VC financing and the entrepreneurship gender gap

Sahil Raina[*]

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Abstract

Women's participation in venture capital-financed entrepreneurship is lower than in other sectors of the economy. And the women that do participate lead startups that perform worse than startups led by men. Does interaction with venture capitalists (VCs) contribute to the low participation and performance gap? To answer these questions, I compare the gender gap in successful exits from VC financing between two sets of startups: those initially financed by VCs with only male general partners (GPs) and those initially financed by VCs that include female GPs. Constructing a novel dataset to perform this analysis, I find a large performance gender gap among startups financed by VCs with only male GPs but no such gap among startups financed by VCs that include female GPs. The disparity is solely due to improved performance among female-led startups. This suggests that VC gender composition has contributed strongly to the performance gap between female- and male-led startups, which could deter women from leading VC-financed projects and lower their participation.

[*]Raina: Alberta School of Business, University of Alberta e-mail: sraina@ualberta.ca. I am very grateful to the members of my dissertation committee, Michael Barr, Norman Bishara, Charles Brown, Ing-Haw Cheng, Amy Dittmar, Martin Schmalz, and especially Sugato Bhattacharyya (chair), for their guidance and support. The paper has also benefitted greatly from conversations with Alexander Ljungqvist, Stefan Nagel, Amiyatosh Purnanandam, and Uday Rajan as well as feedback from seminar participants at Aalto University, Baruch College, Federal Reserve Board of Governors, Fordham University, Norwegian School of Economics, Peking HSBC, Universities of Alberta, Connecticut, Miami, Michigan, and Utah, and Wayne State University.

Anecdotally, Silicon Valley is a difficult 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." Does this translate into worse performance for VC-financed startup led by female entrepreneurs? In this paper, I measure performance using exits from VC financing via IPO or acquisition[1] and find that startups led by one or more female entrepreneurs (hereafter referred to as female-led startups) have a 34% lower rate of exit than startups led by male entrepreneurs (male-led startups), a sizeable performance gap.

What might be the underlying reasons for this gap? Is it that female-led startups are intrinsically less valuable than male-led startups?[2] Or are VC financiers responsible for the performance gap? It could be that some VC financiers are poor at evaluating female-led startups and some may also be poor at advising them. In this paper, I explore whether VC financing contributes to the performance gap among startups. Addressing this question is important both from the perspective of the VC financier and the startup. From the VC perspective, reducing financed startups' potential success means that some VCs are wasting resources invested by their limited partners (LPs). For the startup, financing by the right VC may be the difference between success and failure. If women entrepreneurs believe VC financing may hurt their startups' likelihood of success, they may be less likely to pursue VC-financed entrepreneurial projects.

Reduced female participation would imply that some intrinsically valuable projects in the economy are not undertaken because of the possibility of VC-induced failure. This may be part of the reason for markedly lower female participation in VC-financed entrepreneurship than in other segments of the economy. In 2012, women comprised 47% of the labor force while 36% of small businesses were majority-owned by women (Sewell, 2013; Lichtenstein, 2014). In stark contrast, 15% of VC-financed firms had a woman on the executive team in 2011-2013 and only 2.7% of them

[1] 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).

[2] Given the nature of VC-financed projects, gender differences in risk aversion, competitiveness, and ability that are described in the literature may contribute to this gap. Risk aversion differences between men and women are documented in Powell and Ansic (1997) as well as Barber and Odean (2001). Croson and Gneezy (2009) shows evidence that women are more averse to competition than men. And Tierney (2010) presents the argument made by Larry Summers that the far right tail of the ability distribution may be more populated by men than women.

had a female CEO, according to a survey by The Diana Project.[3]

To explore the potential role of gender in VC-financed entrepreneurship, I compare the performance gap among startups financed by VC syndicates with and without female partners (hereafter, female VCs and male VCs, respectively), and find that, although the two VC groups finance similar startups, the performance gap is large among startups financed by male VCs but nonexistent among startups financed by female VCs. My findings provide strong initial evidence that VC financing has contributed to the performance gap among startups.

To run my analyses, I construct a novel dataset using CrunchBase, a large, crowdsourced database on the activities of high-tech startups. I use CrunchBase not only because it includes data on a large number of startups and financing rounds, but also because it includes biographical information on entrepreneurs and financing VCs' general partners (GPs), which is crucial for this study and not available in most public databases on VC financing. While CrunchBase limits the dataset to high-tech startups, the percentage of female-led startups within this dataset is comparable to that reported for all VC-financed firms (14.5% in my sample versus 15% in The Diana Project data).

My dataset provides a number of interesting insights into VC financing of startups. For instance, 9% of all founders and GPs are female in my dataset, and one-sixth of the startups initially financed by female and male VCs are female-led. The equal representation suggests that the two VC groups do not suffer differentially from any possible evaluation biases against female entrepreneurs. Of course, equal representation could also arise from differences in the intrinsic value of female-led startups seeking initial financing from two (differently biased) VC groups. However, this explanation is inconsistent with another fact revealed by the data: the proportion of portfolio firms that successfully exit VC financing from the two VC groups is the same, approximately 30%. If the intrinsic value of financed startups differed across the two VC groups, it would likely be reflected in their overall exit rates.

Comparing other features of the data across the two syndicate groups, I find that startups that were initially financed by the two VC groups also have similar exit rates via IPO (5%) and acquisition (25%). The duration of VC financing for successful portfolio firms also does not differ

[3]The Diana Project is a non-profit organization focused on female entrepreneurship which releases periodic statistics on female participation in entrepreneurship.

substantially across the two groups (3.5 years), nor the number of financing rounds (2.4 rounds). The number of entrepreneurs in each portfolio firm is similar across the two groups as well (2.0 entrepreneurs). As there is a general dearth of female GPs, syndicates with female GPs tend to be larger, have more GPs per syndicate, have more VC firms per syndicate, and have more prior financing experience across all firms in the syndicate.

To explore whether VC financing plays a role in the performance gap, I compare the annual likelihoods of exit between female- and male-led startups initially financed by female VCs and male VCs using a proportional hazards duration model.[4] If inherent differences between female- and male-led startups explain the performance gap, then the gap in exits should be the same across startups financed by the two VC groups. If the gap differs, then VC financing has an impact on the performance gap. I find that among startups financed by male VCs, female-led startups are 70% less likely to exit in a given year than male-led startups, whereas this gap disappears among startups financed by female VCs. This difference arises from female-led startups' exit rates being significantly higher when financed by female VCs. In constrast, male-led startups' exit rates are the same regardless of the gender composition of the initial financing syndicate.

Could the observed difference in the performance gap be driven by differences in entrepreneurial preference for female versus male VCs? For instance, could the gap be explained by female-led startups of high intrinsic value preferring financing from female VCs? If this were true, female VCs would have greater proportions of female-led startups in their portfolios. However, the representation of female-led startups in the portfolios of the two VC groups is the same.[5] Alternatively, could the difference in the performance gap arise due to female-led startups of all types preferentially seeking financing from female VCs? This conjecture is not consistent with the observed difference across the VC groups in the performance gap. Finally, could it be that all high intrinsic value startups preferentially seek financing from female VCs? In such a case, the overall exit rate would be higher for all startups financed by female VCs. However, as mentioned earlier, the overall exit rate of portfolio startups in the two VC groups is approximately the same. Given my empirical setting, I cannot entirely rule out the possibility that entrepreneur financing choice drives the observed

[4]While a duration model is the correct specification for addressing this question, I perform the analysis using logistic regression and OLS regression as well, and find similar results.

[5]This argument against an entrepreneur choice explanation depends on the assumption that VCs are evaluating startups in terms of expected future performance. If VCs provide financing to all startups or evaluate startups on some other characteristics, this argument does not rule out the entrepreneur choice explanation.

difference in the gap. However, by eliminating these most commonly-posed scenarios, I alleviate much of the concern revolving around this alternative explanation of my findings.

The findings above jointly paint a picture in which VC financing contributes to the performance gap among startups based on founder gender. But *how* do VCs contribute to the gap? Is it due to poor evaluation or poor advising? My extensive data allow me to compare initial financing rounds to subsequent rounds to shed some light on this question. Comparing the difference in the gap across the two VC groups in initial rounds versus later rounds shows that it is much larger in initial rounds, suggesting that female VCs are better at evaluating female-led startups, which helps drive VC contribution to the performance gap.

Can the observed difference in female-led startups' exit rates be attributed to matching female entrepreneurs and GPs or does it arise from some cultural characteristic of VC syndicates that have female GPs? I compare the gap in exit rates between female- and male-led startups initially financed by a single VC to those financed by multiple VCs. Among single-VC financing rounds, each GP is more likely to be directly involved with the financed startup. I find a larger difference in the gap for single VC financing rounds, which suggests that female GP involvement has a direct impact on the performance gap.

This paper has two principal findings. First, it establishes the existence of a gender gap in performance among VC-financed startups. Second, it presents persuasive evidence that the structure of the VC financing industry has contributed to this performance gap. This latter result has three important implications. First, it suggests that some intrinsically valuable firms do not succeed despite getting access to VC financing. Second, VC-induced reduction in success rates means that some VCs waste LP-invested resources. Finally, if women are thus inefficiently dissuaded from entrepreneurship, it implies that some intrinsically valuable projects are not undertaken because of the possibility of VC-induced failure.

1 Related literature

This paper adds to a growing body of literature on the interaction between financing and gender among entrepreneurial firms. Alesina et al. (2013) finds that female entrepreneurs seeking bank loans pay more for credit than do male entrepreneurs. Bellucci et al. (2010) finds that female entrepreneurs face tighter credit availability than male entrepreneurs when seeking bank loans. Bellucci et al. (2010) also finds that female loan officers require lower collateral from female entrepreneurs for loans than from male entrepreneurs. These papers look at the impact of entrepreneur gender on specific financing outcomes, whereas I examine impact on firm performance. In the context of crowdfunding, Marom et al. (2015) discovers a preference among female investors for female-led projects. Bengtsson and Hsu (2010) finds a preference for shared identity along ethnicity and educational background in VC financing pairings between entrepreneurs and GPs. My paper adds to these papers by examining the impact of such pairings across entrepreneurs and financiers on firm performance. Like my paper, Gompers et al. (2014) looks at performance impacts of gender, but within VC firms. 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.

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 matching between VC firms and entrepreneurs also impacts the performance of entrepreneurial firms.

Outside of entrepreneurial finance, this paper also relates to a wider literature examining the role of gender pairings on various outcomes. 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, Tsui et al. (1989) finds that superior-subordinate dissimilarity is associated with lower effectiveness in corporate settings. In education, Lim and Meer (2015) 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. 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 information for both the entrepreneurs leading startups and the financiers financing them. In this section, I (briefly) discuss the structure of the VC financing industry, present basic statistics detailing my dataset and outline the new sources I use for it. For information on how I constructed the dataset, see Appendix A.

2.1 VC financing process

VC financing is a private form of financing for startups whose businesses exclude 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 the early-stage financing of the startups. These investors tend to be institutions such as pension funds but can also be wealthy individuals. 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.[6] 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 the formal channels provided by the VC. Once contact with the startup is made, 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 often needs to be unanimous. Additionally, while the analysts provide quantitative analysis of the startups, there is no "cutoff" above which a startup is certain to receive financing or below which is it certain to be rejected.

The startups that secure VC financing are provided with capital by its financiers in a series of rounds. At each round, the financiers reassess the performance of the startup.[7] The periodic reassessment of startups is one characteristic of VC financing that helps mitigate some of the problems associated with financing high uncertainty, early-stage businesses (Gompers and Lerner, 2004).

2.2 Data description

My dataset contains information on 3,660 entrepreneurial firms (startups). To the extent possible, it includes data on each startup's financing rounds, founders, and whether and how the startup eventually exits VC financing. For their VC financing rounds, of which there are 8,904, I know the date on which the financing round was announced, which VCs were involved in the round, and the GPs of the involved VCs. For founders and GPs, the dataset includes full name and gender information. And, for exits, I know the type of exit (IPO or acquisition) and the date of exit announcement.

All of the startups I observe are in the high-tech sector, with the vast majority in the computing high-tech sector. As can be observed in Figure 1, 90% of my startups are computing high-tech firms, 9% are biotech firms, and the rest are manufacturing high-tech firms. This is reflective of the VC-

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

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

financed sector as a whole. VCs, with their equity-like contracts and intensive monitoring and advising of startups, are better equipped than other forms of private financing for high tech, high information asymmetry sectors.

While my data include 8,904 VC financing rounds, many of them lack the information required for my analyses.[8] For instance, in Table 1, we see that 70% of financing rounds (64% of initial rounds) have gender data for founders, 61% (63%) have gender data for GPs involved in the financing, and 42% (38%) have gender data for both founders and GPs. While less than two-fifths of the data are available for some of my analyses, the overall sample sizes are still large, with well over a thousand initial VC financing rounds with gender data for both founders and financing GPs.

Figure 2 shows that the number of financing rounds reported in CrunchBase generally increases over time. This is reflective of the nature of VC financing. With more firms being added through initial financings each year, more startups are likely to have subsequent financings in each year than in the previous one. Unlike all rounds, we see that the number of initial financing rounds reported each year after 2005 stays between 250 and 500, suggesting a steady flow of information to the database. This suggests that, at some point, the number of financing rounds per year should level off, unless duration of financing is increasing or CrunchBase starts increasing its coverage further.

While I have data for financing rounds as far back as 1995, I limit my analyses to startups with initial financing rounds in 2005 or later. I do this because, although it has data for rounds prior to 2005, CrunchBase was established in 2005. As a result, startups with financings before 2005 reported in CrunchBase differ from the rest of the startups in the data. In particular, they are much more likely to be successful in exiting VC financing. This brings up concerns of backfill bias for pre-2005 financing startups. To avoid problems associated with this bias, I exclude these startups from my analyses. As can be seen in Figure 2, this does not reduce my sample severely as there are far fewer firms in the years before 2005 than following it.

In Figure 2, we also see a dip in initial financings between 2006 and 2011, which coincides neatly with the economic downturn. There is no similar dip in all financing rounds, but the rate at which all rounds increase falls for that period as well. These features suggest that CrunchBase has a good representation of the overall startup economy in each year after its inception.

[8] As I discuss in Section 2.3.1 below, this is one of the shortcomings of using crowdsourced data.

2.3 Sources

I combine data from multiple sources to generate my dataset. These sources include TechCrunch's CrunchBase, Namepedia, SEC's EDGAR data, Thomson One SDC's M&A database, and Thomson One's VentureXpert. I use VentureXpert primarily to define my sample, as I explain in Appendix A. SEC's EDGAR and Thomson One SDC's M&A databases are used to identify VC financing exit events (IPOs and acquisitions) for the startups in my data. In this section, I describe CrunchBase and Namepedia, as these two sources are less familiar to general finance and economics audiences.

2.3.1 CrunchBase

The CrunchBase database provides data on high-tech startup activity. In fact, they claim to be the "most comprehensive information source" for such activity (CrunchBase, 2014). A key feature of the database is that it is crowdsourced. This affords CrunchBase three substantial benefits. The greatest benefit is its extensive coverage of VC financing of startups. I extract data from CrunchBase on startups financed at least once by top VCs, amassing information on 3,660 startups and 10,015 financing rounds from 3,318 investors.[9] For comparison, 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.

Crowdsourcing also limits concerns of bias arising from a limited number of contributors. Most VC databases arise from data provided by a few or even one source. In 2013 alone, over 53,000 sources contributed to CrunchBase (Kaufman, 2013). Having 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 data we have on the industry 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

[9] These numbers include all startups and all financing rounds. For my analyses, focusing on VC financing, I exclude data on angel and debt financing rounds, which is why there are 1,111 fewer rounds overall and 301 fewer initial rounds.

voluntary disclosure. CrunchBase data, while voluntarily provided, are not sourced solely from VCs, LPs, or portfolio firms. Rather, the CrunchBase data are sourced from the general public. This sharply mitigates concerns about biases stemming from voluntary disclosure.

Being crowdsourced is also responsible for CrunchBase's primary weakness: a plurality of observations with incomplete information. For instance, I have founder gender data for 64% of initial financing rounds and GP gender data for 63% of initial financing rounds. This incompleteness of my dataset arises primarily because, for a significant number of startups and VCs, personnel information is not available on CrunchBase.[10]

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).[11]

There are three ways to access the CrunchBase data: full subscription, monthly tabulation, and API access. I use the API (Application Program Interface) access provided by CrunchBase. I detail this procedure in Appendix A, where I describe the construction of my dataset. This API access allows the user to download all information associated with a single object. As there is no way to use the API access to download information on the entire universe of objects in CrunchBase at once, I serially download all information on each object of interest.

2.3.2 Namepedia

Namepedia is the largest information portal for personal names in the world (Namepedia, 2015). I use it to classify by gender those personnel that I cannot categorize myself. Namepedia is partially crowdsourced, much like CrunchBase. Therefore, it possesses many of the same strengths and weaknesses. To improve data quality, Namepedia staff verify crowd-sourced name data. The database also uses national census data and birth statistics to build up its database of name information.

I access Namepedia gender data using a "webscraping" procedure. Webscraping is a method wherein you access a webpage and extract data from the HTML code of that webpage. For my

[10] A much smaller issue that contributes to the high missings rate is that I am unable to match all personnel to their genders.

[11] Additionally, recent evidence based on a comparison of Wikipedia to other encyclopedias suggests that the error rate in crowdsourced data may be lower than data gathered otherwise (Giles, 2005; Casebourne et al., 2012).

purposes, I request the Namepedia webpage for a first name and then, from the provided webpage, extract the field with the name's associated gender. In Figure 8, I show the data that I webscrape from each webpage, using one gender-neutral name and one gender-specific name as examples. Namepedia provides many different gender categories: "Female," "Male," "Neutral," "Unknown," "More female, also male" and "More male, also female." I only use the "Female" and "Male" categorizations to avoid miscategorization problems.

3 Participation

In this section, I explore whether there is any systematic difference in participation within VC-financed entrepreneurship based on gender. First, I examine female and male VC-financed entrepreneurs' participation levels. Next, I consider VC general partners' participation by gender. I find clear evidence of differences in participation by gender in both domains, with a trend towards equality among entrepreneurs which is absent among GPs.

3.1 Entrepreneurs

As presented in Table 2A, I have founder gender data for 2,149 startups, out of which, 311 (14.5%) are led by one or more female founders. The 311 female-led startups are led by 402 female founders in my data, which comprise 8.8% of the 4,568 entrepreneurs in the data with gender information. The 14.5% female participation figure confirms the results of the Diana Project survey in 2011-2013, which found that 15% of VC-financed firms had a female executive (Brush et al., 2014).

While there are a total of 4,859 entrepreneurs, I have gender information for 4,568 entrepreneurs (94%). Similarly, out of 3,359 startups, I have some entrepreneur gender information for 2,149 (64.0%) of them. As explained in Section 2.3.1, the primary reason I lack founder data for 36% of startups is that, for a significant number of startups, founders are not listed in CrunchBase. A secondary reason is that I am unable to categorize an entrepreneur's gender, but, as the 94% match rate implies, this is a much smaller part of the issue than the missing data in CrunchBase.

How do female participation rates in VC-financed entrepreneurship compare to other sectors of the economy? Compared to overall female participation in the US workforce, it is substantially lower. In 2012, 47% of the workforce in the US was female (Sewell, 2013). This is perhaps unsurprising, given that women's participation in STEM fields is known to be lower than in the overall economy and VC-financed startups operate largely in STEM fields. For instance, only 27% of computer science and math positions and only 24% of STEM positions overall were filled by women in 2009 (Beede et al., 2011). But, even compared to females' STEM participation, female participation in VC-financed entrepreneurship is lower, being slightly more than one-third the rate of female STEM workforce participation.

And compared to general entrepreneurship, female participation in VC-financed entrepreneurship is also considerably lower. In 2012, 36% of small businesses in the US were majority-owned by women, according to the Small Business Administration (Lichtenstein, 2014). Of course, the typical firm financed by VCs differs from the typical firm financed by bank loans and other early-stage financiers. But, taken together with the differences between female participation in VC-financed entrepreneurship and in other sectors of the economy, these findings suggest that there is something peculiar about VC-financed entrepreneurship that leads to female participation being lower than in all other comparable settings.

Over time, the difference between female and male participation is declining. As reflected in Figure 3A, approximately 8.5% of startups initially financed in 2005 had a female founder, whereas 19% had a female partner in 2014. We find a similar trend for the percent of entrepreneurs that are female. Figure 3B shows that approximately 5% of entrepreneurs in initial financing rounds were female in 2005 and nearly 10% were female in 2014. This is a dramatic change over the course of a decade. A possible reason for this trend is the emphasis placed on encouraging women's participation in STEM entrepreneurship in the last decade or so through the InnovateHER Women's Business Challenge run by the Small Business Administration and other such programs (see Council of Economic Advisers, 2015).

There is a greater increase over time in female participation in initial financing rounds than in all rounds. As Figure 3A shows, the growth in female-led startups' financing rounds overall has been somewhat lower, increasing from 8.5% to 15% between 2005 and 2014. This could arise for two reasons: (a) female-led startups succeed more quickly than male-led startups (needing fewer financing rounds in the interim) or (b) they fail more quickly than male-led startups. Given the performance results in Section 4, it seems likely that the latter is driving the difference in female participation between the two sets of financing rounds.

3.2 General partners

Much like the startups they finance, VCs tend to have low female participation rates. As presented in Table 2B, out of 5,970 GPs, I have gender information for 5,672, 514 (9.1%) of whom are female. As many GPs in VCs are successful former entrepreneurs themselves, it is not surprising that the rate of female participation is similar in the two groups.

Table 2B also shows that, out of the 8,904 financing rounds, I have some GP gender data for 5,439 rounds (61.1%)[12] and about 63% of these rounds are financed by a VC syndicate with one or more female GPs. The percentage of VC syndicates with female GPs is so high (despite the low prevalence of female GPs) because there are multiple VCs in each syndicate, which dramatically increases the proportion of financing rounds where the financing syndicate has at least one VC with a female GP.

Unlike entrepreneurs, GPs do not exhibit a secular increase over time in female participation. As shown in Figure 3C, approximately 60% of VC syndicates involved in initial financing rounds had VCs with one or more female GPs in 2005 and 45% had female GPs in 2014, which suggests that female participation actually fell among VCs over time. However, as Figure 3D shows, this trend is only found at the syndicate level; overall female GP participation in initial financing rounds is around 7% in 2005 and in 2014. There is no upward trend in female participation among VCs.

Also unlike entrepreneurial participation, initial and all round participation rates are similar. Around 60% of syndicates involved in all financing rounds had one or more female GPs and 7% of GPs were female across all financing rounds in 2005 and 2014.

4 Performance

In this section, I explore the interaction of gender with performance of VC-financed startups. I use VC financing exit, either via IPO or acquisition, as an indicator of good performance. In the first part of this section, I present the overall exit information for the startups in my sample and discuss other measures related to performance. Next, I explore whether founder or GP gender affects performance. I find that there is a large performance gap between female- and male-led

[12] The main reason that 39% of the rounds do not have GP gender information is that, as on the entrepreneur side, data are missing in CrunchBase.

startups but no evidence of a difference in the overall performance of the portfolios of female versus all-male VC syndicates.

4.1 Exit as performance

I measure VC-financed startups' performance using exit from VC financing via initial public offering (IPO) or acquisition. Table 3 presents the exit counts and rates for four subsets of my startups. The second set of columns in the table shows exit statistics for startups initially financed in 2005 or later. These startups have an overall exit rate of 17.4%, with slightly under one-fifth exiting via IPO (3.2%) and the rest exiting via acquisition (14.2%). This four-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 2016 Yearbook, NVCA reported that there were 2,010 IPOs and 7,515 acquisitions of VC-financed startups between 1995 and 2015 (Haque, 2016), which is quite similar to the ratio I observe.

The first column of Table 3 shows the exit statistics for startups initially financed prior to 2005. As can be seen, the rates of exit are higher than in the second column, both overall (37.8%) and via IPO (14.8%) and acquisition (23.0%). The IPO rate is nearly four times higher than in the second column. The higher rates for this sample are evidence of backfill bias among startups reported in CrunchBase prior to its 2005 establishment. The pre-2005 rounds filled in later are more likely to be tied to startups that had financial activity after 2005, otherwise they would be unlikely to be reported. This backfill bias is even observable in the ratio of IPOs to acquisitions, which, in the pre-2005 sample, is far higher (two-fifth are IPO exits) than among startups in the rest of the data and as reported by NVCA for the sector as a whole. To avoid issues tied to this backfill bias, I exclude the pre-2005 startups from analyses.

I exclude startups initially financed after 2010 from my performance analyses because of the noisiness of exit as a measure of performance. This noisiness can be observed in the difference between the third and fourth columns of firms in Table 3, where we clearly observe that the rate of exit for late entrants (startups with initial financing rounds after 2010) is five times lower than that for the other startups. The late entrants have an IPO rate of just 0.8% and an acquisition rate of 4.0%. As both exits are relatively rare in the late entrant sample, exit is a coarse and noisy measure of performance, as 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. Three years out from their initial financing, neither Facebook nor Google would be considered "good" startups.

The noisiness of exit for late entrants can also be confirmed visually in Figure 4. The figure depicts the percentage of all startups that have successfully exited VC financing after a given number of years since their initial financing round. Looking at the figure, it is apparent that, even after two years, less than 5% of startups have successfully exited VC financing, whereas, given ten years, over 15% are able to exit.

Looking at trends in exits over time, I find evidence that acquisitions are more prevalent than IPOs in the early part of the sample, which coincides with the recession of 2006-2009. Figure 5 shows the number of exits, overall and via IPO or acquisition, for each year of exit. It shows that acquisitions make up a much larger portion of overall exits in 2005-2009. However, the greater prevalence of acquisition exits in the early years of the sample is also consistent with acquisition exits generally occurring earlier than IPO exits. This fact is confirmed in Table 4, which shows that IPO exits take one-and-a-half times longer than acquisitions, which, on average, occur 3.5 years after the initial financing round. The shorter time-to-exit for acquisitions may be exacerbated by the recession in the first half of the sample period. Alternatively, startups may have a greater preference for quicker, acquisition exits during recessions.

While exit from VC financing is often used as a measure of performance in the VC literature[13], it cannot distinguish between exits that provide large versus small returns on VC investment. Returns cannot be calculated for startups in the data because of a lack of information about the VC contracts offered to startups in exchange for funding.[14] However, Hochberg et al. (2007) provide 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.

[13] For instance, Hochberg et al. (2007) use portfolio firm exits via IPO or acquisition to measure fund performance. Gompers et al. (2010) use exits via IPO to measure entrepreneur success (and find that results are similar if they include acquisition as a success).

[14] 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, 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.

4.2 Gender effects on performance

Does the gender of a startup's founders play a role in its performance? To examine startup performance by founder gender, I separate the data into two groups: startups with all male founders ("male-led startups") and startups with one or more female founders ("female-led startups"). Comparing the exit rates for these two groups in Table 5A, I find that male-led startups have a 28.1% overall rate of exit and female-led startups have a 18.5% rate, a difference of 9.6% which is highly statistically significant. The difference is also economically large, being slightly more than one-third of the exit rate for male-led startups. Acquisitions and IPOs reveal an economically similar difference between the two groups: female-led startups tend to exit one-third less often than male-led startups for both types of exits. The IPO exits difference is not statistically significant primarily because IPOs occur infrequently, making it more difficult to establish statistical significance. On the other hand, acquisitions are more common and we see that the difference is highly statistically significant.

Startup performance does not vary with GP gender. I split the data into two groups for this analysis: startups initially financed by VC syndicates with all male GPs ("male VCs") and those initially financed by syndicates with one or more female GPs ("female VCs"). As shown in Table 5B, there is almost no difference at all between the two groups in terms of exits, overall or via IPO or acquisition.

How should we interpret these starkly different impacts of founder and GP gender on performance? The worse performance of female-led startups is interesting in that it is inconsistent with screening discrimination predictions. If VCs engage in taste-based discrimination against female-led startups, as defined in Becker (1971), the female-led startups they do finance should be of higher quality and, consequently, perform better. In the data, we see the reverse. Assuming that the quality distribution of female- and male-led startups is similar, this finding suggests that taste-based screening discrimination is not the sole contributor to gender differences in participation rates. The lack of difference in exit rates based on GP gender suggests that startups financed and advised by female VCs and male VCs are similar in terms of performance. Following up on this no-difference finding, in the following sections, I explore whether, rather than having an overall effect, VC gender has any effect on *differences* between the participation of female and male entrepreneurs and the performance of female- and male-led startups.

5 VC effect on participation gap

In Section 3, we observed that women participate far less than men on both sides of the VC financing table. Could this jointly low participation arise from same-gender matching among founders and GPs? That is, could female GPs' and female founders' preference for each other lead to low female participation in VC-financed entrepreneurship? As reported in Table 6, for female VCs, 15.5% of initially financed startups are female-led and, for male VCs, 17.2% of financed startups are female-led. The 1.7% difference in female-led startup representation is not statistically significant.[15] This suggests that there is no same-gender preference among founders and GPs in terms of financing, excluding this same-gender matching explanation.

As shown in Figure 6, the proportions of female-led startups' initial round financed by female and male VCs remains similar over time. While male VCs have a larger female-led startup representation in 2009 and female VCs have a larger representation in 2013, in general, the percentages of initial financings rise in tandem for the two VC groups, from under 5% in 2005 to just over 10% in 2014. The rise in the interim period of female-led startups' initial financings is consistent with the increase in female participation as entrepreneurs discussed in Section 3.

Both the overall similarity of female-led startup initial financings and its persistence over time add to the evidence against taste-based discrimination playing a role in the lower participation of female entrepreneurs. Assuming that the VC groups have differing tastes for discriminating against women, we should expect the group with the lesser taste to finance a greater proportion of female-led startups, which we do not observe in Table 6. Additionally, given that taste-based discrimination may reduce profits, the VC group with less of a taste for discrimination should "crowd out" the other VC group over time with respect to female-led startup financing.[16] Again, we do not see such a crowding out of either VC group in Figure 6. Under the assumption that these VC groups have differing tastes for discrimination, these findings suggest that taste-based discrimination does not drive the lower female participation that we observe.

[15] Even ignoring statistical significance, the difference implies that male VCs prefer female-led startups, which is not consistent with the above hypothesis.

[16] This is another implication of Becker (1971).

6 VC effect on performance gap

Does the performance gap between female- and male-led startups differ based on who finances them? In Figure 7, I present overall exit rates that highlight a stark difference in the performance gap observed for startups financed by the two VC groups. We see that the exit rates for female- and male-led startups are approximately the same for startups financed by female VCs, whereas male-led startups financed by male VCs have an exit rate approximately three times greater (and 25 percentage points) higher than their female-led counterparts. Additionally, the difference in the observed performance gap between the two VC groups is primarily due to better performance of female-led startups initially financed by female VCs. This finding suggests that female VCs are better able to evaluate and/or advise female-led startups. In the following subsections, I examine this hypothesis more rigorously using regression analysis and attempt to separate the above hypothesis from other conjectures consistent with these findings.

6.1 Regression design

In the regression analysis, I test whether startups initially financed by female VCs exhibit a different gap in exit rates based on founder gender than startups initially financed by male VCs. The null hypothesis for this test is that there is no difference in the exit rate gender gap between startups financed by the two sets of VC syndicates. If there is a difference in the exit rate gender gap, I reject the null hypothesis.

The null hypothesis implies that any difference in exit rates between female- and male-led startups stems from differences between female- and male-led startups and their founders. There are a number of gender differences that could drive these differences in exit rates between female- and male-led startups. For instance, a number of papers discuss lower risk tolerance among females (see Powell and Ansic, 1997; Barber and Odean, 2001), which could drive female entrepreneurs to lead startups that have a lower likelihood of extreme right tail outcomes.[17] Larry Summers forwards another theory that the far right tail of the ability distribution may be more populated by males than females (see Tierney, 2010). Finally, there is evidence that females are more averse

[17]Note that there is still debate as to whether there truly exists a difference in risk aversion between men and women. For instance, Nelson (2015) states that contextual influences may be driving some of the risk aversion findings in the literature.

to competition than men (see Croson and Gneezy, 2009), which could explain worse performance in an environment as competitive as VC-financed entrepreneurship.

If the exit rate gender gap is different across the two VC groups, I reject the null hypothesis. There is empirical evidence supporting both a narrowing and a widening of the founder gender-based gap with financing from female VCs. On the narrowing side, the aforementioned Tate and Yang (2014) and Gompers et al. (2014) show that female leadership within a group improves the outcomes of other females in the group as well. On the widening side, Gompers et al. (2012) shows that a shared identity among GPs based on ethnic background reduces the likelihood of investment success.

I employ a Cox proportional hazards model to examine annual likelihood of successful exit from VC financing. Alternatively, I could analyze the performance gap by looking at overall odds of successful exit using logistic regression or overall likelihood of exit using OLS regression. Estimating annual likelihood of success using the Cox duration model is the best measure for a number of reasons. First, as the dependent variable is firm exit, a binary measure, a regression model that handles binary outcomes is preferable. Therefore, OLS is a bad choice due to its assumption of a normally distributed dependent variable. Second, there is right-censoring in the data because I cannot distinguish between startups that fail to exit because they are of bad quality versus those that fail to exit because I do not observe them for enough time. As logistic regression does not account for this right-censoring of the data, it is also problematic. Finally, and relatedly, there is heterogeneity in time to exit even among startups that do successfully exit, so examining overall exit across startups becomes a flawed comparison. In this setting, we should ideally examine performance using annual likelihood of exit. Based on these considerations, I use the Cox proportional hazards model to test what, if any, effect the gender of VC financiers has on the performance gender gap among startups.

The specification for the above-detailed regression is

$$\lambda_i(t) = \lambda_{0i}(t) \exp\left(\alpha + \gamma_1 fem_i^e + \gamma_2 fem_i^v + \beta(fem_i^e \times fem_i^v)\right), \tag{1}$$

where $\lambda_i(t)$ is the hazard (annual likelihood) of exit for startup i in year t, $\lambda_{0i}(t)$ is the baseline hazard for startups in year t, fem_i^e indicates whether firm i has at least one female entrepreneur, and fem_i^v indicates whether firm i has at least one female GP in its initial financing syndicate. If the estimated effect of the interaction between fem^e and fem^v is non-zero, I reject the null hypothesis, as the non-zero effect implies that the startup performance gap is different between startups initially financed by female versus male VCs.

6.2 Regression results

Table 7 shows that the two VC groups are generally quite similar. The main differences between the two VC groups, number of GPs in the VC syndicate and aggregate experience in terms of prior financings of the syndicate[18], motivate an additional battery of tests with those characteristics as controls, which I discuss later in this section. Because the two VC groups are quite similar, differences in the startup performance gap across the two groups may be attributed to VC gender.

Table 8, column (1), presents results for the basic specification from Equation 1.[19] The first row of the table shows that female-led startups financed by all-male VCs have 70% lower chances of exiting in a given year than male-led startups financed by all-male VCs. This effect is moderately statistically significant. The estimate for the interaction term in the third row shows us that, relative to male-led startups financed by female VCs, female-led startups financed by female VCs have a 393% higher likelihood of exit in a given year than female-led startups financed by all-male VCs relative to male-led startups financed by all-male VCs.[20] This is a moderately statistically significant effect that is equivalent to a 75% narrower performance gap ($1/3.931 = 0.2544$). In column (2), I include initial financing year fixed effects and operating sector fixed effects to account for differences between startups due to macroeconomic changes over time and differences in startups due to their operating sectors, respectively. The inclusion of these fixed effects does not greatly alter either the magnitude or statistical significance of these estimates.

Table 8 also shows that the gender gap among female VC-financed startups is so much narrower that it is statistically nonexistent. This can be seen in the first row of the second panel, which

[18]There is also a significant difference in the total number of financing rounds for financed startups, but it is not economically large.

[19]In Appendix B, I present evidence that a proportional hazards model is the best specification for survival analysis of startup exits from VC financing.

[20]Point estimates reported in all regression tables are transformed as appropriate for the regression model. For proportional hazard regressions, I present hazard ratios, for logistic regressions, I present odds ratios, and for linear regressions, I present the raw coefficient. I do not transform interaction coefficients for non-linear models as suggested in Ai and Norton (2003). This is because my analysis focuses on effects on specific subsets of my sample rather than the average marginal effect.

shows the difference in annual likelihood of exit between female- and male-led startups financed by female VCs. Female-led startups are 15% more likely to exit in a given year, but that difference is not statistically significant. The difference becomes smaller and even less statistically significant with the inclusion of fixed effects in column (2).

The narrowing of the gap between the two groups of VCs arises due to better performance of female-led startups that are financed by female VCs. The second row of the bottom panel of Table 8 shows the difference in annual likelihood of exit between female-led startups financed by female VCs and female-led startups financed by male VCs. The difference in performance is large, with female-led startups having a 321.1% greater annual likelihood of exit when financed by female VCs. Additionally, this difference is moderately statistically significant and does not diminish much in economic magnitude with the introduction of fixed effects in column (2). On the other hand, based on the second row of the top panel, we see that male-led startups' performance is the same regardless of the gender composition of their initial financing syndicate. Together, these two findings imply that the narrower gender gap for startups financed by female VCs is due to better performance for female-led startups and not worse performance for male-led startups.

Columns (3)-(6) of Table 8 present results of regressions using the two other models discussed earlier. Columns (3) and (4) present odds ratios based on logistic regression and columns (5) and (6) present OLS regression coefficient estimates. Comparing the Cox and logistic regressions, we find similar ratios for the explanatory variables. And the linear regressions, also show the same direction and similar magnitudes of effects for the explanatory variables as the hazard ratios in the Cox duration regressions. The similarities across the models do not validate the findings of the Cox regression, of course, but they do suggest that the findings are not driven by model selection.

In Table 9, I include control variables for VC size and experience as well as their interactions with female founder presence, based on the differences across VC groups reported in Table 7. I find that, on their own, the controls do not significantly impact findings, but including their interactions with female founder presence reduces the statistical significance of the findings, while the economic magnitude remains largely unaffected. I introduce controls for VC size and experience levels in columns (1) and (2), respectively, and find they have little effect on the findings. Including the interaction of VC size with female founder presence in column (3) slightly reduces the economic magnitude of the difference across VCs in the performance gap from 3.57 to 3.17, a reduction of 13%. The statistical significance drops from moderate to marginal, as well. Introducing the interaction of VC experience with female founder presence in column (4) does not further affect the main interaction effect. While the estimates for the main interaction's effect on performance from columns (3) and (4) are smaller and less statistically significant than in Table 8, column (2), they are still statistically significant at the 10% level and imply an economically large effect on the performance gap between female- and male-led startups. Since none of the controls have statistically significant effects on annual likelihood of exit and they do not improve the goodness-of-fit much either, I base my conclusions on the findings of Table 8, column (2).

6.3 Interpretations

I interpret the reduced performance gap among startups financed by female VCs as evidence that female VCs are better able to evaluate and/or advise female-led startups than male VCs. When female-led startups seek VC financing, female VCs are either better able to judge the startup's future performance or better able to advise the female-led startups that they choose to finance. In this subsection, I consider alternative interpretations of the finding.

Besides my preferred interpretation, there are other possible interpretations of the main finding. Prime among these is one that posits that male VCs may finance a larger proportion of the female-led startups that approach them for financing, which results in their female-led startups having lower intrinsic quality and performance than those financed by female VCs. This would result in a greater performance gap among startups financed by male VCs. However, it would also result in a greater proportion of female-led startups in the portfolios of male VCs. However, Table 7 shows that male VCs do not have a greater proportion of female-led startups than female VCs. This means the male VC overfinancing conjecture is inconsistent with the data.

6.3.1 Entrepreneur financing choice

There are also a number of alternative interpretations tied to entrepreneurs' choice of financing. I cannot rule out all entrepreneur financing choice conjectures. However, in this section, I rule out the three most likely (and most commonly suggested) ones. Ruling out these alternatives greatly improves the likelihood that the observed difference in the performance gap arises from female VCs' ability to evaluate or advise female-led startups better.

For each argument in this section, I make two assumptions. First, I assume that my preferred interpretation of the findings is not true and VC abilities and actions are the same across female and male VCs. Second, I assume that the overall supply of male-led startups is weakly greater than that of female-led startups. This assumption is empirically supported in the data, as Table 2A shows that only 14.5% of startups are female-led.

High value startups seek financing from female VCs. One conjecture about entrepreneur financing choice is that entrepreneurs with high intrinsic value startups preferentially seek financing from female VCs and, therefore, startups financed by such VCs have better exit rates. However, if *all* high intrinsic value startups prefer financing from female VCs and everything else is the same across the two VC groups, the exits of female- and male-led startups should be the same within each VC group and we should observe the same performance gap in both groups. As we see a larger performance gap in startups financed by male VCs, this conjecture is inconsistent with the data.

Building on the simple conjecture above, if the distribution of intrinsic value is more right-skewed for male-led startups, a greater proportion of male-led startups are likely to exit VC financing generally. As a result, the difference in exit rates among male-led startups financed by the two VC groups is narrower than the difference among female-led startups financed by the two VC groups. This generates the observed narrower performance gap among startups financed by female VCs.

This, more nuanced, conjecture also has implications that are inconsistent with the data. If high value startups preferentially seek financing from female VCs, startups financed by them should have higher overall exit rates than startups financed by male VCs. However, Table 7 shows no differences in the exit rates of startups initially financed by the two VC groups. This leads me to rule out this entrepreneur financing choice explanation for the performance gap difference across the VC groups.

Female-led startups seek financing from female VCs. Another conjecture related to entrepreneur financing choice posits that female-led startups preferentially seek financing from female VCs and, therefore, female-led startups financed by female VCs have better exit rates. Unlike the previous conjecture, regardless of the underlying distributions of intrinsic value for female- and male-led startups, this conjecture is inconsistent with the findings of this paper. Such a financing preference among *all* female entrepreneurs has no impact on the performance gap, assuming that the two VC groups are alike in their treatment of startups. As a result, I rule out this explanation of my findings as well.

High value female-led startups seek financing from female VCs. The third entrepreneur financing choice conjecture is a combination of the first two. It posits that high intrinsic value female-led startups preferentially seek financing from female VCs and, therefore, female-led startups financed by female VCs have better exit rates. This conjecture is consistent with the performance gap findings of this paper.

Assuming that VCs carefully scrutinize startups on expected future performance when evaluating them, this conjecture further implies that female VCs have greater proportions of female-led startups in their portfolios.[21] If more high value female-led startups seek financing from female VCs, given the same screening rules across the two VC groups, more female-led startups should pass screening for female VCs and, as a result, female VCs should have a higher proportion of financed female-led startups. This is not what we observe in the data. As Table 6 shows, the two VC groups finance equal proportions of female-led startups. This finding leads me to rule out this conjecture as an explanation of my findings.

7 Further exploration

In this section, I explore questions that arose as a result of the investigation. First, I consider whether the difference in the performance gap between startups financed by the two VC groups arises because of better evaluation or better advising by female VCs. I also explore whether the difference is due to the female GPs within female VCs or the culture of female VCs. Finally, I consider whether the performance gender gap I observe is limited to only IPO or only acquisition exits. In general, I find that the difference likely arises because of the better ability of female GPs within female VCs to evaluate female-led startups and is not limited to either form of exit from VC financing.

7.1 Evaluation and advising

Which of the two VC roles contributes more to the founder gender-based performance gap? VCs may contribute to VC-financed startups' performance through their evaluation of startups seeking

[21] If this assumption does not hold and VCs are passively financing all startups that seek financing from them or evaluating them on some other characteristics, then my counterargument here does not rule out this conjecture.

VC financing and their advising of startups they choose to finance.[22] To shed light on which role matters more for the difference in the performance gap, I compare the difference in the gap across initial and subsequent financing rounds. To the extent that evaluation is more important in initial financing rounds than in subsequent rounds, a greater difference in the gap in initial rounds suggests better evaluation by female VCs of female-led startups plays a role in the different performance gaps for startups financed by the two VC groups.

There are differences between initial and subsequent financing rounds that we need to consider. Foremost is that startups in subsequent financing rounds have already interacted with VCs at least once before. Therefore, it is difficult to disentangle (previous round) VC effect on performance from inherent startup quality. Table 10 shows that the two sets of rounds are also different in observable ways. Startups in later rounds are financed by larger VCs with more experience.[23] Female-led startups also represent a smaller proportion of later financing rounds, which is consistent with female-led startups' earlier exits documented in Figure 3. Their performance is also somewhat different, with initial round startups ultimately getting acquired more often and later round startups going public more often. This is consistent with IPOs requiring more time and financing rounds to occur.

Table 12, column (1), presents the results of the regression specified in Equation 1 run on subsequent financing rounds. Because each startup may have more than one financing round in the analysis, I cluster standard errors at the startup level. We see, based on the interaction marginal effects shown in the third row of the top panel, that there is no statistically significant difference in the performance gap between VC groups among startups financed in subsequent rounds. From Table 8, we know that the analogous estimate for initial financing rounds is a 3.64- to 3.93-times wider and statistically significant performance gap among startups financed by all-male VCs. This comparison of the difference for subsequent versus initial financing rounds suggests that female VCs are better at evaluating female-led startups and this better evaluation ability plays a role in the performance gap between female- and male-led startups.[24]

[22] The performance of VC-financed startups is better if VCs are better able to evaluate and screen out the bad startups from receiving VC financing. Startups' performance is also better if VCs are better able to advise them during their VC financing stage towards a successful exit.

[23] While not directly connected to this research, this is an interesting finding in itself, as it suggests that larger and more experienced firms are less likely to interact with higher risk, earlier financing rounds.

[24] Given the differences between the initial and subsequent financing rounds discussed above, I do not treat this difference between financing rounds as unequivocal evidence of differential impact of VC firms in initial and subsequent

7.2 Matching or culture

Is female-led startups' better performance with female VCs due to the female GPs themselves or because of the general culture of VCs that have females in leadership positions? To help distinguish between these alternatives, I compare the difference in the performance gap between the two VC groups for initial financing rounds with only one VC versus rounds with multiple VCs. A single VC financing round has fewer GPs involved, which means that each GP is more likely to be directly involved in the financed startup. If female GPs are directly responsible for the better performance, the effect of female VCs on performance should be greater in the single VC financing rounds, as female GPs in those syndicates are more likely to be directly involved in those rounds.

Before presenting the findings for single VC financing rounds, let us compare the two initial financing round subsamples. Table 11 presents the differences in characteristics of single VC and multiple VC financing rounds. The differences in number of VCs, GPs, female GPs, and previous financings are mechanically driven by the definition of the two groups. However, the differences in exits are likely due to lower inherent quality of startups initially financed by just one VC. We see that single VC rounds have significantly lower exit rates (20% of startups initially financed by single VCs exit, as compared to 33% of startups initially financed by multiple VCs). This difference holds for IPO exits and acquisition exits separately as well. This is consistent with an intuition that, if a startup is observably of high quality, a lot of VCs will be interested in backing it financially.[25]

Comparing Table 12, column (2), to Table 8, column (2), we see that female-led startups perform even better when initially financed by female VCs in the single VC subsample. The difference in the performance gap is nearly four times bigger than in the overall sample. Note that this regression is performed on 148 firms, only a quarter of the sample size available for the main analysis. Even with the smaller sample, the difference in the performance gap among startups financed by single VCs is large and moderately statistically significant. Keeping in mind the intrinsic differences between the financed startups, these findings suggest that female GPs directly influence the better performance of female-led startups and that the difference in the performance gap between startups financed by female and male VCs is a direct impact of female GPs.[26]

rounds. However, in unreported tests, I find that the difference between initial and subsequent financing rounds are highly statistically significant.

[25] VCs face something analogous to the "winner's curse" found in the IPOs of high quality firms.

[26] In unreported tests, I show that the differences in the performance gap between single and multi-VC initial

7.3 IPO versus acquisition

Do female-led startups perform better with financing from female VCs overall or is the effect limited to IPO exits or to acquisitions? In Table 13, we observe results of regressions run exclusively on IPO exits and acquisition exits in columns (1) and (2), respectively.[27] The first thing we observe is the general lack of statistical significance for the IPO exits regression. This is because the test in column (1) has far less power than the test in column (2). This can be seen based on the less extreme ratios in the IPO exits regression. Because IPO exits are approximately four times rarer than acquisition exits, exit is a rarer and, therefore, noisier measure of performance in the IPO regression than in the acquisition regression.

However, in both columns of Table 13, we observe that the gap among startups financed by male VCs (female-led startups are 53% less likely to exit in a given year via IPO and 73% less likely to exit in a given year via acquisition than male-led startups when financed by all-male VCs) is entirely erased among startups financed by female VCs (female- and male-led startups have statistically indistinguishable likelihoods of exit in each year via IPO and acquisition). For both IPOs and acquisitions, female-led startups have worse performance with male VCs and being initially financed by female VCs is associated with a sharp improvement in their performance. The similar overall pattern of effects across the two forms of exit suggests that female-led startup performance improves with female VC financing overall, rather than only in terms of IPO or acquisition exits.

8 Conclusion

In this paper, I explore the effect of gender on VC-financed entrepreneurship. I find that women's participation in the sector is low both as entrepreneurs and GPs. I also show that there is a large difference by gender in terms of performance: male-led startups perform 37% better than female-led startups. I study whether VC financiers may be responsible for this performance gap and compare the gap between the portfolios of female VCs and male VCs. I find that startups financed by all-male VCs have a large performance gap whereas startups financed by VCs with female GPs have

financing rounds are economically large although they are (barely) not statistically significant.

[27]To cleanly test IPO and acquisition exits, I exclude the other form of exit from the regression sample in each regression. For example, for the IPO exits regression in column (1), I exclude all firms that exit via acquisition.

no performance gap at all. This finding suggests female VCs are better able to evaluate and advise female-led startups and this difference in VCs' abilities contributes to the overall performance gap.

I also explore the roots for the difference in performance gaps between female and male VCs' portfolios. One dimension I study is whether the difference arises from better evaluation or advising. I find evidence that suggests better ability to evaluate female-led startups contributes to the difference in the performance gap between the two sets of VCs. I also study whether female GPs improve female-led startup performance themselves or whether the improved performance is tied to the culture of female VCs. My evidence suggests that female GPs are directly responsible for improved female-led startups' performance.

Why are these findings important? First, VC contribution to the performance gap means that some intrinsically valuable female-led startups do not succeed because of VC financing. Second, VC contribution suggests male VCs' actions worsen the performance of their portfolios, which is a waste of LP-invested resources and implies private inefficiency. If LPs choose to reduce their investment in VC as a result, this inefficiency may have large negative externalities for the VC sector.

The different performance of startups backed by female and male VCs also suggests that GP characteristics impact portfolio firm performance. This is consistent with recent work by Gompers et al. that shows startups advised by female GPs perform worse than startups advised by male GPs but that the performance difference is attenuated by the presence of other female GPs. Both these findings imply that GP composition of a VC impacts the performance of its portfolio firms.

Additionally, if some VCs are inefficiently allocating resources, do we find any evidence of the inefficiency dissipating? There is some evidence, as seen in Figure 6, that female VCs are starting to finance more female-led startups. This trend suggests that the inefficiency may disappear over time.

In the broader economic context, given the role of VC financing for launching economically important firms, the missing successes of potentially important female-led startups may dampen economic growth, as suggested by Robb et al. (2014). Following recent work by Hsieh et al. on improved allocation of labor market talent for minorities and assuming that the observed difference in the gap can be eradicated, a similar improvement in allocation of resources in VC financing may increase VC-financed startups' success by nearly 12%. Given the growth prospects of VC-financed startups, such an improvement could lead to large economic gains.

Finally, if some VCs hurt female-led startups' performance, women may be less likely to lead VC-financed projects. This feedback effect suggests that some valuable project are never undertaken due to the possibility of VC-induced failure. This reduced female participation is the focus of an important debate in policy circles. While much of the policy focus is on increasing the appeal of entrepreneurship for women (for instance, among others, the "InnovateHER Women's Business Challenge" (see Council of Economic Advisers, 2015)), this paper's findings suggest a complementary strategy: focusing on increasing female participation in the VC industry. This strategy may improve not only female participation in entrepreneurship,but also their success.

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Tables and Figures

	All rounds		Initial rounds	
	N	%	N	%
Total rounds	8,904		3,359	
Rounds w/ gender data on				
founders	6,246	70.1%	2,149	64.0%
GPs	5,439	61.1%	2,124	63.2%
founders & GPs	3,767	42.3%	1,281	38.1%

Table 1. Gender information availability for entrepreneurs and GPs by financing round. This table reports the number and percent of rounds in the data that have gender information for entrepreneurs, GPs, and both.

Table 2. Female participation in VC-financed entrepreneurship.

	N	%
Startups	3,359	
with founder info	2,149	
with female founder(s)	311	14.5%
Founders	4,859	
with gender info	4,568	
female	402	8.8%

(A) Female entrepreneurial participation. This table reports the number of initially VC-financed startups in total, with founder gender information, and with female founder(s). It also reports the overall number of entrepreneurs, those with gender information, and those categorized as female.

	N	%
Financing rounds	8,904	
with GP info	5,439	
with female GP(s)	3,406	62.6%
General partners	5,970	
with gender info	5,672	
female	514	9.1%

(B) Female GP participation. This table reports the number of financing rounds in total, with GP gender information, and with female GP(s). It also reports the overall number of GPs, those with gender information, and those categorized as female.

	Initial financing round							
	Pre-2005		2005-2014		2005-2010		2011-2014	
Successful exits	N	%	N	%	N	%	N	%
All	74	37.8	550	17.4	488	26.1	62	4.8
IPOs	29	14.8	102	3.2	92	4.9	10	0.8
Acquisitions	45	23.0	448	14.2	396	21.2	52	4.0

Table 3. Successful startup exits from VC financing. This table provides the number and percent of startups that exit generally, exit via IPO, or exit via acquisition from VC financing. These statistics are provided for four samples. The pre-2005 sample is comprised of startups with initial VC financing rounds before 2005. The 2005-2014 sample is comprised of all startups initially financed in 2005 or later, which coincides with the establishment of CrunchBase. The 2005-2010 sample removes all startups initially financed after 2010. The 2011-2014 sample includes all startups with initial financings after 2010.

	Duration (in years)	
	Mean	Median
All exits	3.85	3.52
IPOs	5.34	5.81
Acquisitions	3.51	3.16

Table 4. VC financing duration for successful startups. This table provides mean and median VC financing durations, in years, for startups initially financed in 2005 or later that successfully exit VC financing via IPO or acquisition. Financing duration is measured from date of initial financing round to date of exit.

Table 5. Performance by gender.

	Female-led startups	Male-led startups	Diff. [t-stat]
Overall exits	18.5%	28.1%	-9.6% ***
	135	985	[2.632]
IPOs	4.4%	6.0%	-1.5%
	135	985	[0.799]
Acquisitions	14.1%	22.1%	-8.1% **
	135	985	[2.455]

(A) Performance of female- and male-led startups. This table presents performance measured by overall exit, IPO exit, and acquisition exit 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 2010, inclusive.

	Female VC syndicates	Male VC syndicates	Diff. [t-stat]
Overall exits	29.8%	30.3%	-0.5%
	665	466	[0.174]
IPOs	5.3%	5.2%	0.1%
	665	466	[0.084]
Acquisitions	24.5%	25.1%	-0.6%
	665	466	[0.228]

(B) Performance of startups initially financed by female and male VC syndicates. This table presents performance measured by overall exit, IPO exit, and acquisition exit for startups initially financed by VC syndicates with one or more female GPs ("female VC syndicates") and startups initially financed by VC syndicates with all male GPs ("male VC syndicates") as well as the difference in performance between the two groups. All the startups in this sample have initial financing rounds between 2005 and 2010, inclusive.

	Female VCs	Male VCs	Diff.
Female-led startups	109	99	
Male-led startups	596	477	
% female-led startups	15.5%	17.2%	-1.7%
N	705	576	[0.830]

Table 6. Female and male VCs' financing of startups by founder gender. This table presents a cross-tabulation of the number of female- and male-led startups initially financed by female and male VCs (VC syndicates with and without one or more female GPs, respectively). It also presents the percent of portfolio firms that are female-led startups for the two VC groups as well as the difference in that percentage across the VC groups (and the t-statistic for that difference). The startups in this sample are all initially financed in 2005 or later.

	Female VCs	Male VCs	Difference
Startups			
Number of entrepreneurs	1.982	1.960	0.023
	682	546	[0.381]
VC financing duration, years	3.494	3.649	-0.155
	222	154	[0.661]
Number of financing rounds, all firms	2.227	2.008	0.219***
	1,110	925	[3.316]
successful firms	2.363	2.399	-0.036
	226	158	[0.206]
Years between rounds	1.372	1.301	0.071*
	1,886	878	[1.878]
VC syndicates			
Number of VCs in syndicate	3.380	2.244	1.136***
	1,110	925	[13.684]
Number of GPs	18.159	8.004	10.154***
	1,110	925	[23.663]
Number of female GPs	1.777	0.000	1.777***
	1,110	925	[50.417]
Total number of past financings	270.085	252.352	17.733*
	1,110	924	[1.851]
% of financed startups exited	29.774%	30.258%	-0.483%
	665	466	[0.174]
% of financed startups exited via IPO	6.972%	6.877%	0.095%
	502	349	[0.054]
% of financed startups exited via acquisition	25.873%	26.471%	-0.598%
	630	442	[0.219]

Table 7. Differences between female and male VC syndicates. The first panel of this table presents differences between startups initially financed by VC syndicates with one or more female GPs ("female VCs") and syndicates with all male GPs ("male VCs"). It includes all startups initially financed in 2005 or later. The second panel presents differences in the characteristics of VC syndicates in the female and male VC groups. It includes all VC syndicates involved in initial financing rounds in 2005 or later. For the rows on exits (the last three rows of the panel), the data are further restricted to financings of startups initially financed before 2011. For each statistic, the table provides the mean for startups financed by the two VC groups in the top row and the sample size for the statistic in the bottom row. The last column shows the difference in the statistic between startups financed by female and male VCs in the top row and the t-statistic for that difference in the bottom row, based on a t-test of means with unequal variances.

	Hazard ratio		Odds ratio		Difference	
	(1)	(2)	(3)	(4)	(5)	(6)
Fem-led startup	0.293**	0.304**	0.226***	0.258**	-0.254***	-0.215**
	[2.39]	[2.32]	[2.70]	[2.42]	[2.94]	[2.51]
Fem VC	0.817	0.815	0.777	0.796	-0.0566	-0.0499
	[1.32]	[1.31]	[1.33]	[1.17]	[1.36]	[1.18]
Fem-led startup × fem VC	3.931**	3.642**	4.325**	4.354**	0.249**	0.240**
	[2.31]	[2.17]	[2.23]	[2.20]	[2.16]	[2.10]
Fem- vs. male-led startups with female VCs	1.153	1.106	0.976	1.124	-0.005	0.025
	[0.48]	[0.33]	[0.07]	[0.32]	[0.07]	[0.33]
Fem vs. all-male VCs for fem-led startups	3.211**	2.967*	3.362*	3.466*	0.192*	0.190*
	[2.04]	[1.90]	[1.93]	[1.94]	[1.79]	[1.79]
Funding year FEs	N	Y	N	Y	N	Y
Sector FEs	N	Y	N	Y	N	Y
R^2	0.0147	0.0295	0.0134	0.0424	0.0148	0.0496
Observations	597	597	599	599	599	599

Absolute t statistics in brackets

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

Table 8. Female GP impact on female- and male-led startup exit. This table presents the results of regression analysis detailed in Equation 1. Columns (1) and (2) present the findings of Cox proportional hazards model regressions, where the dependent variable is the annual likelihood of successful exit from VC financing among startups initially financed in 2005-2010. Columns (3) and (4) present the findings of logistic regressions and columns (5) and (6) present the findings of OLS regressions. The dependent variable in columns (3)-(6) is an indicator of successful exit from VC financing for startups initially financed in 2005-2010. The top panel of the table presents exponentiated coefficients for each of the explanatory variables in the regressions. The explanatory variables, in order, are an indicator for a startup with one or more female founders ("fem-led startup"), an indicator for initial financing of the startup by a VC syndicate with one or more female GPs ("fem VC"), and the interaction of the female-led startup and female VC indicators. The second panel shows the differences between groups of startups. In columns (1) and (2), the differences are in terms of annual hazard ratios for successfully exiting VC financing. In columns (3) and (4), they are in terms of the ratio of odds for successfully exiting VC financing. In columns (5) and (6), they are in terms of the difference in likelihood of successfully exiting VC financing. The first row of the second panel presents the difference between female- and male-led startups financed by female VCs and the second row presents differences between female-led startups financed by female- versus all-male VCs. The R^2 reported for columns (1)-(4) is a goodness-of-fit measure based on the maximum likelihood function used to estimate Cox proportional hazard and logistic model regressions.

	Annual likelihood of exit			
	(1)	(2)	(3)	(4)
Fem-led startup	0.310**	0.309**	0.260**	0.235
	[2.27]	[2.28]	[2.32]	[0.94]
Fem VC	0.789	0.798	0.802	0.803
	[1.49]	[1.39]	[1.36]	[1.35]
Fem-led startup × fem VC	3.560**	3.565**	3.167*	3.137*
	[2.13]	[2.13]	[1.85]	[1.79]
Num GPs	1.008	1.008	1.007	1.007
	[1.05]	[1.08]	[0.84]	[0.84]
Log past deals		0.943	0.946	0.943
		[0.43]	[0.41]	[0.41]
Fem-led startup × num GPs			1.016	1.016
			[0.66]	[0.66]
Fem-led startup × log past deals				1.023
				[0.07]
Fem- vs. male-led startups with female VCs	1.104	1.101	0.825	0.736
	[0.33]	[0.32]	[0.35]	[0.18]
Fem vs. all-male VCs for fem-led startups	2.809*	2.846*	2.541	2.519
	[1.79]	[1.81]	[1.54]	[1.50]
Funding year FEs	Y	Y	Y	Y
Sector FEs	Y	Y	Y	Y
Pseudo R^2	0.0313	0.0316	0.0322	0.0323
Observations	597	597	597	597

Exponentiated coefficients; Absolute t statistics in brackets

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

Table 9. Female GP impact on female- and male-led startup exit, with additional controls. This table presents the results of Cox proportional hazards model regressions detailed in Equation 1 with added explanatory variables. The dependent variable in all columns is the annual likelihood of successful exit from VC financing among startups initially financed in 2005-2010. The top panel of the table presents raw coefficients for each of the explanatory variables in the regressions. The explanatory variables, in order, are an indicator for a startup with one or more female founders ("female-led startup"), an indicator for initial financing of the startup by a VC syndicate with one or more female GPs ("female VC"), the interaction of the female-led startup and female VC indicators, the number of GPs in the initial syndicate, the interaction of the female-led startup indicator and number of GPs, log of the aggregate number of deals financed by syndicate members prior to this financing round, and the interaction of female-led startup indicator and log of prior deals financed by the syndicate. The second panel shows the annual hazard ratios for successfully exiting VC financing between groups of startups. The first row of the second panel presents the ratio between female- and male-led startups financed by female VCs and the second row presents the ratio between female-led startups financed by female- versus all-male.

	Initial round	Subsequent rounds	Difference
Number of VCs in syndicate	2.2	2.7	-0.5***
	3,163	5,012	[10.607]
Number of GPs	8.7	10.6	-1.9***
	3,163	5,012	[7.197]
Number of female GPs	0.6	0.8	-0.2***
	3,163	5,012	[6.795]
Aggregate number of previous financings	203.1	297.3	-94.2***
	2,896	4,338	[16.472]
% female-led startups	15.0%	13.4%	1.6% *
	2,033	3,763	[1.663]
% of financed firms exited	26.1%	22.7%	3.3% ***
	1,872	3,367	[2.688]
% of financed firms exited via IPO	6.2%	8.8%	-2.6% ***
	1,476	2,853	[3.116]
% of financed firms exited via acquisition	22.2%	16.5%	5.8% ***
	1,780	3,116	[4.836]

Table 10. Differences between initial and subsequent financing rounds. This table presents differences between initial and subsequent financing rounds. It includes all startups initially financed in 2005 or later. For the rows on exits (the last three rows of the table), the data are further restricted to financings of startups initially financed before 2011. For each statistic, the table provides the mean for initial and subsequent financing rounds in the top row and the sample size for the statistic in the bottom row. The last column shows the difference in the statistic between startups financed by female and male VCs in the top row and the *t*-statistic for that difference in the bottom row, based on a *t*-test of means with unequal variances.

	Financing round with		
	One VC	Mult. VCs	Difference
Number of VCs in syndicate	1.0	3.6	-2.6***
	1,704	1,459	[53.289]
Number of GPs	1.9	16.6	-14.7***
	1,704	1,459	[46.919]
Number of female GPs	0.1	1.2	-1.1***
	1,704	1,459	[29.234]
Aggregate number of previous financings	149.0	256.3	-107.2***
	1,437	1,459	[13.815]
% female-led startups	14.8%	15.3%	-0.5%
	1,150	883	[0.316]
% of financed firms exited	20.1%	32.7%	-12.6%***
	981	891	[6.205]
% of financed firms exited via IPO	5.0%	7.8%	-2.9%**
	825	651	[2.207]
% of financed firms exited via acquisition	16.6%	28.6%	-12.0%***
	940	840	[6.059]

Table 11. Differences between single and multiple VC syndicates. This table presents differences between initial financing rounds with one VC and multiple VC syndicates. It includes all startups initially financed in 2005 or later. For the rows on exits (the last three rows of the table), the data are further restricted to financings of startups initially financed before 2011. For each statistic, the table provides the mean for initial and subsequent financing rounds in the top row and the sample size for the statistic in the bottom row. The last column shows the difference in the statistic between startups financed by female and male VCs in the top row and the t-statistic for that difference in the bottom row, based on a t-test of means with unequal variances.

	Non-initial rounds (1)	Init. single VC rounds (2)
Fem-led startup	0.783	0.172*
	[0.61]	[1.72]
Fem VC	1.033	0.644
	[0.21]	[1.14]
Fem-led startup $\times$ fem VC	0.795	13.35**
	[0.45]	[2.22]
Fem- vs. male-led startups with female VCs	0.623	2.293
	[1.39]	[1.49]
Fem vs. all-male VCs for fem-led startups	0.822	8.597*
	[0.41]	[1.95]
Funding year FEs	Y	Y
Sector FEs	Y	Y
SE Clustering	startup	-
Pseudo R^2	0.0344	0.0976
Observations	1480	148

Exponentiated coefficients; Absolute t statistics in brackets

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

Table 12. Female GP impact on female- and male-led startup exit in non-initial financing rounds and single-VC initial financing rounds. This table presents the results of Cox proportional hazards model regressions detailed in Equation 1 for non-initial financing rounds in column (1) and for single-VC initial financing rounds in column (2). The dependent variable in both columns is the annual likelihood of successful exit from VC financing among startups initially financed in 2005-2010. The top panel of the table presents raw coefficients for each of the explanatory variables in the regressions. The explanatory variables, in order, are an indicator for a startup with one or more female founders ("female-led startup"), an indicator for initial financing of the startup by a VC syndicate with one or more female GPs ("female VC"), and the interaction of the female-led startup and female VC indicators. The second panel shows the annual hazard ratios for successfully exiting VC financing between groups of startups. The first row of the second panel presents the ratio between female- and male-led startups financed by female VCs and the second row presents the ratio between female-led startups financed by female- versus all-male VCs. For column (1), standard errors are clustered at the startup level.

	IPO	Acquisition
	(1)	(2)
Fem-led startup	0.465	0.269**
	[0.74]	[2.22]
Fem VC	0.844	0.799
	[0.48]	[1.28]
Fem-led startup × fem VC	2.691	4.004**
	[0.81]	[2.03]
Fem- vs. male-led startups with female VCs	1.251	1.075
	[0.34]	[0.21]
Fem vs. all-male VCs for fem-led startups	2.272	3.199*
	[0.70]	[1.76]
Funding year FEs	Y	Y
Sector FEs	Y	Y
Pseudo R^2	0.0714	0.0280
Observations	445	558

Exponentiated coefficients; Absolute t statistics in brackets

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

Table 13. Female GP impact on female- and male-led startup exit via IPO and acquisition. This table presents the results of Cox proportional hazards model regressions detailed in Equation 1 for IPO exits in column (1) and for acquisitions in column (2). The dependent variables in columns (1) and (2) are the annual likelihood of successful exit from VC financing via IPO and acquisition, respectively, among startups initially financed in 2005-2010. The top panel of the table presents raw coefficients for each of the explanatory variables in the regressions. The explanatory variables, in order, are an indicator for a startup with one or more female founders ("female-led startup"), an indicator for initial financing of the startup by a VC syndicate with one or more female GPs ("female VC"), and the interaction of the female-led startup and female VC indicators. The second panel shows the annual hazard ratios for successfully exiting VC financing between groups of startups. The first row of the second panel presents the ratio between female- and male-led startups financed by female VCs and the second row presents the ratio between female-led startups financed by female- versus all-male VCs. For each dependent indicator variable, observations for which the values of the other dependent variable are true are omitted from the regression.

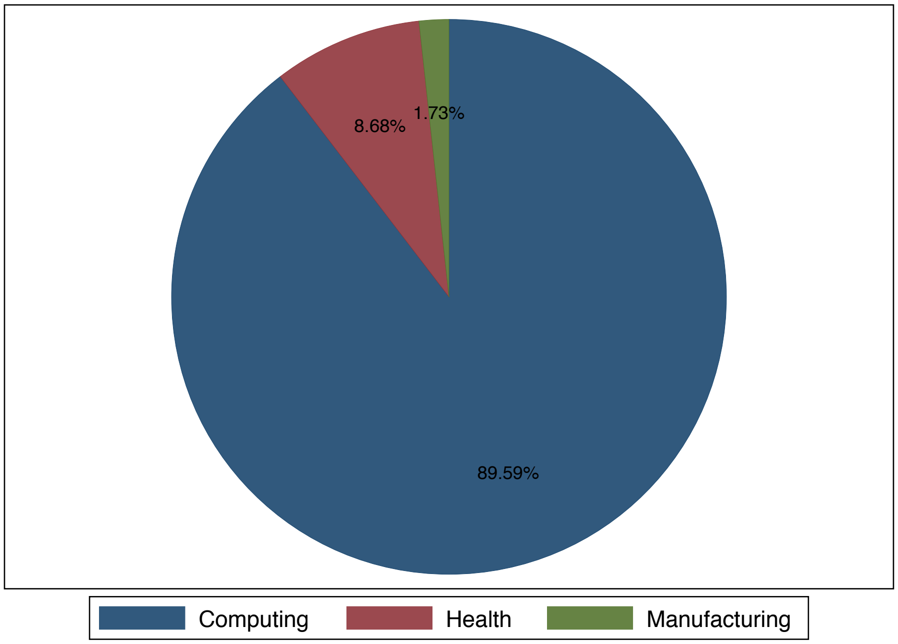


Figure 1. Operating sectors of startups. This figure provides a breakdown of the proportion of startups operating in each high-tech subsector. The categorization is based on textual descriptions of operating fields provided by the startups to CrunchBase.

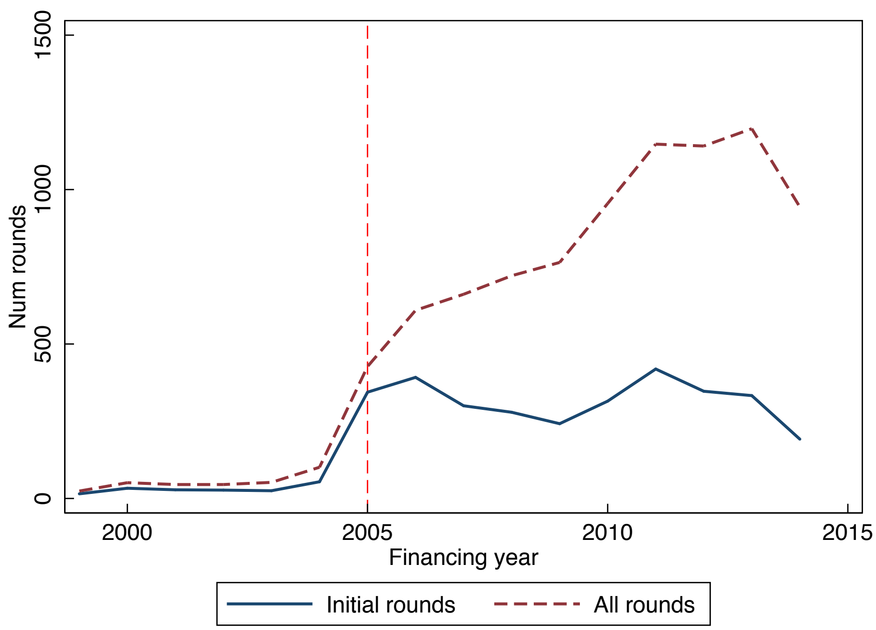
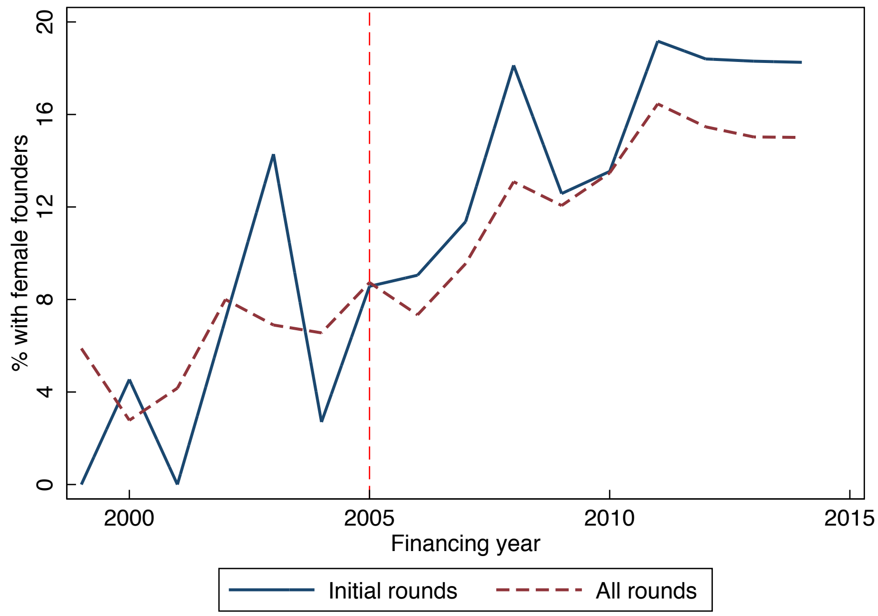
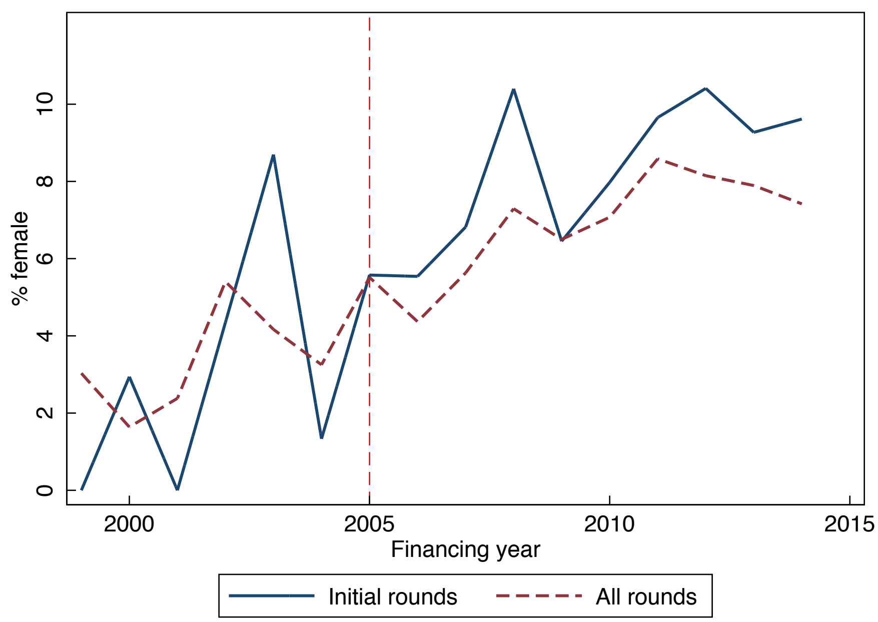


Figure 2. Financing rounds by year. This figure presents the annual number of VC financing rounds in the data from 1999 to 2014. The two plots depict initial financing rounds and all financing rounds (including initial rounds). The vertical red dashed line indicates the establishment of the CrunchBase database in 2005.

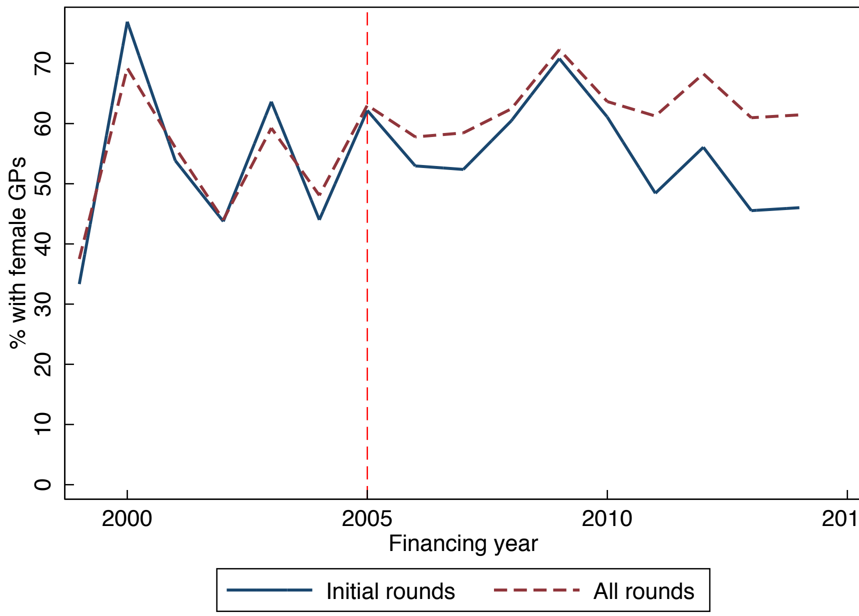
Figure 3. Female participation by year.



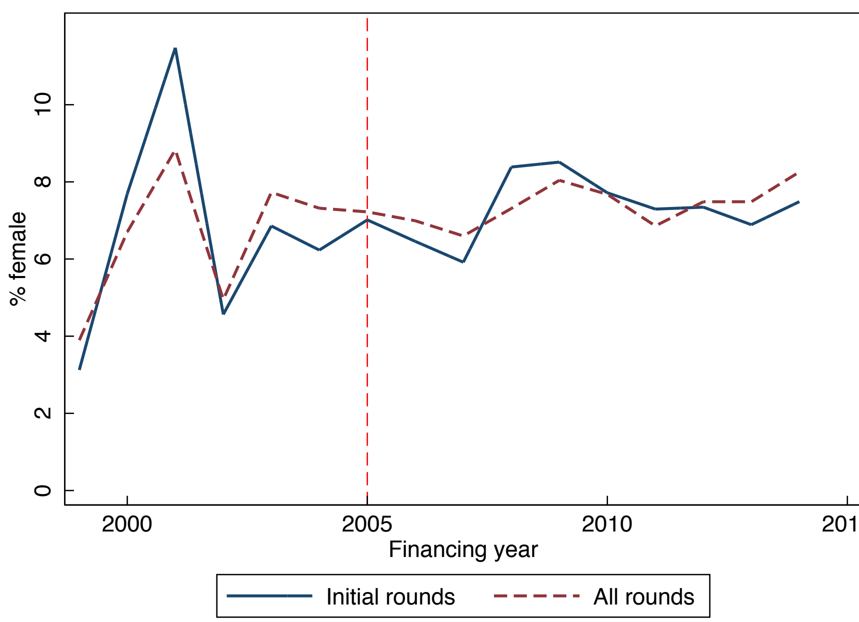
(A) Female-led startups. This figure shows the percent of VC-financed startups with one or more female founders in each year. The plots represent female-led startup participation in initial rounds and all rounds. The vertical red dashed line indicates the establishment of the CrunchBase database in 2005.



(B) Female entrepreneurs. This figure shows the percent of VC-financed entrepreneurs in each year that are female. The plots represent female participation in initial rounds and all rounds. The vertical red dashed line indicates the establishment of the CrunchBase database in 2005.



(C) Female VCs. This figure shows the percent of VC syndicates with VCs led by one or more female general partners in each year. The plots represent female VC participation in initial rounds and all rounds. The vertical red dashed line indicates the establishment of the CrunchBase database in 2005.



(D) Female general partners. This figure shows the percent of general partners financing projects in each year that are female. The plots represent female participation in initial rounds and all rounds. The vertical red dashed line indicates the establishment of the CrunchBase database in 2005.

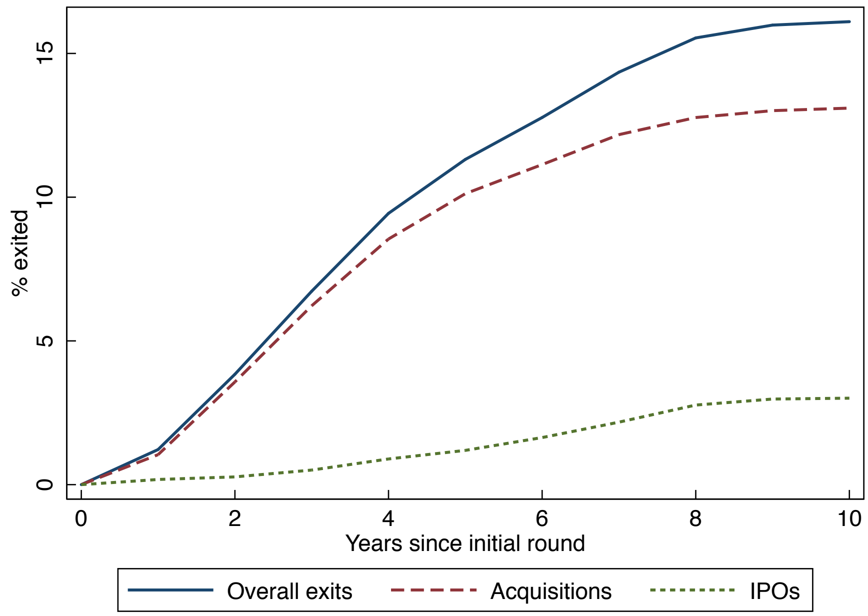


Figure 4. Percent of startups exited, by financing duration. This figure depicts the percentage of startups that have successfully exited VC financing (overall and via IPO or acquisition) after a given number of years, from 0 to 10. Only startups initially financed after 2005 are included in this figure. The vertical red dashed line indicates the establishment of the CrunchBase database in 2005.

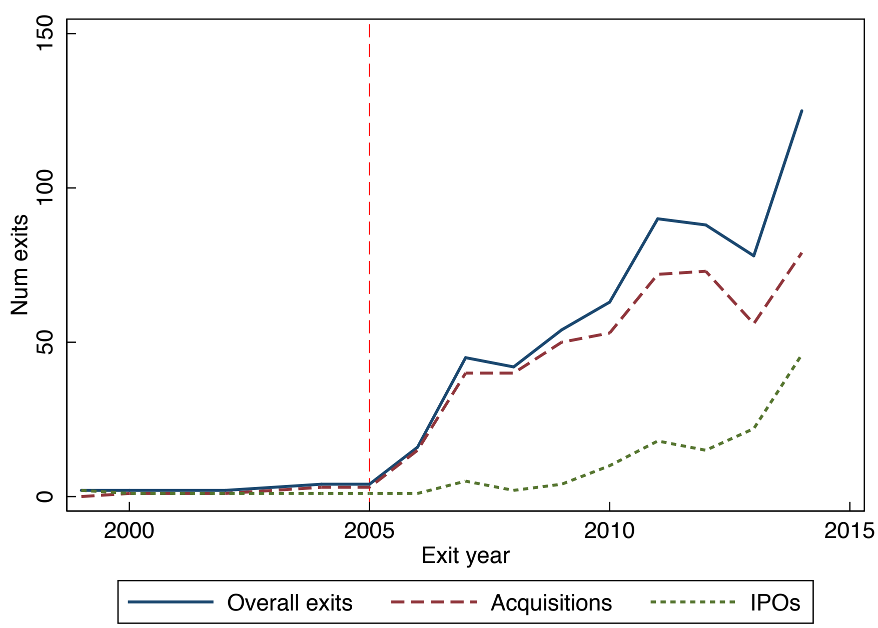


Figure 5. Annual number of exits, overall and via IPO and acquisition. This figure depicts the annual number of startups that have exited VC financing, overall and via IPO or acquisition. The vertical red dashed line indicates the establishment of the CrunchBase database in 2005.

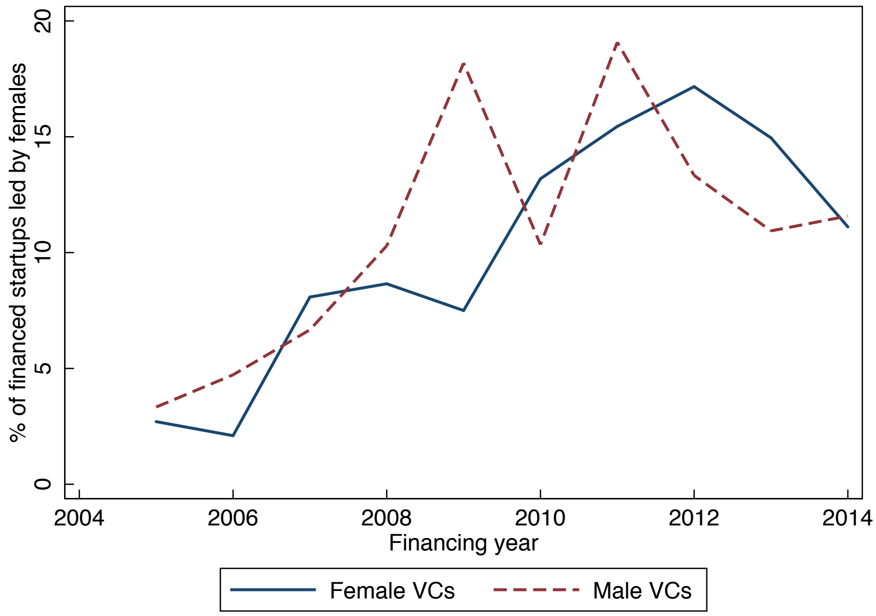


Figure 6. Portfolio representation of female-led startups for female and male VCs, by year. This figures plots the percentage of initial financings that are of female-led startups in each year for female and male VCs. Only startups initially financed in 2005 or later are included in the sample.

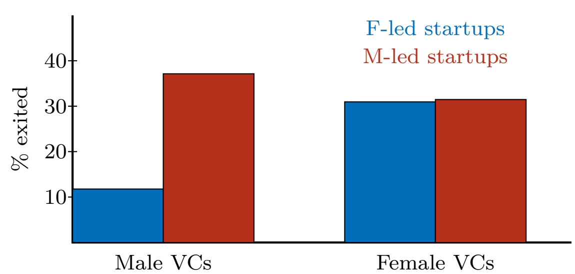


Figure 7. Overall exit rates, by founder-GP gender interaction. This figure depicts the overall exit rates for four groups of startups: female- and male-led startups initially financed either by female and male VCs. Only startups initially financed between 2005 and 2010, inclusive, are included in the sample.

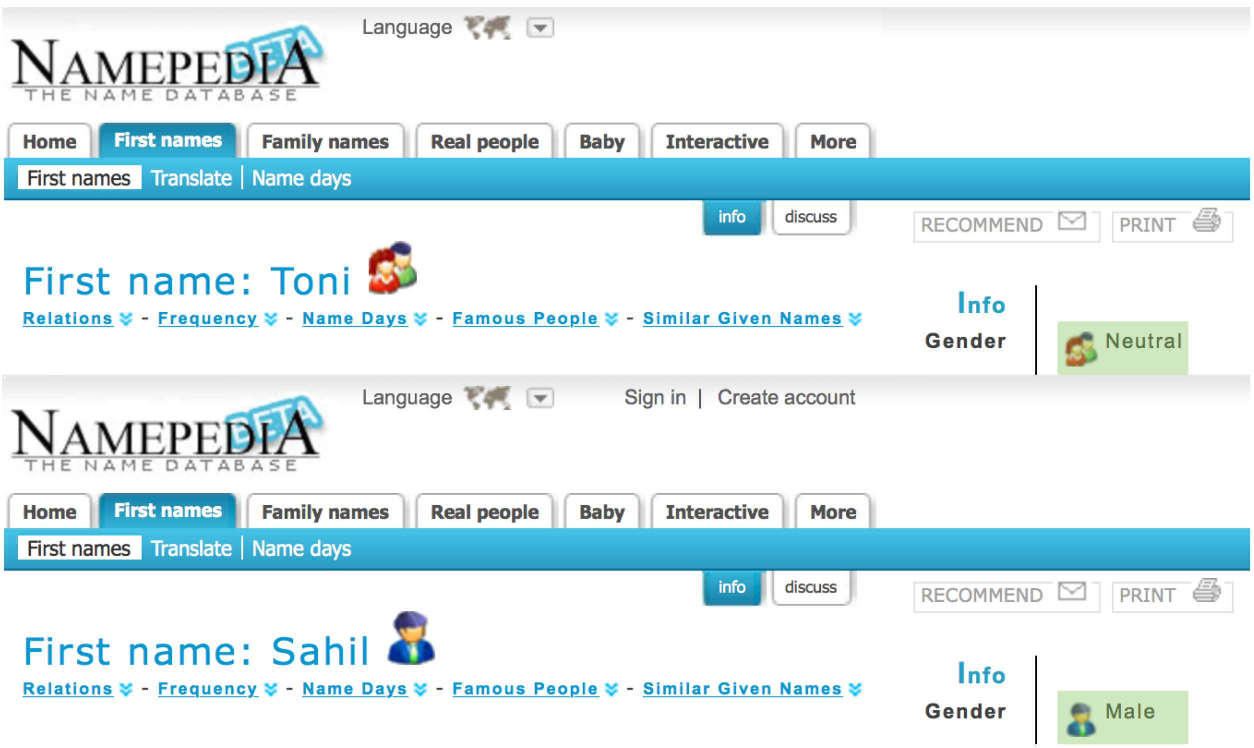


Figure 8. Namepedia name-gender webscraping examples. This figure provides two example of Namepedia's web response to first name queries. The top response is for a gender-neutral name and the bottom response is for a name classified as "Male." The webscraping method is used to extract the data highlighted in the top right corner of the webpage.

Appendix A Dataset construction

In this section, I lay out the process used to build my dataset. As explained in Section 2.3.1, the API access to CrunchBase prevents users from downloading detailed information on all entrepreneurial firms, financing rounds, and VC firms at once. Instead, I use VentureXpert data to find the sixteen VC firms with the greatest number of financings as of late September 2014 and then find all entrepreneurial firms in CrunchBase that ever received financing from these sixteen VC firms. This approach solves two problems at once. First, it reduces the likelihood of including organizations that are not true entrepreneurial firms in my dataset. As the definition of early entrepreneurship is vague, many "firms" 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 firm 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 entrepreneurial firms in my sample, I apply the Python programs described earlier to download all data on the entrepreneurial firm object in CrunchBase and on all associated financing round and VC firm objects in CrunchBase. For instance, to download all information for Cloudera, my programs download all information for the entrepreneurial firm object for Cloudera, all financing round objects associated with Cloudera (including its Series A through F financing rounds), and all VC firm objects associated with it as well (including Accel Partners, Greylock Partners, Ignition Partners, and so on). For an example of the data files provided by CrunchBase, see Figure A1.

Using the data from entrepreneurial firm and VC firm objects, I determine whether each person associated with a given firm is important for my analysis. For entrepreneurial firms, founders are the important personnel, so I take the list of founders provided for each entrepreneurial firm object as important personnel. For VC firms, general partners are important personnel. I take all founders and associated people whose roles signify that they are GPs as important personnel.[28]

Next, I classify all important personnel by gender. First, I categorize as many personnel as possible using my own knowledge of female and male first names. For names that I cannot categorize, I use Namepedia. Table A1 provides a breakdown of gender classification for entrepreneurs

[28] I take any personnel whose role descriptions include the phrases "general partner," "principal," or "founder" to be a GP in the VC firm.

and GPs separately and together. From that table, we can see that I manually classify 94.4% of entrepreneurs and 93.5% of GPs who are successfully classified into gender groups. About 6% and 5% of entrepreneurs and GPs, respectively, are not successfully classified either by me or by Namepedia. To classify personnel into gender group, I submit a query to Namepedia for each name and "webscrape" the gender from the response. Namepedia successfully classifies many of the names I am unable to categorize. I ignore uncertain Namepedia categorizations such as "More male, also female," "More female, also male," and "Neutral" to ensure that my results are not driven by misclassifications.

I link each entrepreneurial firm to potential exit from VC financing via IPO or acquisition. I use SEC's EDGAR filings to link to IPO exits and Thomson One's SDC M&A database to link to acquisition exits. Given the lack of shared identifiers between CrunchBase data and either SEC or SDC, I must match firms between CrunchBase and the two exit data sources manually by firm name. I do this manual matching in two parts. First, I pair observations between CrunchBase and the exits data that have perfectly matching firm names. Next, I run a Levenshtein lexical distance algorithm on all remaining pairwise combinations of CrunchBase-SEC and CrunchBase-SDC observations. I then manually go through all pairs that fall below a normalized Levenshtein distance threshold of 0.2, and find all Crunchbase-SEC and CrunchBase-SDC pairs that refer to the same company. Finally, for potential IPO exits, I manually check whether the firm filed a subsequent withdrawal (Form RW) and reversed its decision to go public at that point. If so, I remove the CrunchBase-SEC pair. By this method, I find all IPO and acquisition exits for entrepreneurial firms in my dataset.

Appendix B Proportional hazards model

The basic assumption for using proportional hazard models in survival analysis is that the hazard ratio is independent of time. In this paper, that equates to assuming that the various independent variables (especially, female-led startup and female VC) have the same effect on the likelihood of exiting VC financing in all years. In this section, I test whether this assumption is violated in the data.

There are a number of tests of the proportional hazards assumption. Following Hosmer et al. (2008), I test whether the slope of the scaled Schoenfeld residuals is zero when plotted against time. The null hypothesis in this test, created by Grambsch and Therneau (1994), is that the slope is zero. I run this test on the regression performed for column (1) of Table 8, to allow for the maximum degrees of freedom for the χ^2 test statistic, and find that I cannot reject the null hypothesis that the slope is zero. This can also be seen visually by plotting the residuals against time for each of the independent variables, as presented in Figure A2. The figures show that, for each of the independent variables, the slope of the line fitting the residuals against time is indistinguishable from zero. I also confirm this finding via tests on the individual regressors. These findings indicate that the proportional hazards assumption is reasonable for the data.

Appendix Tables and Figures

	Entrepreneurs	GPs	All people
All	4,859	5,970	10,829
... Gender matches	4,568	5,672	10,240
... ... Manual gender match	4,313	5,306	9,619
... ... Namepedia gender match	255	366	621

Table A1. Gender classification.
This table reports counts of gender classification of entrepreneurs and venture capitalists. Gender is classified manually by the author or, if the author is unable to classify manually, with the aid of Namepedia. The gender classification is provided for entrepreneurs and GPs separately and for all important personnel together.

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 ...
 "data": {
  "uuid": "f267a617e1cefa6eb4409adb8ff09caf",
  "type": "Organization",
  "properties": {
   "role_company": true,
   ...
   "founded_on": "2008-10-13",
   "founded_on_trust_code": 7,
   "permalink": "cloudera",
   ...
   "closed_on": null,
   ...
   "founders": {
    "items": [
     {
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      "name": "Mike Olson",
      "path": "person/mike-olson-2",
      "created_at": 1410023922,
      "updated_at": 1424979282
     },
     {
      "type": "Person",
      "name": "Christophe Bisciglia",
      "path": "person/christophe-bisciglia",
      "created_at": 1224039872,
      "updated_at": 1424965495
     },
     {
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      "name": "Amr Awadallah",
      "path": "person/amr-awadallah",
      "created_at": 1218178635,
      "updated_at": 1427790738
     }
    ]
   },
   "investors": [
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     "name": "EquityZen",
     "path": "organization/equityzen"
    },
    ...
   ]
  },
  "relationships": {
   "past_team": {
    "items": [
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      "last_name": "Sammer",
      "title": "Engineering Manager",
      "started_on": null,
      "started_on_trust_code": null,
      "ended_on": null,
      "ended_on_trust_code": null,
      "path": "person/eric-sammer",
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      "updated_at": 1427886689
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      "first_name": "Frank",
      "last_name": "Artale",
      "title": "Advisor",
      "started_on": "2009-01-01",
      "started_on_trust_code": 4,
      "path": "person/frank-artale",
      "created_at": 1202470740,
      "updated_at": 1424993700
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   },
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      "last_name": "Hammerbacher",
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      "started_on_trust_code": null,
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      "updated_at": 1424964507
     },
     {
      "first_name": "Amr",
      "last_name": "Awadallah",
      "title": "Founder & CTO",
      "started_on": "2008-08-01",
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      "path": "person/amr-awadallah",
      "created_at": 1218178635,
      "updated_at": 1427790738
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    ]
   },
   ...
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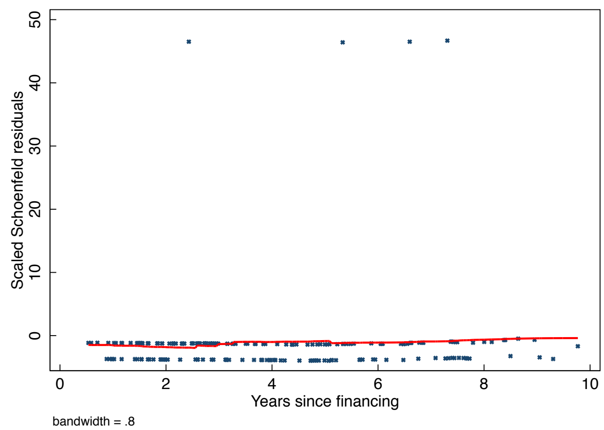
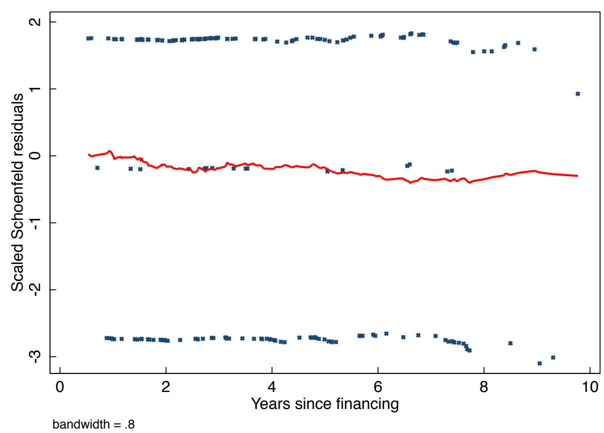
      "updated_at": 1415820090
     },
     {
      "type": "FundingRound",
      "name": "Cloudera raises 0 in venture round",
      "path": "funding-round/c47e8ad2f90fcd312af1e84d89c95b52",
      "created_at": 1396448533,
      "updated_at": 1427415033
     },
     ...
    ]
   },
  }
 }
}
```


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.

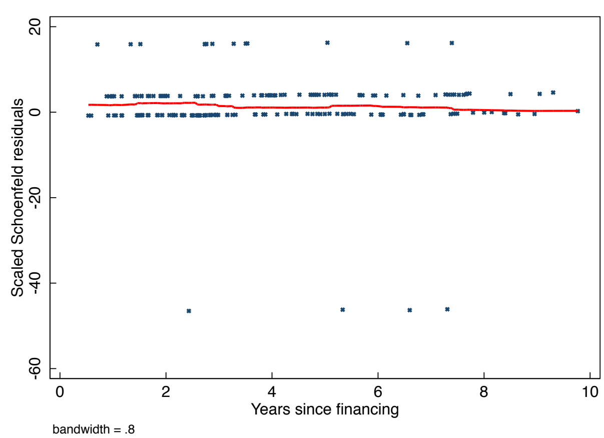
Figure A2. Tests of Proportional Hazard assumption.



(A) Female-led startups. This figure plots the scaled Schoenfeld residuals for the female-led startup explanatory variable in Equation 1 against time since initial financing round in years and a line representing a linear fit of those residuals against time since initial financing.



(B) Female VC. This figure plots the scaled Schoenfeld residuals for the female VC explanatory variable in Equation 1 against time since initial financing round in years and a line representing a linear fit of those residuals against time since initial financing.



(C) Female-led startup and female VC interaction. This figure plots the scaled Schoenfeld residuals for the female-led startup and female VC interaction explanatory variable in Equation 1 against time since initial financing round in years and a line representing a linear fit of those residuals against time since initial financing.