Founders, and the Performance Gender Gap

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Abstract

VC-financed startups led by women perform worse than startups led 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 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.

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Anecdotally, Silicon Valley is a harsh environment for female entrepreneurs. In an article published in *The New York Times* in April 2014, the author notes 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 describes the venture capital (VC) industry in northern California as a "boys' club" and implies that the industry's actions create "a particularly toxic atmosphere for women in Silicon Valley." A survey of female founders found that founders who experienced discrimination or harassment from an investor usually chose to end those relationships (Lenz and Aspan, 2018), which could hurt their startups' future success. If these anecdotes and survey evidence are true, VC financing may present a substantial 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[1], such impediments may 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 successful exit via IPO or acquisition[2] of female- and male-led startups differently.

To establish whether female- and male-led VC-financed startups perform differently, I compare successful exits from VC financing for startups with all male founders with exits of startups with at least one female founder. I find that the female-led startups have a 24% lower likelihood of exit than the male-led startups, which is a sizeable performance gap.[3]

While the presence of a performance gap helps verify the anecdotal and survey evidence from female entrepreneurs, 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 this finding. 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 syndi-

[1] For instance, Amazon, Apple, Dell, Facebook, Google, Intel, Microsoft, Netflix, Starbucks, and Uber all went through a VC-financed stage. Interestingly, all of them also have exclusively male founders.

[2] 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).

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

cates led by VCs with and without female general partners (GPs), which, hereafter, I refer to as "syndicates with female lead GPs" and "syndicates with all male lead GPs". If intrinsic differences between female- and male-led startups fully explain the performance gap, then any gap in exit likelihoods should be the same across startups financed by the two sets of syndicates. If the gap differs, then VC financing influences the performance gender gap. 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 whereas there is no gap among startups financed by syndicates with female lead GPs. The difference in gaps arises from significantly higher exit rates for female-led startups financed by syndicates with female lead GPs. In constrast, male-led startups' exit rates are the same regardless of the gender composition of the initial financing syndicate.

The findings above may seem inconsistent with some of the findings reported in Ewens and Townsend (2018). That paper presents empirical evidence that angel investors on the AngelList platform are biased towards founders of their own gender in terms of who they finance. To confirm this bias, the paper shows that opposite-gender founders financed by angel investors are more likely to subsequently raise venture capital (and, in doing so, successfully exit angel financing). The better performance of female-led startups with male angels and male-led startups with female angels runs opposite to my findings summarized above. However, there are key differences between angel and VC financing that help explain the opposite findings. First, there are far more independent agents monitoring VC investment decisions, due to the fact that angels invest independently whereas VCs' invest alongside limited partners (LPs), who commit the vast majority of capital invested by the VC. Second, GPs invest four times as much as angels in each startup, as VCs tend to invest later in the lifecycle of a startup, when more capital is required, than angels. Both these differences imply that, if angels and GPs both have gender-based biases, an angel's investment decisions are more likely to reflect those biases than the decisions of the VC that a GP owns and operates. Ewens and Townsend (2018) and this paper are, in a way, complementary projects that focus on the impact of gender in two equally important sources of early-stage financing: angel and VC financing. Moreover, that paper sets the stage for this research in that it shows the influence of angel investors on entry into entrepreneurship and progress towards VC financing, which leads to the topic addressed in this paper: the influence of VCs on exit from entrepreneurship and VC financing.

A 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, what I refer to as the "founder preference" hypothesis. I present two findings that imply that founder preference cannot be solely responsible for the gap and VC actions must also play a role. First, I compare the performance gender gap among startups financed by syndicates whose GP gender composition changes in the 90 days prior to the financing round to the performance of startups financed by syndicates whose gender composition remains unchanged. A change in GP composition in the last 90 days before financing should not affect founders' decision of where to seek financing. On the other hand, it may affect VCs' evaluation and advising of startups. My findings show that there is a substantial widening of the performance gender gap when female lead GP presence falls in the 90 days prior to the initial financing round. Second, I examine whether female founders impose their preference for female financiers by studying differences in gender composition of female- and male- led startups' lead GPs and board appointees. I find no evidence that there are more female lead GPs or female board appointees among female-led startups. These results imply that founder preference does not drive the performance gap difference on its own. Differences in VC actions must impact the performance gap among female- and male-led startups, as well.

The findings above present a performance gender gap that is influenced by VC actions. But *how* do VCs contribute to the gap? Is it due to poor evaluation or poor advising or both? Based on the following empirical tests, I find that syndicates with female GPs narrow the performance gender gap by evaluating female-led startups better and find no evidence that they are better at advising them. First, 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 insight 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 influence the performance gap, which strongly suggests that female GPs narrow the gap by evaluating female-led startups better. Second, I compare proportions of female-led startups in the portfolios of syndicates with and without female lead GPs and find slightly lower proportions of female-led startups among syndicates with female lead GPs. This suggests that female GPs may be more choosy in the startups they evaluate. Third, I compare the difference in exits between female- and male-led startups initially financed by syndicates that appoint a female GP to the startup board and those who appoint a male

GP based on the notion that board appointee GPs' additional impact is exclusively on advising. I find no difference in the performance gender gap between syndicates that appoint female GPs to the board and those who appoint male GPs, which suggests that female GPs do not narrow the gender gap by better advising female-led startups. Finally, as surveyed female founders report that a lack of mentorship and useful connections are major gaps in their support network when they are VC-financed (Robb et al., 2014), I test whether female-led startups initially financed by syndicates with female lead GPs are more likely to be financed by syndicates with female lead GPs in the subsequent round, as well. This allows me to test whether female GPs ameliorate the survey-reported issues in VC advising. However, I find no evidence that female-led startups financed by female lead GPs have more access to female GPs in subsequent rounds, further evidence that female GPs do not impact the performance gap by advising female-led startups better. In all, these tests provide strong evidence that the narrowed performance gender gap among startups financed by syndicates with female lead GPs arises from these syndicates' better ability to evaluate female-led startups.

The rest of the paper is organized as follows. First, in Section 1, I provide a short summary of the literatures to which the paper contributes. Next, in Section 2 I present the novel dataset on VC financing that I construct, including an explanation of why I need the dataset, a description of the primary data source, a brief discussion how I construct the analysis dataset from the source, and a summary of the dataset. I then present analyses that present the findings described above in Section 3: differences in female- and male-led startups overall performance; evidence of VCs' influence on the performance gap; and reasons for VCs' influence. After that, in Section 4, I summarize my findings and offer conclusions.

1 Related literature

This paper most directly contributes to a small but growing body of literature on the impact of gender on entrepreneurial firm financing. One of the papers in this literature, Gompers et al. (2014), focuses on the difference in overall performance of individual GPs' portfolios by GP gender and the impact of female GPs on the performance gap between the portfolios of 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 firm has multiple female GPs. Both Gompers et al. (2014) and this paper find that female GP presence narrows performance gaps, but in quite different contexts.

A more recent paper in the literature, Ewens and Townsend (2018), uses data from AngelList, an online angel investing platform, and 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.[4] To show that this behavior is consistent with screening bias (as in Becker, 1971), it finds evidence that startups whose founders share gender with their angel investors are less likely to subsequently secure VC financing.[5] In two specific ways, Ewens and Townsend (2018) is useful for the research presented in this paper. First, its primary focus sets the stage for my research question. It investigates the potential hurdles to entry into entrepreneurship posed to female-led startups by early-stage investors whereas I study potential hurdles to exit from entrepreneurship posed to female-led startups by early-stage investors, a natural follow-up to theirs. Second, in confirming angel investors' screening biases, that paper finds that same-gender pairs of investors and founders are less likely to exit angel financing whereas I find same-gender pairs of female-led investors and founders are more likely to exit VC financing. These opposing findings highlight key differences between two important early-stage investors: angels and VCs. First, angel investors invest their own money whereas VCs are investing money committed by a number of limited partners (LPs). As a result, many more agents carefully monitor VCs' investment decisions. Therefore, even if an angel and a GP share the same biases, the angel's investments are far more likely to reveal the biases than the investments of the VC that the GP owns and runs. Second, angel investment occurs earlier in the lifecycle of a startup than VC investment. Consequently, investment amounts in angel financing rounds are much smaller (approximately $35,000 in 2015 according to Huang et al. (2017)) than in VC financing rounds (approximately $13.5 million in 2015 according to Franklin and Haque (2017)). 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. Assuming angels and GPs have similar wealth levels, this implies that GPs have four times as much of their personal wealth invested in the average startup. Therefore, if they recognize their

[4] Marom et al. (2015) show similar evidence for crowdfunded projects using Kickstarter data.

[5] 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.

biases, GPs have greater incentives to avoid acting upon them than angels. The research question and the findings of Ewens and Townsend (2018) are useful for motivating and contextualizing this paper, respectively. Its question focuses on entry into entrepreneurship and naturally leads to mine: exit from entrepreneurship. Its findings provide a comparison for mine and help to highlight the differences between two important early-stage investors: angels and VCs.

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. Bellucci et al. (2010) also finds 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 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 very different sorts of small businesses.[6] Finally, my paper examines the impact of such pairings across entrepreneurs and financiers on firm performance whereas the focus of these papers is more on financing outcomes.

This paper also adds to the literature on entrepreneur and VC characteristics that affect entrepreneurial firm performance. 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 interested in 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 impacts the performance of entrepreneurial firms.

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

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. Ahern and Dittmar (2012) finds that constraints on the gender composition of corporate boards has an impact on firm value. In a labor setting, Tate and Yang (2014) 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 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 some of 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 Appendix A.

2.1 VC financing process

VC financing is a private form of financing for startups whose businesses generally preclude financing via debt. 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.[7] 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.[8] Often, 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 those 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 and on what terms to invest in the startup.[9] The periodic reassessment of startups is one characteristic of VC

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

[8] 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.

[9] 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 that helps mitigate some of the problems associated with financing high uncertainty, early-stage businesses (Gompers and Lerner, 2004).

2.2 Data

In this section, I present my main source of data: Crunchbase. Next, I describe the sample of startups, VCs, and financing rounds I use for my analyses.

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" (Crunchbase, 2018). A key feature of the database is that it allows anyone to update the database ("Crunchbase is the free database of technology companies, people, and investors that anyone can edit" (Crunchbase, 2014)). This affords Crunchbase three substantial benefits. The greatest benefit is its extensive coverage of VC financing of startups. As of June 2018, the database has information on over 221,000 financing rounds involving over 44,000 investors. It also contains information on over 600,000 startups.[10] For comparison, SDC's VentureXpert database has information on just under 149,000 financing rounds involving approximately 8,000 investors.[11] And, while I do not have accurate financing round information for it, the Burgiss database has data on 775 VC funds, which means their data are, at most, based on 775 VCs' data (Harris et al., 2014). Similarly, the Venture Economics database has data on 1,114 VC funds. In terms of startup financing round coverage, Crunchbase is quite dominant.

Second, crowdsourcing limits 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 (Freytag, 2014). Additionally, as of mid-2018, over 3,600 VCs, accelerators, and incubators provide up-to-date portfolio company information to Crunchbase directly (*Crunchbase Venture Program*, 2018). These investors provide at-least-monthly updates to Crunchbase in exchange for access to Crunchbase data. Hav-

financing rounds.

[10]These numbers are based on a June 25, 2018 snapshot of the Crunchbase database.

[11]VentureXpert observation counts are based on a January 2015 snapshot of the database. For a detailed comparison of round coverage between VentureXpert and Crunchbase, please refer to Appendix B.

ing a wider base of contributors reduces the likelihood of a bias tied to single perspective or few perspectives.

Further, crowdsourcing mitigates issues tied to voluntary disclosure. Most of the existing data on VC-financed firms come from voluntarily disclosed information. These data are more likely to be biased in a manner that favors the data provider than data coming from involuntary disclosure. 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.[12] 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: news article citation for any database alteration, authentication of a data provider's identity, and algorithmic and manual verification of all database changes (Crunchbase, 2014). In 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-based data and find that Crunchbase data on IPOs within the US match SEC records perfectly. Additionally, Crunchbase also incorporates data on international IPOs. These comparisons, detailed in 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 a recent

[12]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.

article, The Wall Street Journal cited it when presenting the capital raised by funding rounds of General Mills' corporate VC wing (Back, 2018). The New York Times cited Crunchbase for data on the number of financing rounds providing over $100 million in capital to startups in 2017 (Griffith, 2018). Experienced angel and VC investors such as 500 Startups, Accel Partners, a16z, and Draper Fisher Jurvetson partner with Crunchbase for access to its data (*Crunchbase Venture Program*, 2018). Additionally, the database has been used as a data source for teaching startup valuation at respected business schools (Neumann, 2018). Based on this frequent usage by well-established VCs and news media, Crunchbase data are likely of fairly high quality.

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 constrain the study to only examine startups that were financed at least once (as of June 2018) by the fifty VCs with the greatest number of financings according to VentureXpert. This reduces potential noise in the sample by excluding hobbyists, garage projects, etc. that may be masquerading as legitimate startups. This cut reduces my sample to 5,232 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. As a result, 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 1'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%). With some calculation, 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 1'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, based on the bottom panel of Table 1, we see that the 2005 to 2013 sample has an exit rate of 37.7%. Startups financed post-2013 have an exit rate of 7.9% (calculated using data from the table). This is a large difference. We can also easily observe the overall downward trend in exit rates over time in Figure 2. Earlier "vintages" of startups have greater likelihoods of exit simply because it takes time for startups to successfully exit VC financing and earlier "vintages" 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, we know that 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 1. 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 (including rounds not involving VCs), I know the date on which the financing round was announced, VCs who 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.[13] In Figure 1, we 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 the largest markets 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, all of which are high-tech product markets with high-information asymmetry, where VCs tend to operate.

I focus primarily on initial financing rounds involving VCs and, for some analyses, on second VC rounds. We see in Table 1 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. For initial rounds, 89% of 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 somewhat more VCs in each second round, 2.5 compared to 2.0 in the first round. Overall, the first and second VC financing rounds of startups have similar characteristics.

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 2, we observe that there are 3,801 founders in the data. Of these, 243 are female (6.4%) and the rest are male. Per startup, on average, there are 0.12 female founders and 1.78 male founders. This disparity arises on the investor side, as well. 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 GPs in lead VCs 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.[14]. For second VC financing rounds, the disparities are smaller but still large for "important"

[13] 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 almost a meaningless categorization for startups.

[14] As I point out in the analysis involving board members discussed in Section 3.4, the low number of female appointees reduces the power of any test that employs it.

GPs in each financing round.[15]

3 Analysis

In this section, I present the main analyses of the paper, which can be divided into four parts. First, in Section 3.1, I provide overall data on startup exits from VC financing. Second, in Section 3.2, I document a large founder gender-based gap in startups' performance. I also explore whether the gap differs across markets and years. Next, in Section 3.3, I explore the effect of VC gender composition on the gap. I show that the performance gap is much larger when startups' initial VC financing rounds are led exclusively by male GPs. Finally, in Section 3.4, I present evidence that female GPs' presence narrows the performance gap because syndicates with female lead GPs are better able to evaluate female-led startups.

3.1 Overall performance

In this section, I document the overall performance of VC-financed startups. I use VC financing exit, either via IPO or acquisition, as an indicator of success. I present overall startup exit information and discuss other measures related to performance.

I measure VC-financed startups' performance using exit from VC financing via initial public offering (IPO) or acquisition. The last panel of Table 1 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 sector exits, as 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 (Franklin and Haque, 2017), which is quite similar to the ratio I observe.[16]

Looking at trends in exits over time, I find that older startups are more likely to have exited and

[15] 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%).

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

that there is an upward trend in exits per year at the start of the analysis period and a downward trend near the end. We can see this in Figure 2, 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). We also see that acquisitions make up a much larger portion of overall exits than IPOs. 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 exit 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.[17] 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.[18]

While exit from VC financing is often used as a measure of performance in the VC literature[19], it cannot be used to 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 contracts offered to startups in exchange for funding.[20] Hochberg et al. (2007) provides some assurance that, at the fund level, exit rates are positively correlated with returns: based on Freedom of Information Act suits, 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, albeit an imperfect, measure of startup performance available.

[17] Note, however, that the SEC began enforcing the relevant parts of the JOBS Act in 2016, not 2012 (*SEC Adopts Rules to Permit Crowdfunding*, 2015).

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

[19] 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. (2018) uses exits via IPO to measure VC performance.

[20] 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.

3.2 Founder gender-based performance gap

In this section, I explore differences in startups' performance based on founder gender. First, I document the overall difference in success rates between female- and male-led startups. Second, I discuss potential reasons for such a performance gender gap. Next, I separate success into IPO and acquisition exits and discuss why the gender gap in performance exists primarily in acquisitions. Finally, I explore whether there are any differences in the performance gender gap across financing years and product markets.

There are marked differences in the performance of female- and male-led startups. As we see in Table 3, 33% of female-led startups successfully exit VC financing whereas nearly 41% of male-led startups have successful exits. This performance gender gap of 8% is large (one-fourth of the exit rate of female-led startups) and statistically significant with a p-value of 0.028. To my knowledge, this is the first study to document this performance gap between female- and male-led VC-financed startups.

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, a large gap in the far right tail of quantitative ability, for which we have some evidence, could help explain the performance gap we observe. For instance, Ellison and Swanson (2010) 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 Croson and Gneezy (2009) points out, some experiments and field studies 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.

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 ("1+ female founders" and "All male founders", respectively) against the startups' initial financing year. I find that 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.[21]

Turning to startups' product markets, I find that the gap is present in almost all 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.[22]

3.3 VC effect on performance gap

In this section, I explore the influence of VCs on the founder gender-based performance gap presented in the previous section. First, I discuss possible reasons that VCs may influence the gap. Next, I explain why VC gender is a reasonable dimension to utilize in exploring VCs' impact on the gap. Finally, I empirically test whether VC gender plays any role in the gap.

In both evaluating startups to be financed and advising financed startups towards success (and their own exits), VCs could influence the performance gender gap. In their evaluation role, if 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 advising role, if 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. In both roles, it is possible for VCs to impact the performance gender gap we observe.

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 GP gender because syndicates with female GPs should have a different likelihood to widen 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 more experienced in evaluating the sorts of projects led by female entrepreneurs or information may transfer more easily

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

[22] 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.

between founders and GPs of the same gender. Alternatively, female GPs may be partial towards female founders and finance female-led startups of worse quality. If VCs have difficulty advising female-led startups to success, female GPs may have less difficulty with that as well. 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 connections to female founders that help their startups succeed. For all these potential reasons, if financing affects the performance gap, we should be able to observe differing impacts across syndicates with and without female lead GPs.

I focus on female GPs of lead VCs rather than female GPs of all VCs in the syndicate or female VC appointees to the startup's board. Lead GPs are preferable to other GPs because the lead VC is always involved in both roles of the VC syndicate, whereas other VCs may not be involved in evaluating or advising the startup. Alternatively, I could narrow the focus of the analysis further to the gender of GPs appointed to a startup's board. However, by focusing exclusively on board appointees, I would exclude non-board appointees and lose the impact of input from other lead GPs 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. [23] 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 choose to 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. Table 4 presents 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 four columns of the table include different sets of fixed effects: no fixed effects, initial financing year fixed effects, product market fixed effects, and both fixed effects. The exact specification of the regression, excluding fixed effects, is

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

[23] While I do not use board appointees in the primary analysis for the stated reasons, I do employ board appointee data in Section 3.4 to explore reasons for the performance gender gap differences I discover.

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 every unit increase in the explanatory variable. In the first row of the top panel of Table 4, 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 massive 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 when financed by syndicates with female lead GPs is statistically indistinguishable from that of their male-led counterparts. This implies that there is no performance gap among startups initially financed by syndicates with female lead GPs. These two results of Table 4 are illustrated in Figure 6, which confirms that there is a much smaller and virtually non-existent performance gap among startups initially financed by syndicates with female lead GPs.

The regression results also imply 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 4, I show that female-led startups are 2.2 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 clearly, where we find 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.

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 (standardized) distributions of these characteristics for initial financing rounds with and without female lead GPs.[24] The overall lack of female GPs in VCs (Table 1 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[25], 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 4. 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 the potential pitfalls of financing them. While such explanations could drive the performance gender gap differences we observe in Table 4, findings presented in Section 3.4.3 show that even if we use the component of lead VC gender orthogonal to lead VC size, age, and experience, we find differences in the performance gap across the two sets of syndicates. These findings effectively rule out the possibility that lead VC age, size, or experience drive the different performance gaps we observe for syndicates with and without female lead GPs.

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 8 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 8 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

[24]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.).

[25]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.

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 8. 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 like 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 9 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 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 a bit depending on the startup's product market but the overall impact of female GPs is similar.

3.4 Reasons for the VC effect

In this section, I explore why VC gender composition impacts the performance gap. First, I show that the difference in performance gap does not arise because of whom founders choose to ask for financing but must be driven by VCs, as well. Next, I compare the importance of female GPs' ability in evaluating and advising female-led startups via four sets of analyses. Together, these four tests are consistent with the hypothesis that female GPs are better at evaluating good female-led startups and do not present any evidence that they are better at advising female-led startups. Finally, I provide evidence that the impact of female lead GP presence is not driven by its covariates: VC age, size, and experience.

3.4.1 Founder preferences

In this section, I discuss the idea that different founders' preferences for VCs based on GP gender may drive the difference in the performance gender gap between syndicates with and without female lead GPs and present evidence why that is not the only mechanism driving the paper's findings. First, I describe this founder preference hypothesis. Next, I present two tests of the hypothesis. First, I test the hypothesis using lead GP entry and exit just before a financing round, based on the notion that GP turnover just before a round will not alter startup financing choice but may affect VC financing decisions. I also compare board appointees' gender across female- and male-led startups, based on the idea that founders' preferences on GP gender should extend to board appointees. Taken together, the results of these two tests imply that the founder preference hypothesis cannot completely explain the performance gender gap difference between syndicates with and without female lead GPs.

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 test whether founder preferences entirely drive the difference, I compare the performance gap among startups financed by syndicates that have no change in their lead GP composition in the 90 days before their initial financing round to startups whose lead GP gender composition increases or decreases within that time window. Assuming that VCs take at least 90 days to properly study a potential investment, any changes in the lead GP gender composition after that date would not affect startups' choice of financier.[26] On the other hand, such a change *would* affect VCs' ability to properly evaluate applicants and advise financed startups. Consequently, if the performance gap difference arises solely due to startup founders' preferences about who finances them, there should be no difference in the performance gap between startups financed by syndicates who experience an increase or a decrease in lead GP gender composition in the 90 days before initial round and those that do not experience such a change. As I am comparing changes in female lead GP presence, I exclude all-male lead GP syndicates as those syndicates cannot reduce their female lead GP presence. Put into a regression framework, I perform the following logistic regressions on the data:

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

where all previously defined variables retain their definitions and $dfem_i^{v-}$ ($dfem_i^{v+}$) is an indicator for whether the proportion of female lead GPs in syndicate v reduced (increased) in the 90 days prior to startup i's initial financing round. If founder preference in the two-sided matching between startups and VCs is solely responsible for the performance gap difference, β_1 should be 1 and β_2 should be 1. If VC actions play a role in the performance gap difference, 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).

In Table 5, I present the differences in the number of startups experiencing pre-initial round changes in lead VC gender composition that motivate me to focus on syndicates with female lead GPs prior to the round for this analysis. In that table, we see that, not only do syndicates without female lead GPs prior to the round have no negative changes in VC gender composition, but their GP gender does not increase much either (only 4% of rounds experience an increase in female lead GP presence). On the other hand, syndicates with female lead GPs have somewhat more variation in GPs before a round and are able to increase and decrease female lead GP representation. The asymmetry in possible changes to and relative stability of their GP gender composition are my motivation for excluding initial financing rounds with all-male lead GP syndicates from this

[26] I perform the same test under the assumption of 30, 45, and 60 days, as well, and find no substantive differences in the results.

analysis.

I present the results of the regression detailed in Equation 2 in Table 6. The first column results are without any fixed effects whereas the second column has initial financing year and product market fixed effects. Both columns include all startups financed by syndicates with female lead GPs 90 days before the round. Focusing on the second column, in the top row, we see that there is no performance gap for startups with syndicates that experience no change in lead GP gender composition. Moving down to the fourth row, we observe that female-led startups' performance relative to male-led startups worsens by 78 to 83% when they are financed by syndicates that experience a reduction in female lead GP representation. In the first row of the second panel, we see that their performance is 78 to 82% worse than female-led startups financed by syndicates with no change. Both the change in the performance gap and the worsening of female-led startup performance are statistically significant. The last row of the top panel and the second row of the second panel show that while the performance gap seems to narrow when female GP representation increases and female-led startups' performance is better, this narrowing is not statistically significant. The asymmetry in impact of increase and decrease can be explained by the fact that a drop in female lead GP representation often removes the only female lead GP in the syndicate[27] whereas an increase adds a female lead GP where one was already present. The wider performance gap among startups financed by syndicates that have reduced female GP representation implies that founder preference cannot entirely drive the performance gap and VCs must influence the gap, as well.

If female founders prefer to work with female GPs and are able to push their preferences onto their financiers, we should observe a greater presence of female lead GPs and female board appointees for female-led startups. However, we do not find any such evidence. In Table 7, I show the distribution among female- and male-led startups of financing rounds with and without female lead GPs as well as financing rounds after which only male and female GPs are appointed to the startups' boards. For lead GPs, we find a statistically significant 7.8% percentage point *lower* likelihood of having a syndicate with a female lead GP for female-led startups. While there is no similar reversal among board appointees, we do not find a greater proportion of female board members appointed for female-led startups, either. These findings jointly imply that, even if female founders prefer female financiers, they do not impose those preferences on their financiers in terms

[27] In Table 2, I report that there are 2.2 female lead GPs in a typical initial VC financing round.

of the VCs they approach and board members they appoint. Together, these findings and the pre-round GP composition change findings imply that the performance gap difference between syndicates with and without female lead GPs is driven by VCs and not solely caused by founder preference over GP gender.

3.4.2 Evaluation versus advising

In this section, I run a series of tests to determine whether VCs influence the performance gap through differences in their ability to evaluate or advise. First, I compare the performance gap difference across syndicates with and without female lead GPs between initial and second financing rounds. Next, I study differences in founder gender representations across portfolios of syndicates with and without female lead GPs. Third, I examine the impact of board member advising on the performance gap. And finally, I study whether female lead GPs advise female founders better by offering them access to more female mentors. Jointly, these tests imply that female GPs' advantage with female-led startups lies in their ability to better evaluate female-led startups and provide no evidence that female GPs are better advisors of female-led startups.

Initial versus second rounds

To determine how VCs impact the performance gap, I compare the impact of initial and second financing rounds' founder and GP genders on successful exit. 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 across initial and second financing rounds. 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 by comparing the level and interacted impacts of founder and lead GP genders in initial and subsequent rounds 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 may be represented as

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

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 likely 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 one or less than one), female GPs likely narrow the performance gap by improving VC evaluation of female-led startups.

Comparing the interacted impact of founder and lead GP gender on successful exit across initial and subsequent rounds strongly implies that syndicates with female lead GPs are better evaluators of female-led startups.[28] In Table 8, we see the results of the logistic regression detailed in Equation 3 above, with standard errors clustered by startup. 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 of the difference in the performance gap between syndicates with and without female lead GPs. The coefficient indicates that the performance gap difference between the two groups of syndicates actually narrows by 71% from the first round to the second round. This change between the two sets of rounds is statistically significant, as well. The smaller difference in the performance gap in the second round tells us that syndicates with female lead GPs have better performance among their female-led startups relative to syndicates with all-male lead GPs only in the initial financing round. Given the greater emphasis on evaluation in the first round, this is strong evidence that syndicates with female lead GPs narrow the performance gender gap by evaluating female-led startups better.

[28] 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.

Additionally, the regression shows that the main change between the two rounds is that the performance gap among startups financed by all-male lead GP syndicates narrows in the second round. In the first row of the second panel of Table 8, we see that the performance gap for syndicates without female lead GPs is 69% narrower in the second round than in the first round. This narrowing is statistically significant (with a p-value below 0.01) and tells us that all-male lead GP syndicates' performance gap is much narrower when evaluation does not matter as much. Figure 10 presents the same finding visually. The dark-hued bars 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. Furthermore, I find that the performance gender gap among startups financed by syndicates with female lead GPs does not narrow further in the second round. If anything, the bottom row of the second panel of Table 8 shows that the gap is 7% wider for startups financed by syndicates with female lead GPs in the second round, though this is not a statistically significant change. The light-hued bars in Figure 10 illustrate this relative steadiness of the performance gap of startups financed by syndicates with female lead GPs, as well. This lack of difference between rounds for syndicates with female lead GPs is hard to interpret as the gap is already quite narrow after the first financing round. Or, if female GPs possess an advantage only in evaluation and not in advising, the lack of difference could be due to the lesser importance of screening in the second round. However, the far narrower performance gap in the second round for all-male lead GP syndicates is strong evidence that syndicates with female lead GPs possess an advantage in evaluating female-led startups since, when that advantage is less important, all-male lead GP syndicates' performance gap narrows, both in absolute terms and relative to syndicates with female lead GPs.

Portfolio founder gender differences

Syndicates with female lead GPs finance lower proportions of female-led startups, which suggests that they are better at evaluating female-led startups. We see this in Table 9, 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' portfolios have 30% greater female-led startup representation in their portfolios) and statistically significant. Under some reasonable assumptions about VC rationality and deal flow to VCs[29], we could interpret this as evidence that syndicates with female lead GPs are more selective in the female-led startups they choose to finance, which would suggest that they are perhaps 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. 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 (e.g., Y Combinator, 2018). While the differences in portfolio composition are only suggestive evidence that syndicates with female lead GPs are better at evaluating female-led startups, they are consistent with the other findings reported here that more strongly imply that conclusion.

Board member advising impact

To study the advising role of VCs, I examine the interacted impact of founder and VCs' board appointees' gender on exit and find no evidence that female GPs are better at advising of female-led startups. As stated in Section 3.3, studying VC gender composition impact on the performance gap using VC appointees to startup boards excludes the contribution of non-appointees in evaluating which startups to finance. Here, I use the narrower focus of board appointees to test whether advising plays a role in the different performance gender gaps.[30] 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 lacks statistical power. As we observe in Table 2, only 30 of the board appointees I observe are female. Even though my sample is large, the low proportion of appointees that are female may weaken statistical results. I present the results of this regression in Table 10. 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

[29]Namely, we would have to 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.

[30]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.

placed on their board, female-led startups do not perform worse than male-led startups either.[31] 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 how syndicates with female GPs achieve a narrower performance gender gap.

Improved connections through female GPs

As part of their advising role, VCs provide startups with connections to useful entities (e.g., other investors, lawyers, investment bankers, etc.). Some surveys suggest 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. For instance, female founders often report a lack of mentors (Robb et al., 2014). A plausible hypothesis for the narrower performance gap for syndicates with female lead GPs may be that female GPs provide female founders with greater access to female mentors in the future, who, in turn, help them navigate towards success. With my data, I can 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 connect female founders to other female GPs, 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 11 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 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 suggests that female founders paired with female GPs do not have additional female investor contacts 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,

[31] Moreover, although neither estimate is statistically different from no effect, we find that the gap with female board appointees is much larger (71% worse performance) than among startups with all male board appointees (13% 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.

imply that syndicates with female lead GPs are better at evaluating female-led startups.

3.4.3 Lead GP gender covariates

As previously discussed in Section 3.3, presence of female GPs in lead VCs covaries strongly with VCs' age, size, and experience (see Figure 7). Lead VCs with female GPs are generally older, larger, and more experienced. This covariation could mean that the different performance gender gaps for syndicates with and without female lead GPs could be driven by one of those three covariates. In this section, I show that the different performance gaps are not driven by lead VC age, size, or experience.

To show that lead VC age, size, and experience covariates do not drive the difference in the performance gender gap between startups financed by syndicates with and without female lead GPs, I perform 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.[32] Next, I use this residual to build an indicator variable for whether a financing syndicate has 1 or more female lead GPs, made independent of VC age, size, and experience. I then repeat my analyses from Section 3.3, replacing lead VC female GP presence with this new variable, and present the results in Table 12. Comparing Table 12 to Table 4, we see 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 large (the gap is between 2.1 and 2.4 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 (the improvements are statistically significant in two of the four specifications and a bit smaller in economic magnitude than in Table 4). These findings imply that the difference in the performance gap is not due to lead VC age, size, or experience but, rather, is primarily driven by female lead GP presence.

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

4 Conclusion

In this paper, I explore the effect of gender on 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 and compare 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, the narrower gap for startups financed by syndicates with female lead GPs comes from better performance of female-led startups rather than worse performance of male-led startups. Finally, I find compelling evidence from multiple tests that a better ability to evaluate female-led startups likely drives 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 evaluating 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 is the focus of an important debate in policy circles.

Most policy debates focus on increasing the appeal of entrepreneurship for women (see Council of Economic Advisers, 2015). This paper's findings suggest a complementary strategy: 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. 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	3,960	3,032	1,993
with founder data	79.6%	90.2%	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	3,582	2,780	1,968
with founder data	85.7%	95.0%	94.4%
with GP data	97.5%	97.7%	98.1%
with founder & GP data	83.8%	92.9%	92.7%
VCs per VC financing round	2.718	2.731	2.707
initial round	2.073	2.096	1.972
second round	2.623	2.631	2.487
% 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	6.04	4.99	5.30
for IPO startups	5.82	5.21	5.91
for acquired startups	6.08	4.95	5.18

Table 2. 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, 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	3,801	243	3,558
per startup	1.91	0.12	1.78
For initial VC rounds			
GPs	49,274	7,106	42,168
per round	24.70	3.56	21.14
GPs in lead VCs	25,779	2,848	22,931
per round	20.20	2.23	17.97
Appointed board members	1,010	30	980
per round	1.37	0.04	1.33
For second VC rounds			
GPs	62,926	9,541	53,385
per round	32.04	4.86	27.18
GPs in lead VCs	28,119	4,244	23,875
per round	19.49	2.94	16.55
Appointed board members	860	45	815
per round	1.28	0.07	1.21

Table 3. 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 dimensions.

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

Table 4. 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)
Fem-led startup	0.322***	0.384**	0.300***	0.367***
	[3.03]	[2.51]	[3.20]	[2.60]
Fem GP in lead VC	1.010	0.985	1.017	1.002
	[0.07]	[0.10]	[0.11]	[0.01]
Fem-led startup × fem GP in lead VC	2.438**	2.245*	2.442**	2.190*
	[2.01]	[1.78]	[2.00]	[1.71]
Fem- vs. male-led startups with fem GP in lead VCs	0.786	0.862	0.732	0.803
	[1.01]	[0.61]	[1.29]	[0.88]
Fem vs. all-male lead VCs for fem-led startups	2.462**	2.212*	2.483**	2.193*
	[2.15]	[1.85]	[2.16]	[1.82]
Init. fin. year FEs		X		X
Prod. mkt. FEs			X	X
R^2	0.0121	0.0606	0.0281	0.0771
Observations	1044	1044	1044	1044

Absolute t statistics in brackets

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

Table 5. 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 6. 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	0.990	1.077
	[0.03]	[0.24]
Fem lead GP prop drop	1.089	1.025
	[0.44]	[0.12]
Fem lead GP prop rise	0.778	0.879
	[0.95]	[0.46]
Fem-led startup × fem lead GP prop drop	0.220**	0.170**
	[2.13]	[2.39]
Fem-led startup × fem lead GP prop rise	1.646	1.808
	[0.62]	[0.71]
Lead GP fem proportion drop vs. no change diff in fem-led startups' success	0.218**	0.183**
	[2.34]	[2.51]
Lead GP fem proportion rise vs. no change diff in fem-led startups' success	1.630	1.947
	[0.65]	[0.86]
Init. fin. year FEs		X
Prod. mkt. FEs		X
R^2	0.0112	0.0852
Observations	724	712

Absolute t statistics in brackets

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

Table 7. 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 8. 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	0.385** [2.43]
Fem GP in lead VC	0.982 [0.12]
Second round	0.798 [1.55]
Fem-led startup × fem GP in lead VC	2.178* [1.66]
Fem-led startup × second round	3.243*** [2.79]
Fem GP in lead VC × second round	1.036 [0.18]
Fem-led startup × fem GP in lead VC × second round	0.288** [2.27]
First vs. second round founder gender gap with no fem GP in lead VCs	0.308*** [2.79]
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
R^2	0.0885
Observations	2334

Absolute t statistics in brackets

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

Table 9. 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 1+ female GPs	Lead VC in syndicate has no female GPs	Diff. 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 10. 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	0.874
	[0.49]
Fem board appointee	2.491*
	[1.85]
Fem-led startup × fem board appointee	0.327
	[1.00]
Fem- vs. male-led startups with fem board appointees	0.286
	[1.16]
Fem vs. all-male board appointees for fem-led startups	0.815
	[0.20]
Init. fin. year FEs	X
Prod. mkt. FEs	X
R^2	0.1185
Observations	695

Absolute t statistics in brackets

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

Table 11. 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	2.221***	2.432***	2.451***
	[4.58]	[4.81]	[4.32]
Fem-led startup			1.625
			[1.18]
Fem-led startup × fem GP in lead VC			1.429
			[0.66]
Init. fin. year FEs		X	X
Prod. mkt. FEs		X	X
R^2	0.0339	0.0689	0.0813
Observations	615	597	557

Absolute t statistics in brackets

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

Table 12. 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.

	Overall likelihood of success			
	(1)	(2)	(3)	(4)
Fem-led startup	0.389***	0.475**	0.364***	0.463**
	[2.69]	[2.06]	[2.86]	[2.12]
Resid. fem GP in lead VC	0.866	0.878	0.859	0.881
	[1.07]	[0.92]	[1.12]	[0.89]
Fem-led startup × resid. fem GP in lead VC	2.293**	2.093*	2.384**	2.092*
	[2.12]	[1.83]	[2.20]	[1.81]
Fem- vs. male-led startups with fem GP in lead VCs	0.893	0.994	0.869	0.968
	[0.65]	[0.03]	[0.79]	[0.18]
Fem vs. all-male lead VCs for fem-led startups	1.987*	1.838	2.048*	1.843
	[1.87]	[1.60]	[1.93]	[1.60]
Init. fin. year FEs		X		X
Prod. mkt. FEs			X	X
R^2	0.0049	0.0772	0.0151	0.0846
Observations	1742	1742	1721	1721

Absolute t statistics in brackets

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

Figure 1. Startup product markets. This figure graphs the most common product market reported by each startup to CrunchBase, except “Software”.

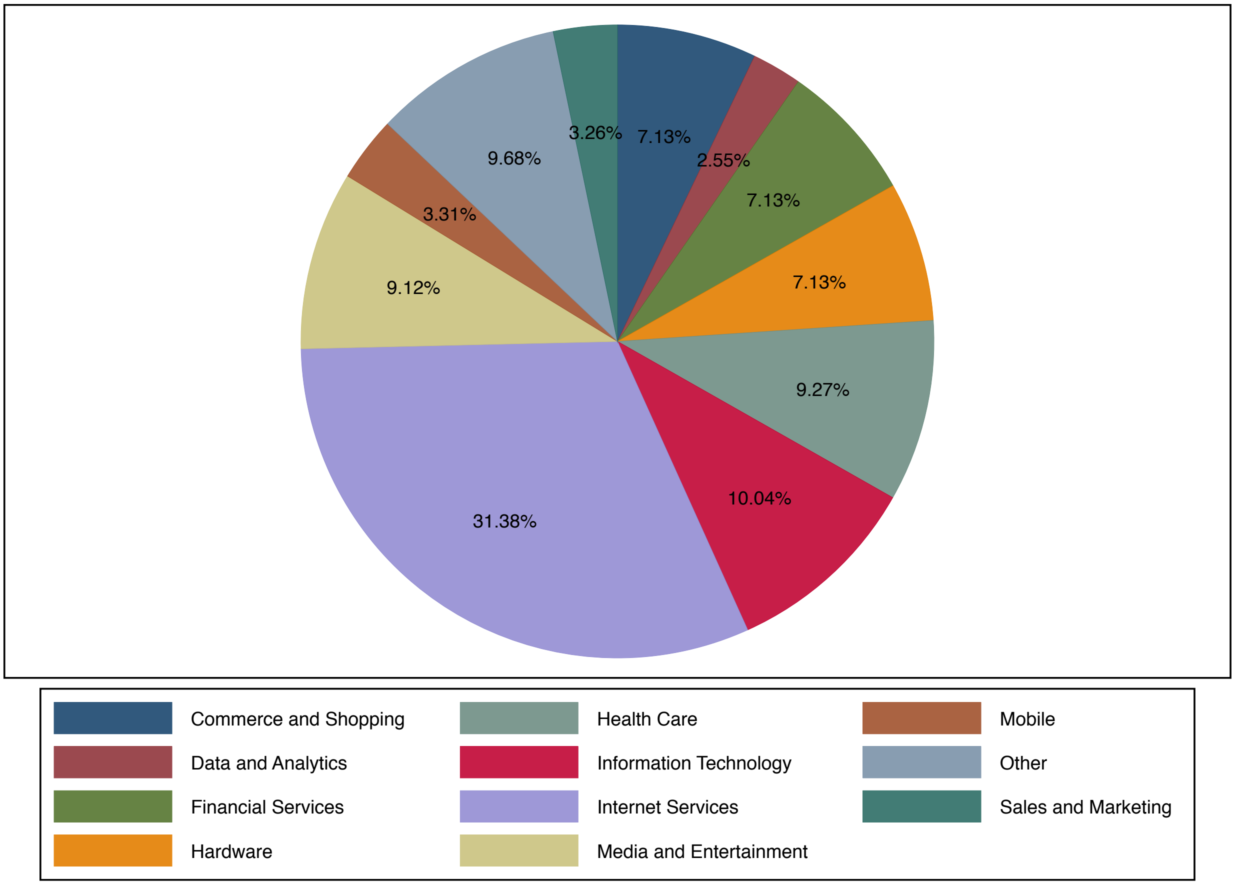


Figure 2. Performance across initial financing years. This figure presents startup performance measured by overall exit, IPO, and acquisition for each initial financing year, from 2005 to 2018.

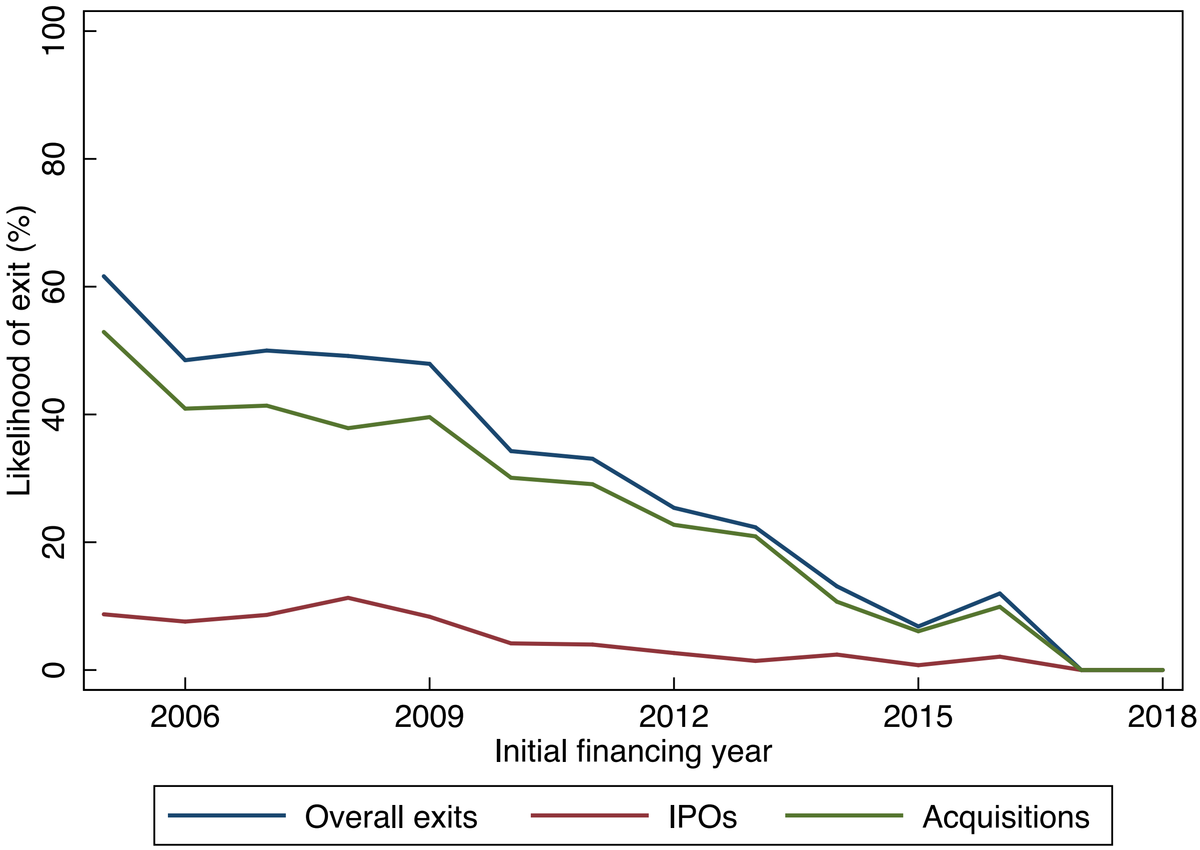


Figure 3. Performance across exit years. This figure presents startup performance measured by overall exit, IPO, and acquisition for each exit year, from 2005 to 2018. The sample is all startups initially financed by VCs in 2005 to 2013.

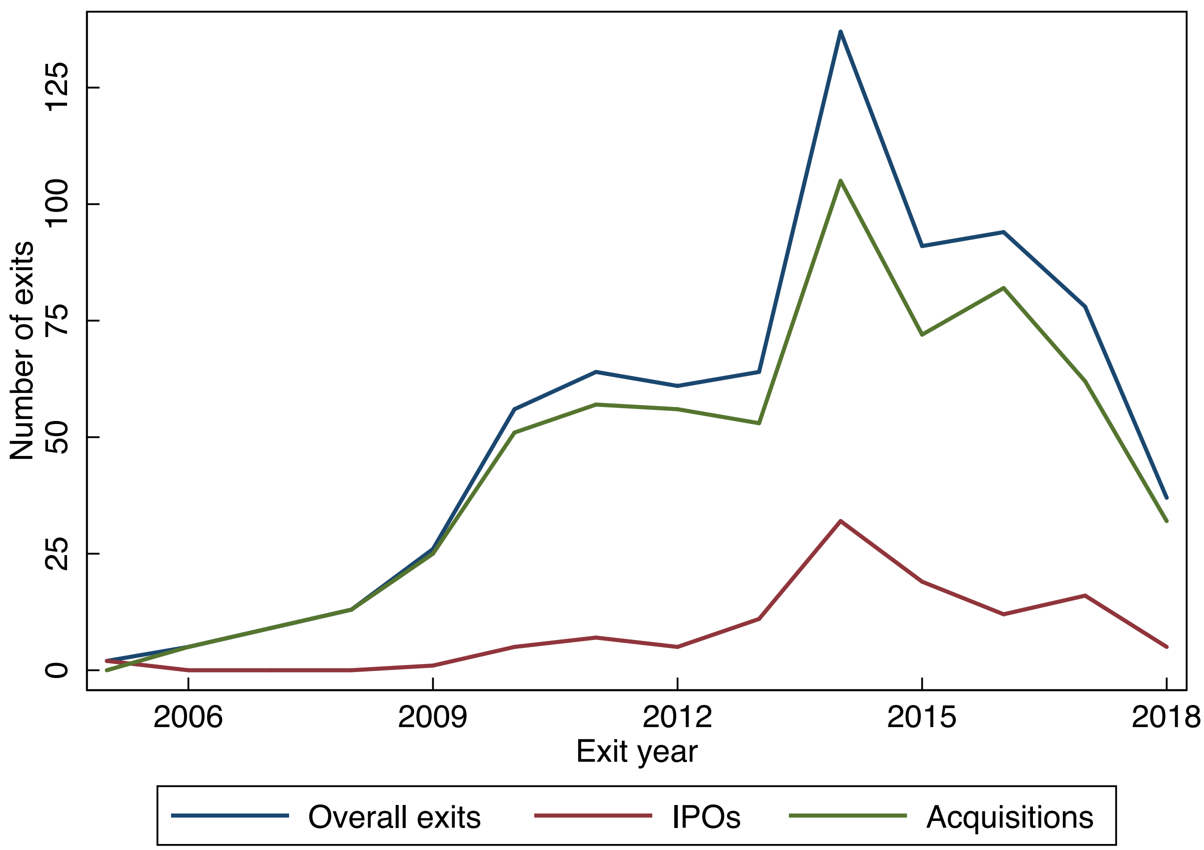


Figure 4. Performance by founder gender across initial financing year. This figure compares performance measured by overall exit for startups led by one or more female founders to startups led by all male founders within each initial financing year, from 2005 to 2013.

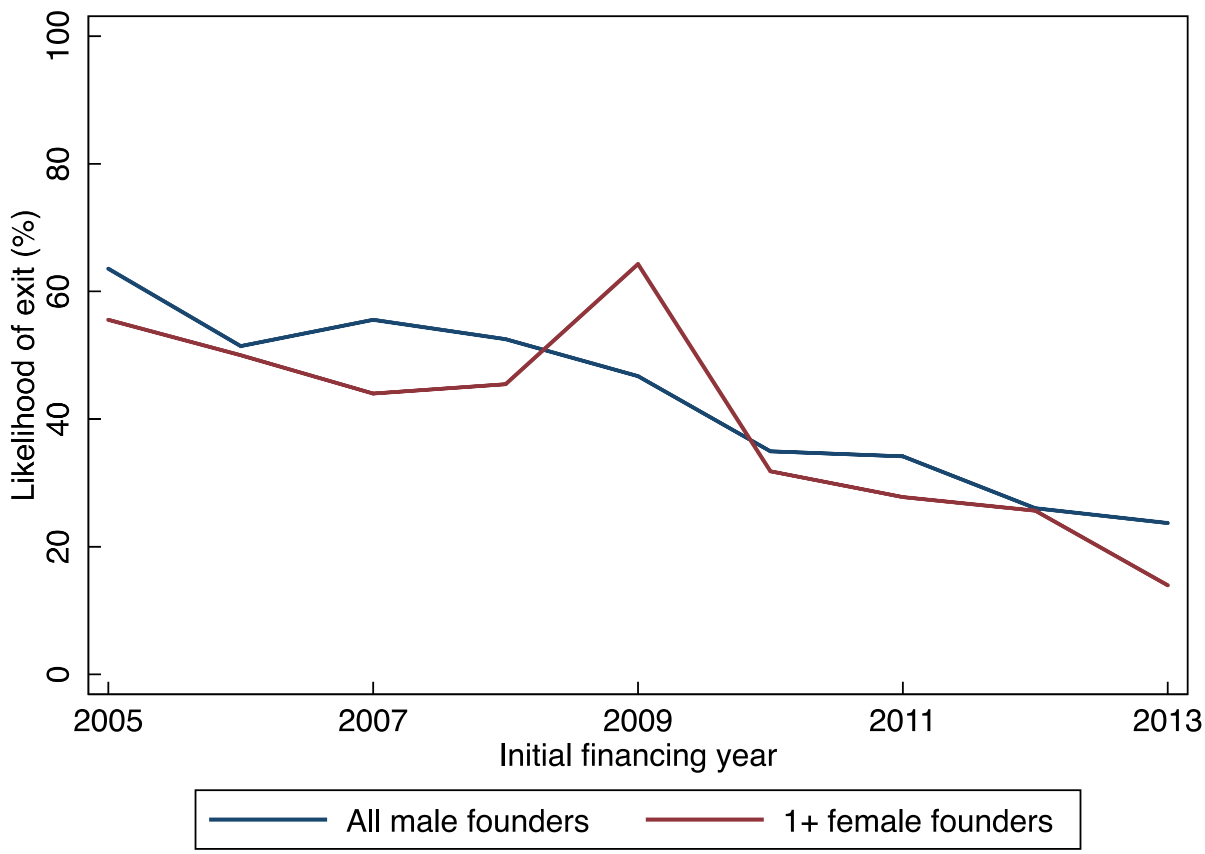


Figure 5. Performance by founder gender across product markets. This figure compares performance measured by overall exit for startups led by one or more female founders to startups led by all male founders across product markets. All startups in this sample have initial financing rounds between 2005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

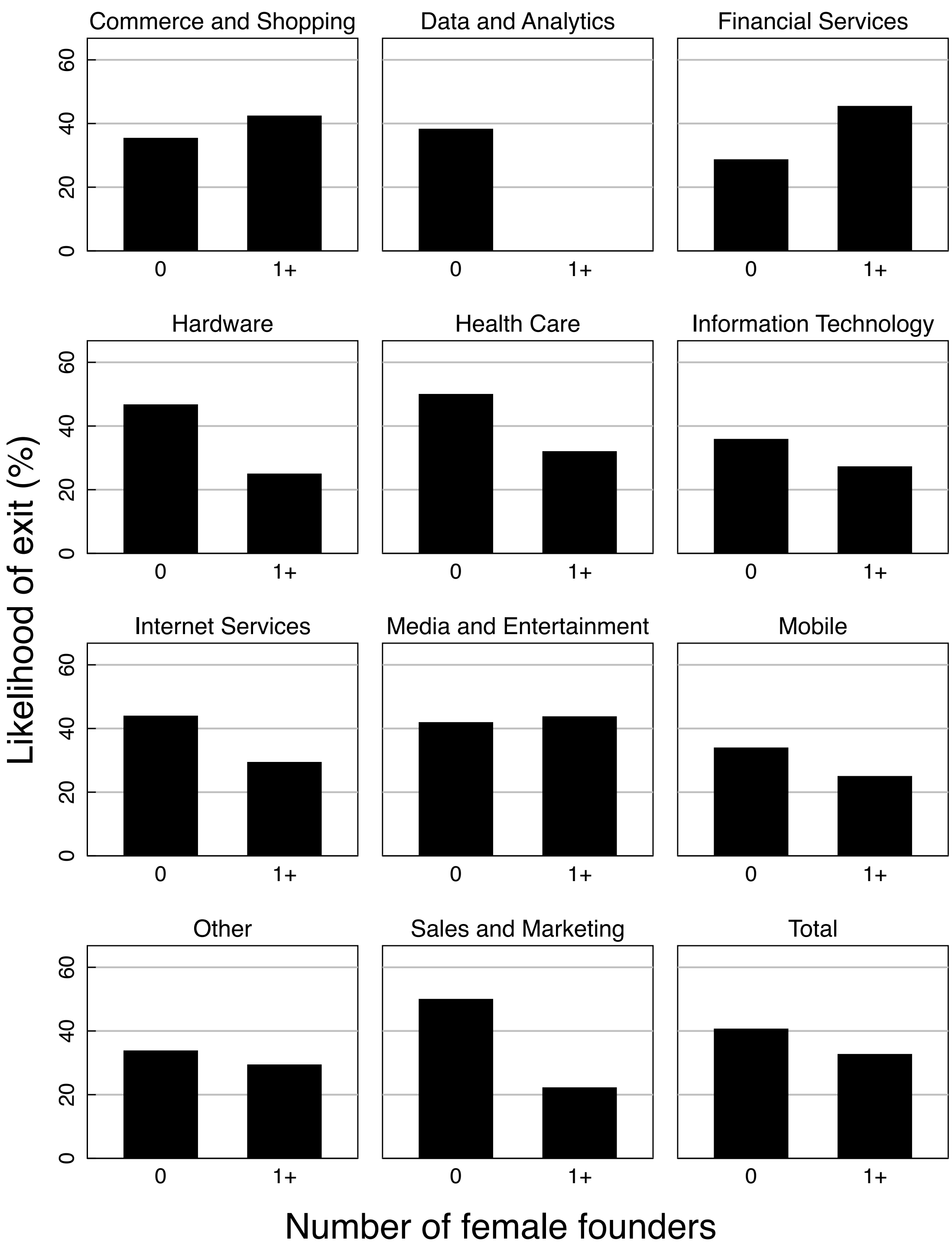


Figure 6. Performance by founder and lead VC GP gender. This figure compares performance measured by overall exit for startups led by one or more female founders to startups led by all male founders across startups initially financed by syndicates with no female general partners (GPs) in the lead investor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

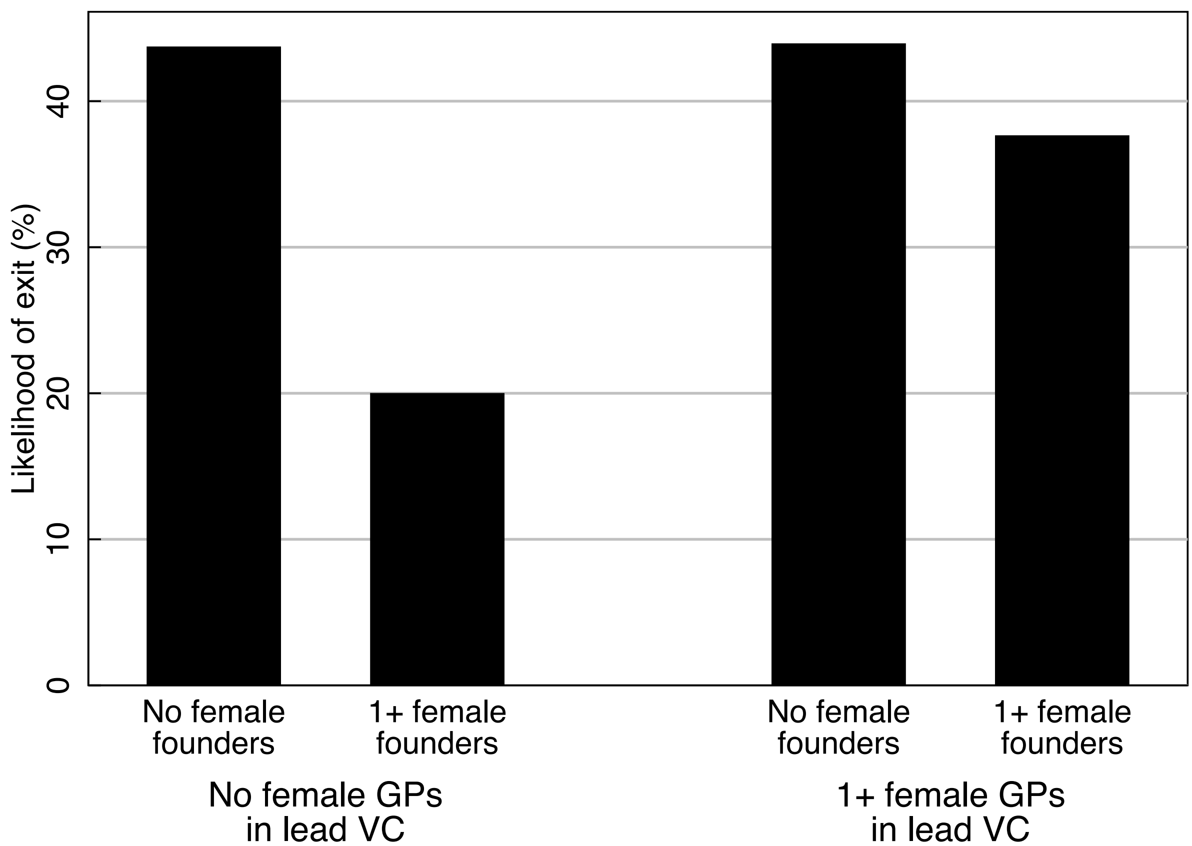


Figure 7. Distribution of lead VC characteristics by lead VC GP gender. This figure presents the distributions of three lead VC characteristics for initial financing rounds with and without female lead GPs. The distributions are presented as box and whisker plots. All startups have initial financing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

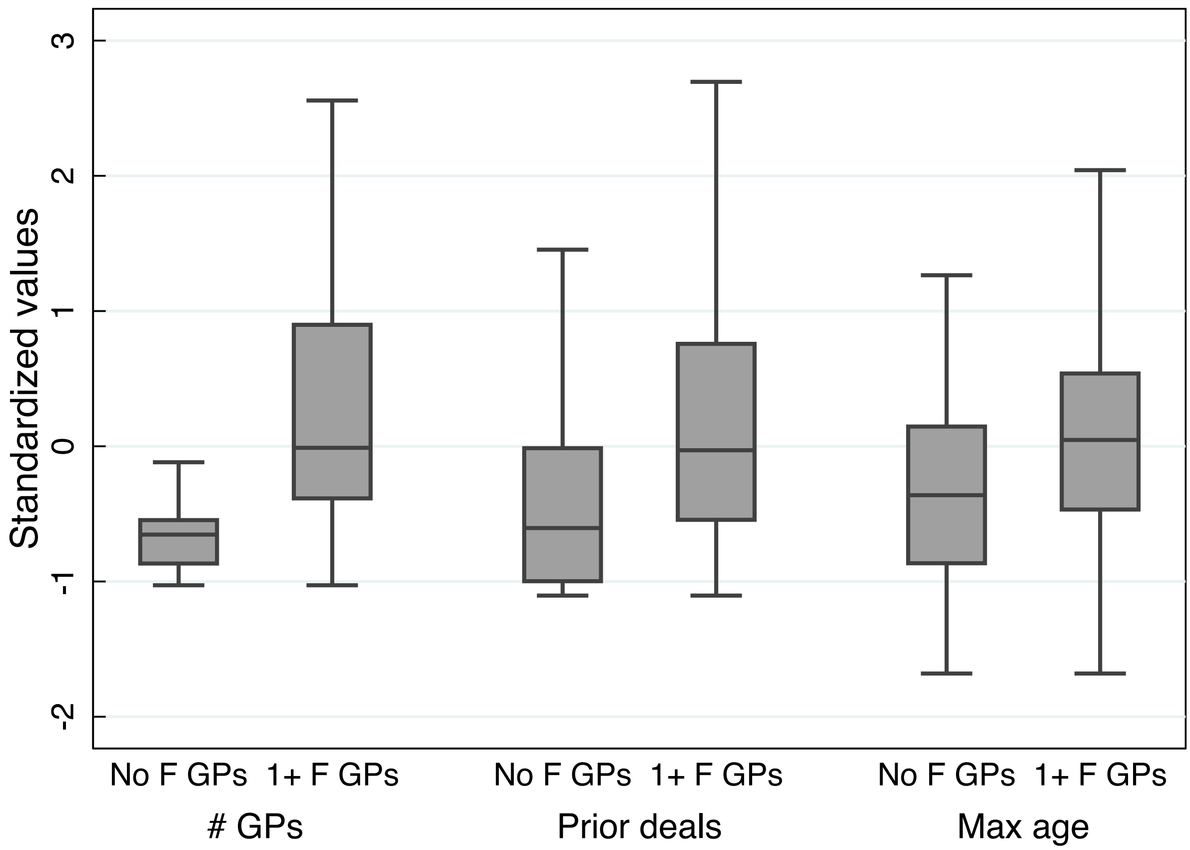


Figure 8. Impact of female GPs in lead VC on startup performance over time. This figure presents the ratio of exit likelihood for female- and male-led startups financed by syndicates with female GPs in the lead VCs relative to those financed by syndicates with all male lead VCs for two time intervals: 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.

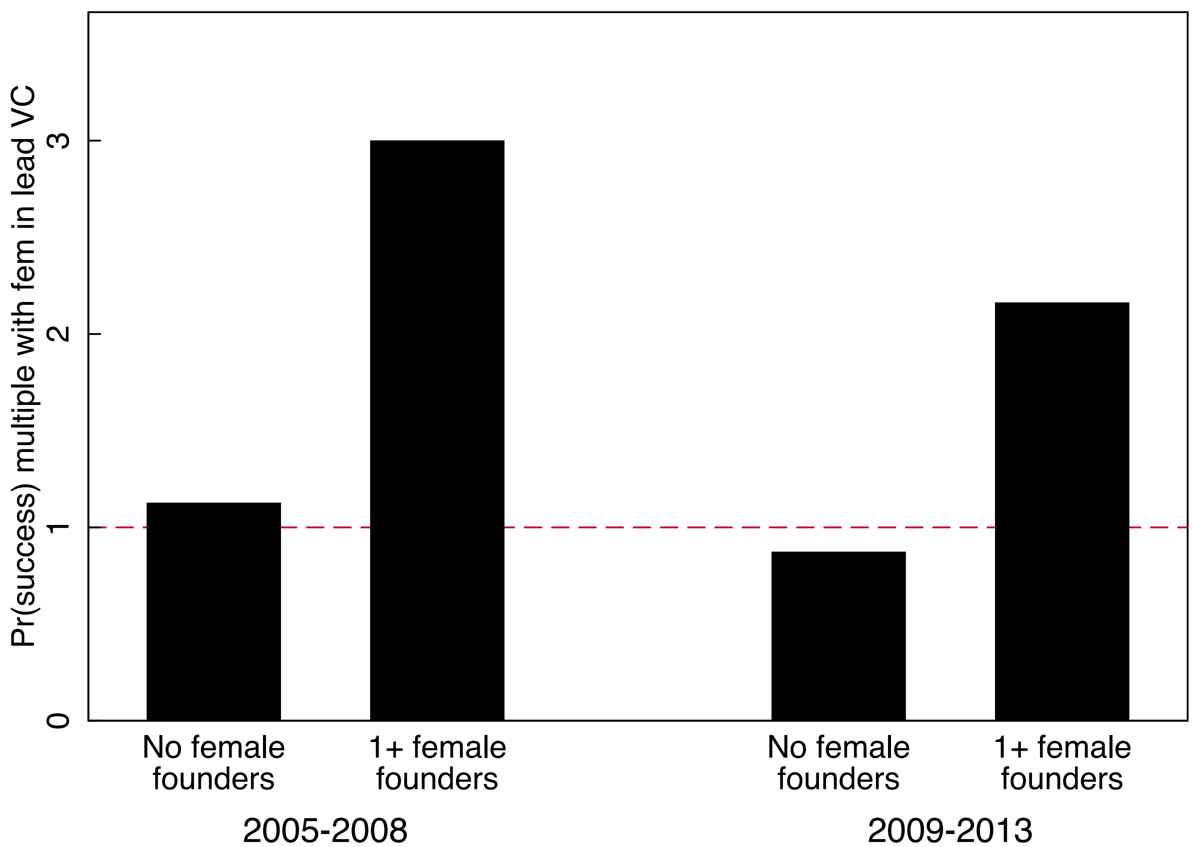


Figure 9. Impact of female GPs in lead VC on startup performance across product markets. This figure presents the ratio of exit likelihood for female- and male-led startups financed by syndicates with female GPs in the lead VCs relative to those financed by syndicates with all male lead VCs for different 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.

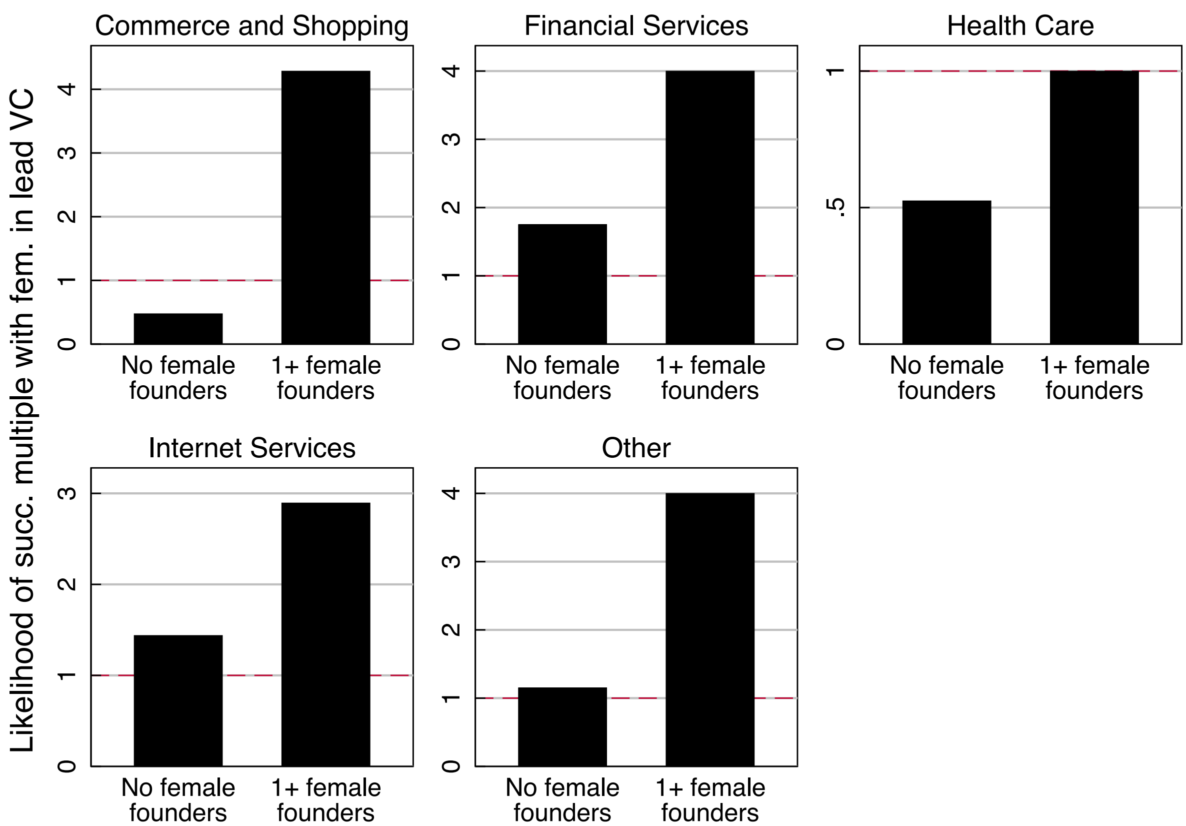
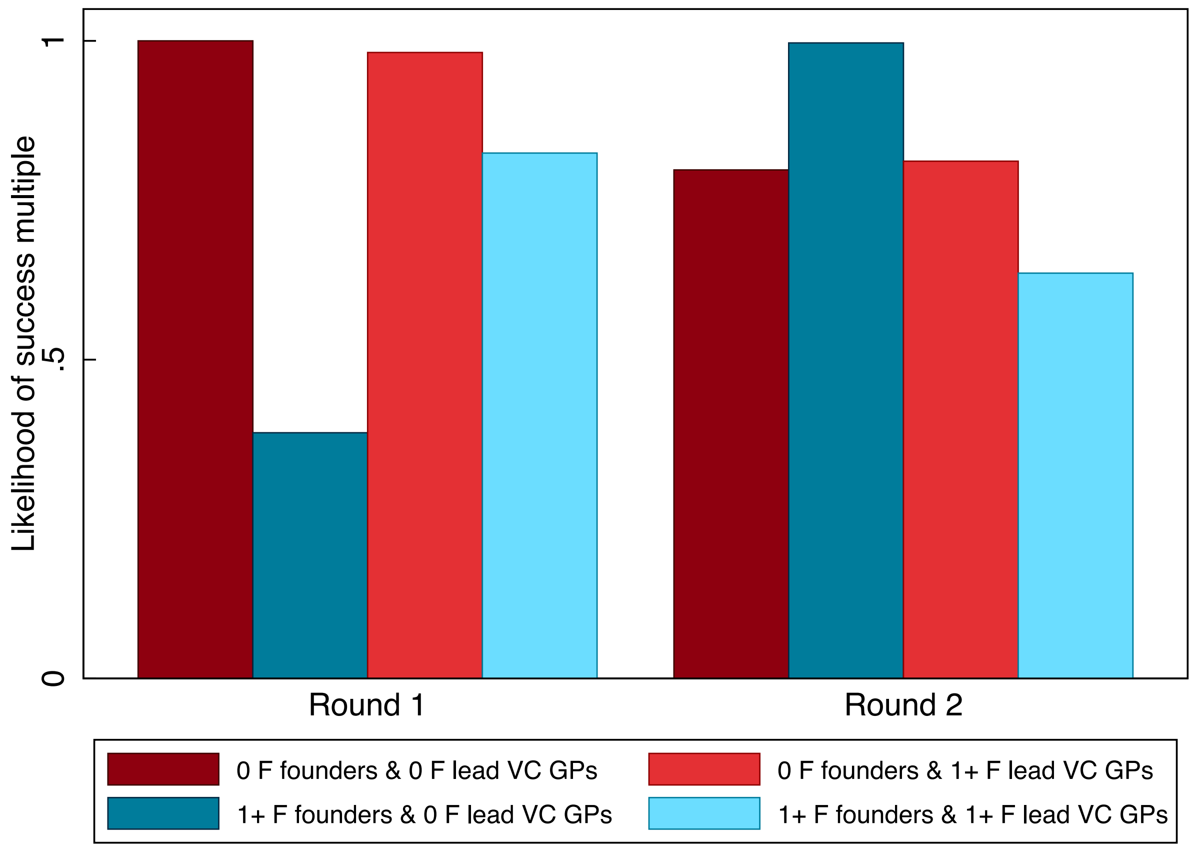


Figure 10. Performance by founder and lead VC GP gender in initial and second financing rounds. This figure presents the likelihood of successful exit multiple for startups based on founders' gender, lead VC GPs' gender, and round of financing. The baseline startup relative to which the multiple is defined 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 8. All startups have initial financing rounds between 2005 and 2013, inclusive.



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.[33]. 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 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

[33] 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.

‘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.

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).[34] Moreover, there were no startups for whom the EDGAR-collected data showed IPOs that Crunchbase did

[34] 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.

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.

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

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.