# A "Glass Ceiling" in Venture Financing: Evidence from Business Accelerator Graduates

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**Abstract**

Over the past decade, more women found success in fundraising, but the gender gap in average venture capital (VC) raised widened. Our analysis focuses on tech startup founders graduating from business accelerators using a two-sided matching model. After controlling for startup quality revealed through the accelerator admission process, women-founded startups show similar survival, exit, and VC securing rates but are less likely to receive large VC investments. Evidence does not support potential explanations such as gender differences in risk aversion and relocation preferences. Methodologically, we develop a fast and convenient estimation algorithm for the model of Sørensen (2007).

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# 1 Introduction

Innovation is the engine for economic growth, and women are as innovative and creative as men (Proudfoot, Kay & Koval, 2015). Any barrier to women's entry into the STEM will lead to suboptimal economic outcomes. However, while 40% of STEM students are women (Koning, Samila & Ferguson, 2021), they represent only 28% of the STEM workforce (Piloto, 2023). The gender gap has been narrowing over the past decade, but the process appears to be stalling. As there is an increasing awareness and correction for the gender bias on the employer side (Bertrand & Mullainathan, 2004; Booth & Leigh, 2010; Carlsson, 2011), recent literature focus on explaining the remaining gap with gender differences in preferences and choices (Bertrand, 2020). On the other hand, anecdotal evidence still suggests that women in STEM face greater challenges to succeed, especially in leadership roles (*Women in the Workplace study*, 2022). Why do these two streams of evidence contradict each other? We analyze the gender gap in development and resource acquisition among startup founders that is not explained by their abilities and preferences.

In particular, we examine the gender gap in securing venture capital (VC) among founders of high-tech, high-growth startups in the IT industry. Venture financing is an essential resource for these emerging companies (Da Tin, Hellmann & Puri, 2013). Thanks to the increasing social pressure to help more female entrepreneurs, the gender gap in the VC market has been gradually decreasing over the past decade. However, the disparity in average fundraising amounts has been widening. Between 2011 and 2020, the gender gap in average funding amounts expanded from approximately two million to over six million USD.

This paper brings this decade-long divergence in the gender gap to the forefront and investigates whether this gap in the VC market can be explained by differences in startup quality or founder preferences. Using a novel dataset and a theory-based structural estimation method, we find that startups with a female founder (hereafter, women-founded startups) have similar success rates in fundraising but are less likely to secure large VC deals, e.g., deals of more than two million USD – the starting level of a Series A round [1] – compared to similar startups with only male founders (hereafter, men-founded startups). Moreover, our analysis of the startups' survival, exit, and relocation decisions does not support the explanation of the gender gap by risk aversion or relocation preferences, the two main explanations for the gender gaps in the literature, indicating the potential role of gender bias in the VC market.

Most recent studies on the gender gap in the VC market focus on the probability of obtaining smaller investments (Ewens & Townsend, 2020; Gafni, Marom, Robb & Sade, 2021; Gornall & Strebulaev, 2020). Less attention is paid to the diverging difference in larger VC deals. Understanding the potential gender bias in larger venture investments is critical even though only a small percentage of startups ever secure a large amount of venture investment. Such bias can divert earlier-stage investors away from women-founded startups in anticipation of lower returns from future rounds, perpetuating statistical discrimination. However, it is ex ante unclear whether there is a severe gender gap beyond quality concerns for larger venture investments. When the stakes are higher, investors can be overall more biased since there is less incentive to enforce a gender-balanced portfolio[2], or they could be less biased since larger investment decisions depend more on startup quality and less on "gut feelings."

Examining the reasons for the gender gap in venture investment is often difficult because investment decisions can be based on startup information that is unavailable to researchers. Recent studies on smaller angel investments (Ewens & Townsend, 2020; Gafni et al., 2021; Gornall & Strebulaev, 2020) provide evidence of bias against female entrepreneurs using platform data on startup characteristics or by conducting experiments that send out mock-up fundraising emails to investors. These approaches are not suitable for multimillion-dollar VC deals that are usually made based on more in-depth informa-

[1] The size of the angel/seed round of fundraising is approximately 0.1 million USD to 2 million USD. The size of a Series A round is approximately 2 million USD to 15 million USD

[2] In contrast, when the stakes are low, it is considerably more affordable to invest in women-founded startups to maintain a gender-balanced reputation.

tion about the startups beyond those available through online platforms or email pitches.

To answer this question, we construct a novel dataset that tracks the performance of all the startups graduating from investor-led accelerators across the U.S. and entering the VC market around 2010 and apply the two-sided matching model of Sørensen (2007) to analyze the gender gap in venture fundraising outcomes. When startups apply to join these accelerators, accelerators can observe private startup information during the screening and selection process. We leverage this admission process to reveal the information that is not directly available in the data. Then, we control for the omitted information in analyzing the startups' post-accelerator performance in the VC market. In the analysis, the model of Sørensen (2007) is used to control for correlations between the assessments by accelerators and those by VCs. We propose a novel algorithm to estimate this model for the entire U.S. market.

A cornerstone of our approach is the correlation between accelerators' assessments of startups and VCs' investment decisions. Accelerators are fixed-term, cohort-based programs that provide mentorships, networking opportunities, and other assistance to enhance startups' venture performance (Cohen & Hochberg, 2014; González-Uribe & Leatherbee, 2018). Investor-led accelerators, such as Y Combinator, are typically for-profit programs managed by successful VC investors and/or serial entrepreneurs (Cohen & Hochberg, 2014; Hallen, Cohen & Bingham, 2020). They receive funding from traditional venture investors and generate profits by taking equity from participating startups (Clarysse, Wright & Van Hove, 2016). Consequently, investor-led accelerators focus on selecting complementary startups with high growth potential (Hallen et al., 2020). They consider various factors that can impact venture performance during the admission process. Startups that graduate from these accelerators generate significant interest in the VC market and often present to numerous VC investors during demo days at the end of the accelerator programs.[3] The emergence of accelerators significantly increases local venture

[3]For examples, see https://www.businessinsider.com/highlights-from-dreamit-demo-day-2012-8; https://techcrunch.com/2011/10/19/techcrunch-roundup-12-startups-500-investors-at-techstars-nyc-

investment (Fehder & Hochberg, 2019). In recent years, accelerator graduates have received approximately one-third of Series A VC in the U.S.[4] At present, multiple investor-led programs have accumulated billions of USD in their portfolio.[5] Overall, investor-led accelerators have interests that are closely tied to those of VCs.

We present a novel dataset encompassing U.S. accelerators and their participants from 2008 to 2011, providing details on startup attributes and their post-graduation performance. This period corresponds to the onset of the diverging trends described in the first paragraph. During this period, accelerators primarily concentrated in the IT sector and were predominantly investor-led programs. Programs with different missions, such as those emphasizing ecosystem development or diversity, were rare and excluded from our analysis.[6] Our exclusive focus on investor-led accelerators enables us to employ the modeling framework proposed by Sørensen (2007) to control for the unobserved quality revealed during admission.

To see the intuition, suppose that during accelerator admission, men-founded startups have on average higher quality than women-founded startups. Consequently, women-founded startups that manage to secure admission to high-quality programs would inherently possess a systematically higher, albeit unobservable to the researcher, quality level than otherwise identical men-founded startups. When this unobservable quality also impacts a startup's performance in the VC market, it is an omitted variable that causes the error term in venture performance correlates with the gender variable. Such endogeneity can be addressed using the modeling approach of Sørensen (2007). In our context, the model allows the accelerators' assessment during admission to correlate with

demo-day/; https://www.ycombinator.com/demoday/; and https://www.crunchbase.com/event/500-startups-demo-day-2018-batch-23.

[4]See http://www.ianhathaway.org/blog/2019/4/9/accelerated-companies-at-series-a

[5]At the end of 2021, the value of the top 30 graduates from Y Combinator was approximately 575 billion USD. As of October 2022, TechStars reports a combined portfolio value of 71 billion USD, and 500 Startups report having 49 companies valued at over 1 billion USD and more than 150 companies valued at more than 100 million USD.

[6]We exclude programs that received funding from non-investors (e.g., local governments, universities) or programs that do not charge participants' equity. We ultimately exclude 5% of the startup observations in our data. More specifics about the institutions and background information are provided in Section 3.2.

the startups' post-accelerator performance in the VC market. The key identification assumption is that the outcomes of accelerator admission depend on the presence of other participants in the admission market, while a startup's performance after the accelerator program relies solely on the startup itself and the accelerator with which it is associated.

We estimate the model in two stages. In the first stage, the accelerators and startups attempt to match with partners that maximize the expected startup value (e.g., NPV) upon graduation from accelerators (maximize the value of both their equity shares). The expected startup value depends on an accelerator's characteristics that measure a program's quality, the startup characteristics, the complementary factors between startups and accelerators (such as location-proximity), and potentially other unobserved qualities. Startups and accelerators form partnerships in a competitive process that is subject to capacity constraints.[7] The equilibrium of the matching process is determined by pairwise stability, as in Roth and Sotomayor (1990).

In the second stage, we model a startup's fundraising outcome (and other outcome variables) as a variable that depends on the observables as well as an unobserved variable that is correlated with the unobserved match quality in the first stage. We show that such a correlation can be equivalently captured using the imputed match quality in the first stage as a control.

We find that women-founded startups have similar chances of receiving VC deals after graduation from accelerators. They also perform comparably to the men-founded startups in terms of survival rates and exit rates up to five years after graduation. However, there is a "glass ceiling" in fundraising. Specifically, women-founded startups have a significantly lower probability of receiving funding greater than two million USD within one year after graduation. Women also have a significantly lower probability of cumulatively raising more than five million USD by the end of the fifth year after graduation.

[7] Each accelerator can admit a limited number of startups, and each startup can attend only one accelerator. This is qualitatively different from a discrete choice model. For example, in a discrete choice model where startups choose accelerators, accelerators do not have capacity constraints. Therefore, the market competition faced by startups is not considered and can lead to biased estimates.

Apart from the startups' unobserved quality, our analysis does not support that the glass ceiling can be explained by the following founder-side factors. One frequently discussed such factor is the gender difference in risk aversion (Buser, Niederle & Oosterbeek, 2014; Croson & Gneezy, 2009). However, there has been limited evidence to suggest that risk preferences play a significant role in explaining funding outcomes (Ewens, 2023). Moreover, Gafni et al. (2021) have found that gender differences in risk aversion disappear when industry factors are taken into account. After controlling for industry effects, we observe no gender differences in the probability of bankruptcy or acquisition among startups. This suggests that there is little difference in project riskiness between the two genders within a given industry.

Our evidence does not support the explanation that the gender gap is due to differences in relocation preferences, such as women being unable to contact more investors because of location constraints (Barbanchon, Rathelot & Roulet, 2021; Bielby & Bielby, 1992) or women being unable to fully devote themselves to startup development for family reasons (Bertrand, Goldin & Katz, 2010; Core, 2022; Zandberg, 2021). We find that women-founded startups that relocated to another state to join accelerators are significantly more likely to receive small-amount funding upon graduation from accelerators. Nonetheless, even this group of startups performed significantly worse than men-founded startups in raising large amounts of VC.

It is also unlikely that the glass ceiling is due to potential differences in women's pitch styles and networking abilities (Brooks, Huang, Kearney & Murray, 2014; Exley & Kessler, 2022; Howell & Nanda, 2023; Hu & Ma, 2021). First, accelerators conduct interviews during the admission process (Hallen et al., 2020; Stross, 2012) and may evaluate pitch styles, especially since many accelerator managers in our dataset have backgrounds in VC. Additionally, they provide training to participants on pitch styles in preparation for the VC market (Clingingsmith, Drover & Shane, 2022). Therefore, any gender differences in this regard can be mitigated by considering the quality of the accelerator attended.

However, our analysis reveals that a gender gap persists in larger investments even after controlling for the quality of the accelerator program. Similarly, it is known that female investors may be more supportive of female entrepreneurs, offering better assistance and networking opportunities (Hebert, 2023; Raina, 2021). Nevertheless, our findings indicate that women founders face similar challenges in breaking through the glass ceiling, even when participating in accelerators led by women.

Last, our findings are not due to accelerators favoring women during admission. Instead, we find that accelerators prefer men-founded startups in the first-stage matching model after controlling for other detailed background variables.[8]

Overall, our findings are consistent with the presence of gender bias in the VC market but such bias is only present in relatively large-amount investments.

## 2 Literature

To the best of our knowledge, this paper is the first to document and study the divergence in VC deal amounts between the two genders. Existing literature almost exclusively concentrates on the gender gap in the probability of receiving funding and frequently assesses startup qualities using observed startup characteristics (Coleman & Robb, 2014; Ewens & Townsend, 2020; Gafni et al., 2021; Gompers & Wang, 2017; Gornall & Strebulaev, 2020; Guzman & Kacperczyk, 2019; Hebert, 2023; Raina, 2021). We adopt a novel approach to control for startup quality by integrating market-wide accelerator admission outcomes alongside observed differences in startup characteristics. This approach provides the additional confidence necessary to explore the gap in funding amounts, which can be influenced by unobserved qualities.

Empirically, this paper relates to studies of accelerators (Cohen, Bingham & Hallen,

[8] See Section 3.2.3 for more details. Conversely, if the women-founded startups faced greater discrimination during accelerator admissions than during fundraising, one would expect to find women-founded startups receiving more funding after graduation. This is inconsistent with our findings.

2018; Cohen, Fehder, Hochberg & Murray, 2019; Fehder & Hochberg, 2019; González-Uribe & Leatherbee, 2018; González-Uribe & Reyes, 2021; Hallen et al., 2020; Winston-Smith & Hannigan, 2015; Yu, 2020). Due to challenges in data and methodology, much of the existing literature evaluates the treatment effects of a single or a homogeneous group of accelerators by comparing the startups that completed accelerators to those that did not. Instead of studying the accelerator treatment effect, our empirical question is to estimate the gender effect for accelerator graduates in the VC market. Specifically, we examine the fundraising performance among different accelerator graduates rather than compare startups' performance with and without accelerators. To control for the startups' quality at graduation, we use a structural approach to analyze the accelerator admission market. To the best of our knowledge, this paper contains the first market-wide data and analysis of accelerator admission outcomes.

This paper broadly relates to the extensive literature on the gender gap in the labor market (Alesina, Giuliano & Nunn, 2013; Biasi & Sarsons, 2022; Dahl, Kotsadam & Rooth, 2021; Ghazala & Ferrer, 2017; Goldin & Rouse, 2000; Kenneth & Dittmar, 2012; Niederle & Vesterlund, 2007; Pedro, Coffman, Gennaioli & Shleifer, 2019). It relates to the literature on the "glass ceiling" (Albrecht, Bjorklund & Vroman, 2003; Arulampalam, Booth & Bryan, 2007; Bertrand, 2018; Bertrand, Black, Jensen & Lleras-Muney, 2018). By providing evidence for gender bias in the amount of venture fundraising, this paper connects to the labor economics literature on demand-side explanations for the gender gap (Goldin, 2014; Goldin, Katz & Kuziemko, 2006; Matsa & Miller, 2011).

Our structural model follows the framework established by Sørensen (2007). While our data-generating process aligns with Sørensen (2007), we introduce a novel estimation procedure that separately estimates the first and second stages. This approach enables us to effectively estimate the model with market sizes as large as the entire U.S. This is essential for our analysis because a significant 27.17% of startups in the dataset join accelerators outside their home states. Our model is convenient enough to allow for bootstrapping the estimator standard errors, even for larger market sizes. One potential drawback of this approach is that it may lead to a slightly lower overall goodness-of-fit when compared to joint-estimation methods, as compared to Sørensen (2007). However, this concern is not significant for our empirical context, considering the relatively strong level of fit demonstrated in our analysis. Furthermore, the proposed estimation approach offers the advantage of easily analyzing multiple second-stage outcome variables, which are crucial for our empirical analysis.

# 3 Background and Institutional Details

## 3.1 The Diverging Gender Gap in Funding Size

In the past decade, the percentage of VC deals going to women-founded startups in the US has been increasing steadily. However, the gender gap in terms of average amount of funding has been expanding.

Using data from the *PitchBook-NVCA Venture Monitor* (2022) and the *All In: Female Founders in the US VC Ecosystem* (2021), we calculate by gender both the VC deal counts and the average VC deal sizes from 2011 to 2020. The two gender gaps show different trends as illustrated in Figure I. Such patterns are robust across different definitions of "women-founded startups" as shown in Appendix A.2.

We further decompose the gap in the average deal size by stage of VC investment. As shown in Figure II, it is clear that the gap in funding sizes is mainly driven by investments that occur later in the life-cycle of a startup, for which the amounts of funding are typically larger. When measured as a percentage of the corresponding average investment sizes to all-men-founded startups, the gap in funding size in the Angel/Seed stages has been slowly decreasing. However, the trend is the opposite in Early Stage VC deals and is worsening more quickly in Later Stage deals.[9]

[9] The concepts and data of angel/seed, early stage, and later stage are directly from pitchbook.com.

FIGURE I. **Gender Gaps in the VC Market**

This figure shows two different gender gaps in the VC market from 2011 to 2020 (year in the horizontal axis). The dotted line shows, with the vertical axis on the left in percentages, ($\frac{\text{\# deals all-men founded}}{\text{\# all deals}}$ - $\frac{\text{\# deals women-founded}}{\text{\# all deals}}$). The solid line shows, with the vertical axis on the right in million USD, (*avg. funding for all-men founded* - *avg. funding for women-founded*). A women-founded startup is defined as one with at least one women founder.

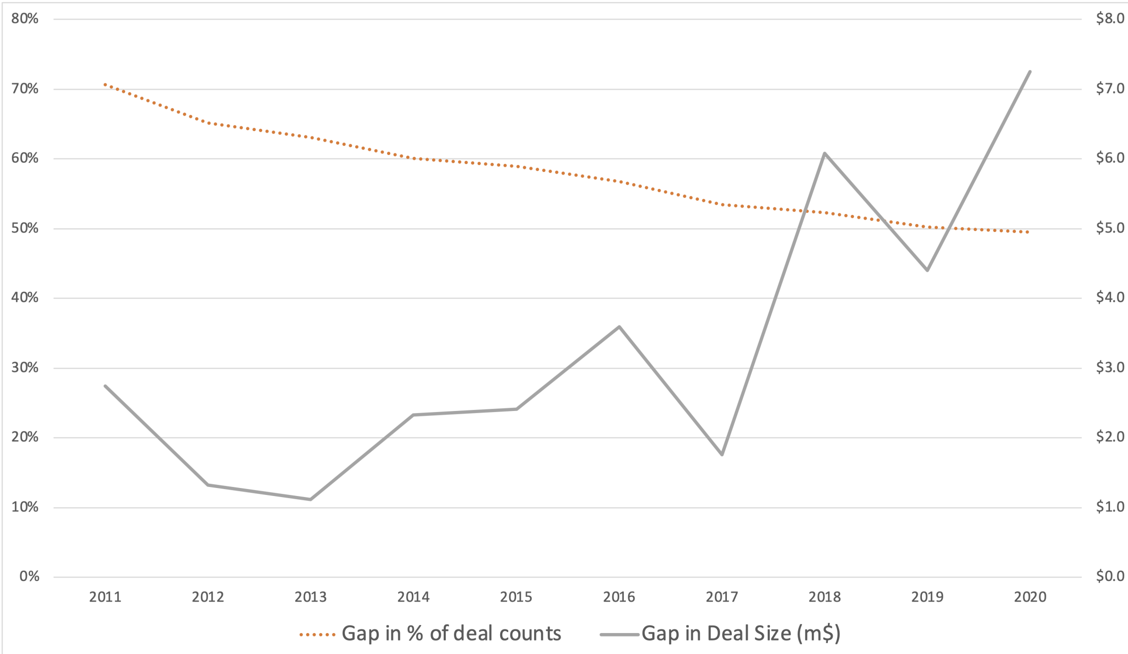
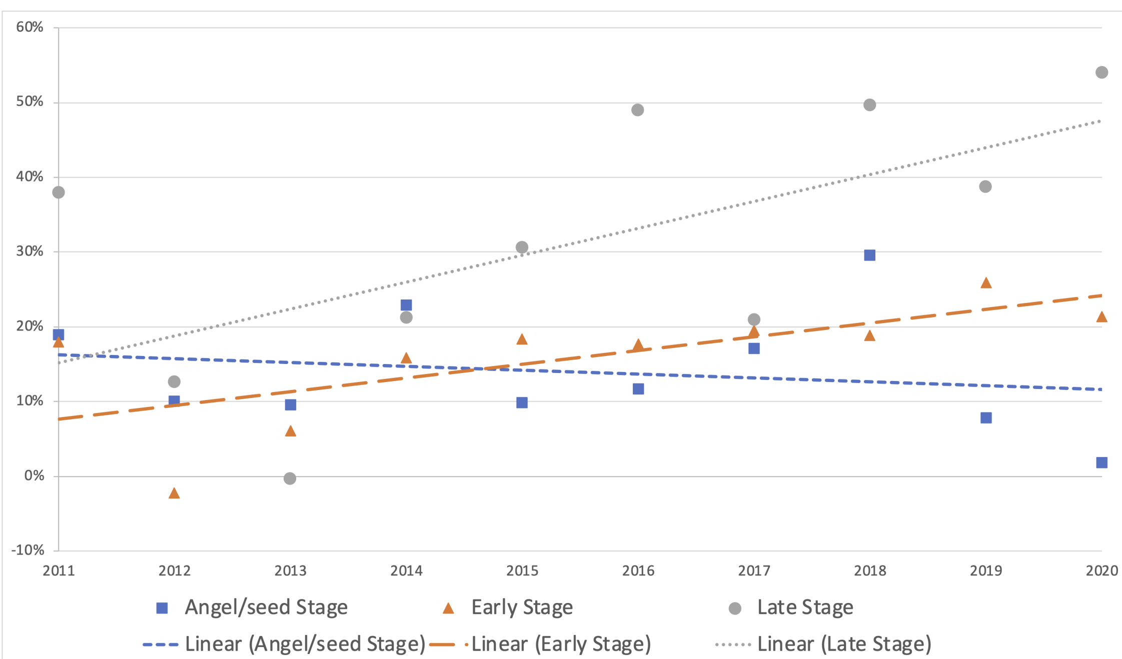



FIGURE II. **Gender Gap in Average Investment Sizes of VC Deals by Stages**

The figure plots the linear trend of the gaps as a percentage of average investment sizes to all-men founded startups, i.e. ($\frac{\text{avg. funding for all-men founded} - \text{avg. funding for women-founded}}{\text{avg. funding for all-men founded}}$), across different stages of VC investments. The Y axis is in percentages, and the X axis is the years.



## 3.2 Accelerators vs. VC Investments

### 3.2.1 What are Accelerators?

In this paper, we focus on startups that graduated from accelerators around 2010 and track their performance up to five years after graduation. This is also the period when the divergence trend started as described in the previous section.

Accelerators are also called "seed accelerators" or "startup accelerators". Most accelerators during our data period focused on high-tech startups, especially in IT-related industries. They targeted early-stage startups that were ready to raise VC. Most accelerators take some small amount of equity, typically 5%, from each admitted startup.[10] See Appendix A.1 for how accelerators work.

### 3.2.2 Accelerated Startups are Favored by VCs

According to Cohen and Hochberg (2014), investor-led accelerators can serve as deal aggregators for venture investors. The unique structure of accelerators helps VCs select startups by combining the funds of many investors and spreading risk across more portfolio firms. In practice, accelerator fund investors often increase their investments in their favorite startups post-accelerator program.

The startups that have graduated from accelerators in our dataset also attract venture investors who do not directly invest in accelerators. In our data, over 40% of accelerator graduates received VC immediately after graduation. In comparison, only approximately 3% of high-tech startups ever receive VC investments according to the Kauffman Foundation Survey.[11]

Table I compares the funding received by accelerator graduates and by comparable startups in the VC market. Startups of similar age as fresh accelerator graduates are typ-

[10] Accelerators also typically provide some seed money, which is often considered a stipend for participating entrepreneurs during their attendance of an accelerator program (Cohen & Hochberg, 2014).

[11] The Kauffman Firm Survey (KFS) is a panel study of 4,928 businesses founded in 2004 and tracked over their early years of operation, through 2011.

ically in the "seed" and "angel" stages in the VC market. When funded, they receive no more investments than accelerator graduates of the same cohort. Funded accelerator graduates perform comparably to other funded startups in the market in the longer term. This is indicated by the comparison of the average yearly funding between accelerator graduates and other funded startups of comparable age within five-year periods.

TABLE I. **Funding Comparison**

The first table presents the mean VC deal-size comparison between the accelerator graduates in our dataset and the VC market data obtained from Pitchbook.com during the same period. Panel A focuses on the accelerator graduates' average fundraising within one year after graduation. The comparable startups, based on startup ages, received seed-stage or angel-stage VC deals during the same year. Panel B focuses on accelerator graduates' average fundraising within five years after graduation. *Accelerator Grads (5y total)* and *Accelerator Grads (per age)* are the total and per-age (total/5) fundraising for a graduate during the five-year period, respectively. The comparable startups are those startups that received seed-stage, angel-stage, early-stage, or late-stage VC deals during the same periods (2008-2012, 2009-2013, 2010-2014, 2011-2015). We construct the corresponding *Synthetic Cohort (total)* as total VC amounts in all stages divided by number of startups received angel or seed investment in the same period. *Synthetic Cohort (total per age)* is calculated as the *Synthetic Cohort (total)* divided by 7, which is the median age of startups that received late-stage funding. Panel C shows the average startup funding size by industry. All accelerator participants are in *Tech*, and most of them are in *Software*. The second table presents the startup ages when they receive different stages of VC deals.

Average VC Deal Size in Million USD

| Cohorts | 2008 | 2009 | 2010 | 2011 |
|---|---|---|---|---|
| ***Panel A: Funding Sizes in Each Year*** | | | | |
| Accelerator Grads | 0.82 | 1.37 | 1.36 | 1.45 |
| Comparable Startups (Seed+Angel stage) | 1.06 | 1.00 | 0.86 | 0.87 |
| ***Panel B: Within 5y After Graduation*** | | | | |
| Accelerator Grads (5y total) | 7.75 | 33.48 | 12.08 | 10.31 |
| Accelerator Grads (total over median age) | 1.55 | 6.70 | 2.42 | 2.06 |
| Synthetic Cohort (total of all stages) | 18.46 | 14.37 | 13.70 | 13.67 |
| Synthetic Cohort (total over median age) | 2.64 | 2.05 | 1.96 | 1.95 |
| ***Panel C: Market Avg Funding by Industry*** | | | | |
| All industries | 7.64 | 6.04 | 5.73 | 6.55 |
| Tech | 7.12 | 7.63 | 6.19 | 4.81 |
| Software | 5.79 | 5.13 | 4.41 | 5.49 |

Distribution of Startup Age

| | 25th Prctile | 50th Prctile | 75th Prctile |
|---|---|---|---|
| Accelerator Grads (1y after grad) | 1.00 | 1.75 | 2.00 |
| Accelerator Grads (5y after grad) | 5.00 | 5.75 | 6.00 |
| Market Seed Stage | 0.34 | 0.96 | 1.94 |
| Market Angel Stage | 1.09 | 2.49 | 5.26 |
| Market Early Stage | 1.43 | 2.52 | 3.88 |
| Market Late Stage | 5.60 | 7.70 | 10.44 |

### 3.2.3 Accelerators' Admission of Women-founded Startups

In this section, we show that 1) there is little evidence that women-founded startups are favored by accelerators during our data period, 2) accelerators do not admit more women than VCs, and 3) there is no clear evidence that women-founded accelerator participants are worse than their men-founded counterparts.

Accelerators were relatively new players in the venture market with approximately 800 startups that had ever graduated by the end of 2011. Gender diversity was usually not considered a factor for selection during that period. For instance, according to Stross (2012), Y Combinator did not attempt to balance gender among applications, and it focused only on the potential growth of startups during admission. In fact, they began to receive criticism for constantly admitting too few women only after they began to gain attention post-2012.[12] Y Combinator, which may be most likely to be the target for such criticism due to its popularity and low admission rate of women-founded startups, was criticized for this reason in 2013.[13]

To further confirm that public opinion has little impact on accelerators' admission of women in our data period, we follow Giuli and Kostovetsky (2014) and regress the accelerator's admission of women on political preference of the local public during the 2008 presidential election. As shown in Table II, we do not find any significant associations with the admission of women-founded startups and the states' political preferences.

TABLE II. **Accelerator Admission and Political Environment**

This table shows the regression coefficients of voting for the democratic party in the 2008 presidential election. The dependent variables for the first two models are indicators of whether the accelerators' participating start-ups are founded by women. The dependent variables for the last two models are the percentages of women-founded startups.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Acc in Democratic State | 0.007 | 0.012 | 0.025 | 0.028 |
| | (0.032) | (0.032) | (0.032) | (0.033) |
| Year Fixed Effects | | Y | | Y |
| $N$ | 736 | 736 | 74 | 74 |
| $R^2$ | 0.000 | 0.002 | 0.009 | 0.022 |

Accelerators also do not prefer women-founded startups when compared with VC's

[12]More than 800 new graduates in 2012 alone.

[13]See: http://www.paulgraham.com/ff.html

decision to invest. In 2010 and 2011, 9.17% of accelerator participants were women-founded startups. During the same period, 11.83% of tech startups that received VC deals were founded by women.[14]

# 4 Data

We construct a novel dataset covering U.S. accelerators that existed from 2008 to 2011. Collecting data on startup companies is known to be challenging. We started by identifying accelerators from seed-db.com, which is one of the best known public repositories of accelerator programs.[15] However, we found the Seed-DB lists on accelerator participants are not complete, especially for less popular programs. Therefore, we used Google news and other platforms such as TechCrunch to find the press release and announcement back to the year when the cohorts were held. To the best of our knowledge, we have covered all participants in all the cohorts.

The majority of accelerators during the period were investor-led programs focusing on IT industries. Many currently well-known accelerators also emerged during this period. We exclude accelerators with objectives other than making a profit, such as those with restrictions on the community that they serve, those that receive funding from the government or other not-for-profit institutions, and those that do not take any equity. Doing so allows us to construct a dataset in which all accelerators seek to maximize expected return. We also omit startups with missing information on startup characteristics.[16]

We use CrunchBase, AngelList, CapitalIQ, CBinsights, VentureXpert, and Linkedin to obtain details on each program and its participants, which are provided below. Data

[14] Calculated using data from Pitchbook.com. US VC deals in Tech: 4257 in 2010, 5475 in 2011; US VC deals in women-founded startups in Tech: 444 in 2010; 707 in 2011. No such data are provided before 2010.

[15] With some slight difference in the definition that it uses, Seed-DB covers very similar programs as those under the definition proposed by Cohen and Hochberg (2014).

[16] The omitted startups mostly have already ceased operation. However, we do not find the omitted firms to be systematically different from other failed startups in the data. The exclusions are unlikely to cause a significant impact because they represent approximately 5% of the total dataset.

on private firms often lack information and can suffer from self-reporting bias since successful startups are more likely to release information to the public. To mitigate such concerns, we cross-check each firm by searching for related news and press releases. The self-reporting bias in this paper is mild because we found information for most startups thanks to the publicity and popularity of accelerators.

Hereafter, we define a "program" as a cohort of startups. Some accelerators run multiple programs in various locations over time. In total, we identified 74 programs representing 27 accelerators and 736 startup graduates.

Table III shows the summary statistics of the accelerators in our dataset. Approximately 37% of the accelerator programs were found in startup hubs (CA, MA, NY). This clustering effect is representative of the current geographic distribution of accelerators, with approximately 40% of all accelerators in the U.S. located in the well-known technology startup hubs and major cities of San Francisco-Silicon Valley, Boston-Cambridge, and New York.

TABLE III. **Summary Statistics: Accelerator Profiles**

| | |
|---|---|
| Number of Accelerators | 27 |
| Number of Programs without Female Founder(s) | 56 |
| Number of Programs with Female Founder(s) | 18 |
| Number of States Represented | 21 |
| Programs in Startup Hubs (CA, NY, MA) | 27 |
| Average Cohort Size | 17.70 |
| Number of Startup Graduates | 736 |

Table IV shows the summary statistics of the accelerator participants in our dataset.[17] There is a small difference among the two gender groups overall. We control for such differences across startups in the analysis.

[17] Industries are categorized according to the six digit level of 2012 NAICS: IT Service - 519190; Software - 511210; Data Processing and Hosting - 518210; Internet and Web - 519130; Others: Healthcare, Mobile Devices, etc.

TABLE IV. **Summary Statistics: Startup Profiles**

| | All | | Women Founded | | Men Founded | |
|---|---|---|---|---|---|---|
| | Mean | Stdev | Mean | Stdev | Mean | Stdev |
| Female Founder | 0.086 | 0.280 | | | | |
| Startup Age | 0.762 | 0.899 | 0.889 | 1.018 | 0.750 | 0.886 |
| At Least One Serial Founder | 0.376 | 0.485 | 0.286 | 0.455 | 0.385 | 0.487 |
| Founding Team Size | 2.264 | 0.788 | 2.016 | 0.729 | 2.287 | 0.790 |
| Team Average Age | 28.776 | 5.568 | 30.630 | 6.651 | 28.603 | 5.430 |
| At Least One Graduate Degree | 0.353 | 0.478 | 0.429 | 0.499 | 0.346 | 0.476 |
| At Least One PhD Degree | 0.075 | 0.263 | 0.111 | 0.317 | 0.071 | 0.258 |
| At Least One Engr/Sci Degree | 0.644 | 0.479 | 0.317 | 0.469 | 0.675 | 0.469 |
| Industry: IT Services | 0.382 | 0.486 | 0.317 | 0.469 | 0.388 | 0.488 |
| Industry: Software | 0.186 | 0.389 | 0.222 | 0.419 | 0.183 | 0.387 |
| Industry: Data Processing&Hosting | 0.268 | 0.443 | 0.317 | 0.469 | 0.263 | 0.441 |
| Industry: Internet&Web | 0.092 | 0.290 | 0.032 | 0.177 | 0.098 | 0.298 |
| Industry: Others | 0.072 | 0.259 | 0.111 | 0.317 | 0.068 | 0.253 |
| Observations | 736 | | 63 | | 673 | |

## 4.1 The Gender Gap in Startup Performance

Table V shows a summary of startup performance after graduation from accelerators. Women-founded startups had a similar probability of successfully raising VC funds within one year after graduation. Additionally, women-founded startups tend to raise smaller amounts of funds from VCs. In contrast, women-founded startups are associated with lower failure rates within one year after graduation but higher failure rates in the longer term.

Table VI decomposes fundraising performance by the amounts of money obtained from VC. While the performance at smaller amounts was comparable, substantially fewer women-founded startups were able to raise more than 2 million USD.

A straightforward bootstrapping test, as reported in Table VII, shows that among the funded startups, the difference in the mean log-investment size between men- and women-founded startups is not significantly greater than zero. The distribution of the log-investment size of men-founded startups has significantly more variance. Under the null hypothesis that the two distributions have the same mean but possibly different variances, a bootstrapping test shows that the log-investment size distribution of men-founded startups is significantly more skewed to the right than that of their women-founded counterparts.

TABLE V. **Summary Statistics: Startup Performance**

*Funded* presents the ratio of startups obtained VC deals within one year and five years after graduation. *InvestSize* is the average amount of capital received from VC for all startups. *Failed* and *Exited* are the ratios of startups that failed and were acquired.

| | All | | Women Founded | | Men Founded | |
|---|---|---|---|---|---|---|
| | Mean | Stdev | Mean | Stdev | Mean | Stdev |
| ***VC Investments*** | | | | | | |
| Funded 1yr | 0.442 | 0.497 | 0.429 | 0.499 | 0.443 | 0.497 |
| Funded 5yr | 0.510 | 0.500 | 0.429 | 0.499 | 0.517 | 0.500 |
| InvestSize(m$) 1yr | 0.609 | 1.442 | 0.352 | 0.540 | 0.633 | 1.497 |
| InvestSize(m$) 5yr | 6.544 | 34.406 | 1.341 | 2.769 | 7.031 | 35.935 |
| ***Operation Status*** | | | | | | |
| Failed 1yr | 0.045 | 0.207 | 0.032 | 0.177 | 0.046 | 0.210 |
| Failed 5yr | 0.345 | 0.476 | 0.444 | 0.501 | 0.336 | 0.473 |
| Exited 5yr | 0.228 | 0.420 | 0.206 | 0.408 | 0.230 | 0.421 |
| Observations | 736 | | 63 | | 673 | |

TABLE VI. **Summary Statistics: Startup VC Funding**

This table shows the number and percentage of startups that received VC funding: not funded, funded, funded with more than 1 million USD, funded with more than 2 million USD, and funded with more than 5 million USD.

| One Year | Null | Funded | >1m | >2m | >5m | Total |
|---|---|---|---|---|---|---|
| Men Founded | 375 | 298 | 119 | 46 | 22 | 673 |
| (%) | (55.7) | (44.3) | (17.7) | (6.8) | (3.3) | (100.0) |
| Women Founded | 36 | 27 | 9 | 1 | 0 | 63 |
| (%) | (57.1) | (42.9) | (14.3) | (1.6) | (0.0) | (100.0) |
| All | 411 | 325 | 128 | 47 | 22 | 736 |
| (%) | (55.8) | (44.2) | (17.4) | (6.4) | (3.0) | (100.0) |
| **Five Year** | **Null** | **Funded** | **>1m** | **>2m** | **>5m** | **Total** |
| Men Founded | 325 | 348 | 223 | 174 | 123 | 673 |
| (%) | (48.3) | (51.7) | (33.1) | (25.9) | (18.3) | (100.0) |
| Women Founded | 36 | 27 | 18 | 12 | 5 | 63 |
| (%) | (57.1) | (42.9) | (28.6) | (19.0) | (7.9) | (100.0) |
| All | 361 | 375 | 241 | 186 | 128 | 736 |
| (%) | (49.0) | (51.0) | (32.7) | (25.3) | (17.4) | (100.0) |

# 5 Empirical Model

## 5.1 Empirical Strategy and Identification

We adopt the theoretical model of Sørensen (2007). During admission, accelerators conduct evaluations of the applicants with teams of experienced venture investors and in-

TABLE VII. **Summary Statistics: Startup VC Funding**

This table shows the *log(InvestSize)* distribution moments for VC funded startups. The last column presents the *p value* of whether the corresponding moment for women-founded startups is larger than that of their male counterparts.

| | Women Founded | Men Founded | $p$ value of W>M |
|---|---|---|---|
| ***log(InvestSize 1yr)*** | | | |
| Mean | 6.427 | 6.562 | 0.293 |
| Variance | 0.777 | 1.624 | 0.027 |
| Skewness | -1.065 | -0.397 | 0.114 |
| ***log(InvestSize 5yr)*** | | | |
| Mean | 7.388 | 7.768 | 0.160 |
| Variance | 1.602 | 3.768 | 0.004 |
| Skewness | -0.204 | 0.048 | 0.032 |

dustry insiders. High-quality startups and accelerators or pairs with complementarity such as location proximity are likely to form matches during admission.[18] For this reason, part of the unobserved quality of a startup can be well measured by the quality of the accelerator program that it attends. We use the model to impute the residual match quality during the admission process.

Our model identification follows directly from Sørensen (2007) since we use the same data generating process. We provide the following brief explanation. The key is to separate the sorting by gender and the effect of gender on the second-stage outcomes. Suppose that there is a women-founded startup $s$ and a men-founded startup $s'$. The two startups are otherwise comparable. In other words, they have similar unobserved match qualities (the error terms) if they attend the same accelerator. If there is sorting by gender during admission, and since $s$ and $s'$ differ only in their founders' gender, they are unlikely to be admitted to the same accelerator (or accelerators of similar quality) when in the same admission market. However, the admission outcomes depend on the characteristics of other agents in the market. For $s$ and $s'$ in different markets, the differences in the other agents of the two markets can cause $s$ and $s'$ to join similar accelerators. Implicitly, this outcome facilitates a direct comparison between $s$ and $s'$. To summarize, the identifying assumption is the exogeneity of the presence of agents in each market. That is, the unobserved quality of potential matches in the model is independent of other agents' characteristics. More details can be found in Section III of Sørensen (2007).

[18] Hallen et al. (2020) provide evidence for assortative matching between startups and accelerators.

## 5.2 The Matching Model with Non-transferable Utility

Accelerator admissions are modeled as a two-sided matching game with non-transferable utility between accelerators and startups in the spirit of Roth and Sotomayor (1990). In our context, each potential accelerator–startup match creates a joint match value that is split according to a fixed equity share. The match value is determined by observed and unobserved (latent) characteristics of both accelerators and startups, including quality measures and measures of complementarity. The equity share is exogenous and the same for all matches in our model.[19] Agents from both sides of the market maximize payoffs by choosing partners on the other side. The equilibrium is given by pairwise stability, which states that agents have no profitable deviations in matching with other willing partners. As shown in Sørensen (2007), there exists a unique equilibrium under stable matching. We use a maximum simulated likelihood algorithm to estimate the parameters for this matching game.

### 5.2.1 Market Definition

In our estimation, each market refers to the accelerators and their program participants in the entire U.S. within a six-month period, with the first market starting in January 2008 and the last beginning in June 2011. This imposes less geographical restriction of a market compared to the analysis in Sørensen (2007) since there is a nonnegligible fraction of out-of-state matches.[20] In terms of the temporal restrictions, many seminal papers on matching-related studies adopt a semiannual or annual definition of markets (see, e.g., Choo and Siow (2006); Sørensen (2007) among others). We choose the semiannual frequency because some accelerators run two programs per year, six months apart. For example, Y Combinator runs two cohorts, one in January and the other in June. Our

[19]This modeling assumption is supported by the data. The average accelerator equity share is approximately 6.2%, with a standard deviation of approximately 1%. All matches within an accelerator have the same equity share.

[20]When focusing on VC investments, Sørensen (2007) imposes a stronger restriction on the scope of markets to half years and smaller regional areas.

definition of half-year markets avoids self-overlapping for these accelerators. We do not find qualitative differences in the estimates when we adjust the market windows. Following existing applications of matching models (Fox, 2018; Sørensen, 2007), we treat each consecutive market as independent and do not capture dynamic features or timing issues between markets, as highlighted by previous papers using matching models (Akkus, Cookson & Hortacsu, 2016, 2020; Fox, 2018; Mindruta, 2013). In our context, we do not intend to address dynamics in the market because each startup typically attends accelerators only once.

### 5.2.2 The Information Structure

We assume that all startups that want to participate in some accelerator program know all programs in the same market. In fact, the public announcements by accelerators are easy to find online months before the start of admission. We do not assume that accelerators know all potential startups in the market.

### 5.2.3 Portfolio Selection

To guarantee the existence of a stable match, this paper abstracts from potential gains from complementarities in accelerator portfolio selections. Specifically, we assume that an accelerator's preference for one startup is independent of its preference for another.

This assumption is commonly adopted in most empirical papers using two-sided matching models (Akkus et al., 2016, 2020; Fox, 2018; Honoré & Ganco, 2020; Mindruta, Moeen & Agarwal, 2016; Pan, 2017; Sørensen, 2007). In practice, it can be difficult for an accelerator to carefully set a portfolio given there are competing accelerators. It is also not rare to observe two direct competitors in the same cohort (Stross, 2012).

#### 5.2.4 Model Setup

Let $A$ be the set of accelerators and $S$ the set of startups in a market. A potential match is denoted by $(a, s)$ for $a \in A$ and $s \in S$. For the pair $(a, s)$, $a$ and $s$ share a total match value $U_{as}$. Let $U^a_{as}$ and $U^s_{as}$ be the payoffs for $a$ and $s$ from match $(a, s)$, respectively. We have:

$$U^s_{as} = (1 - E) \times U_{as} \tag{1}$$

$$U^a_{as} = E \times U_{as} \tag{2}$$

where $E$ is the exogenous equity share of $a$ and is not match-specific.

According to this setting, an accelerator $a$ strictly prefers startup $s$ over startup $s'$ whenever $U_{as} > U_{as'}$, and startup $s$ strictly prefers $a$ over $a'$ if and only if $U_{as} > U_{a's}$.

A matching is a function $\mu$ from the set of startups $S$ to the set of accelerators $A$. The equality $\mu(s) = a$ indicates that $s$ is matched to $a$ under matching $\mu$. The solution concept relies on the "no-blocking condition" in Roth and Sotomayor (1990): A pair $(a, s)$ is blocking for $\mu$ if its two entries are not matched but prefer each other over one of their current match(es). Mathematically, if $(a, s)$ is a blocking pair for $\mu$, then we have $\mu(s) \neq a$ and simultaneously,

$$\begin{cases} U_{as} > U_{\mu(s),s} \\ U_{as} > \min_{s' \in \mu^{-1}(a)} U_{as'} \end{cases}.$$

That is, $s$ prefers $a$ to its current match $\mu$, and $a$ prefers $s$ to at least one of its current matches in $\mu^{-1}(a)$. A matching $\mu$ is stable if there is no blocking pair. It is shown in Sørensen (2007) that given the values of all $U_{as}$, there exists a unique stable matching $\mu$.

Let the observed covariates of $a$ and $s$ be $X^{as}$. Given the distribution of $\epsilon^{as}$, our first-stage estimator recovers the matching parameters $\beta$ in the expression

$$U_{as} = X^{as}\beta + \epsilon^{as}. \tag{3}$$

The term $\epsilon^{as}$ contains idiosyncratic unobserved factors that affect the match value for the pair $(a, s)$.

In the second stage, post-matching performance, $Y^{as}$, is modeled as

$$Y^{as} = X^{as}\alpha + \eta^{as}.$$

Here, $Y$ can be any startup's performance after it finishes the accelerator program. In particular, the coefficient of gender is our parameter of interest, and it lies in $\alpha$.

The second-stage error term is $\eta^{as}$ correlated with $\epsilon^{as}$. This is because the VC's decision $Y$ is also correlated with the unobserved match quality $\epsilon^{as}$, which is observed by the accelerator managers and the startups during the admission process. For each potential pair $(a, s)$, we model the random vector $(\epsilon^{as}, \eta^{as})$ using a bivariate normal distribution. Without loss of generality in our context, we normalize the variances so that

$$\begin{bmatrix} \epsilon^{as} \\ \eta^{as} \end{bmatrix} \sim \mathcal{N}\left(0, \begin{bmatrix} 1 & \rho\sigma \\ \rho\sigma & \sigma^2 \end{bmatrix}\right).$$

## 5.3 Model Estimator

We first estimate the first stage of the matching model. Given the estimated parameters, we impute the unobservables $\epsilon$. We then control for the unobservables in the second-stage performance equations. This separated estimation allows the researcher to conveniently analyze different second-stage outcome variables. Additionally, the algorithm can still be used to analyze who matches with whom when there is no second-stage outcome variable in the data.

### 5.3.1 First Stage: Estimating the Matching Model

We express the likelihood function using potential blocking pairs. For convenience, we denote by $\bar{U}_{as} := X^{as}\beta$ the deterministic component of the value from the potential pair

$(a, s)$. For any pair $(a, s')$ where $\mu(s') \neq a$, it is not a blocking pair of $\mu$ if

$$\epsilon^{as'} > \left( \min_{s \in \mu^{-1}(a)} U_{as} \right) - \bar{U}_{as'} \quad \text{and} \quad \epsilon^{as'} > U_{\mu(s'),s'} - \bar{U}_{as'}$$

do not hold simultaneously. Define

$$\underline{U}_{as'} = \max \left\{ U_{\mu(s'),s'} - \bar{U}_{as'}, \left( \min_{s \in \mu^{-1}(a)} U_{as} \right) - \bar{U}_{as'} \right\}.$$

Note that $\underline{U}_{as'}$ depends on $\epsilon^{as}$ for $s \in \mu^{-1}(a)$ and $\epsilon^{a's'}$ for $a' = \mu(s')$. Therefore, given the unobservables $\epsilon^{as}$ for each observed pair $(a, s)$ that satisfies $a = \mu(s)$, the probability that $\mu$ is the equilibrium is

$$\prod_{a \neq \mu(s')} \Phi \left( \underline{U}_{as'} \right)$$

where $\Phi$ is the c.d.f. of a standard normal distribution. Since this product readily integrates out all unmatched pairs $(a, s')$, the overall likelihood of an observed matching $\mu$ is therefore

$$\Pr(\mu | X) = \int \left( \prod_{a = \mu(s)} \phi(\epsilon^{as}) \right) \left( \prod_{a \neq \mu(s')} \Phi \left( \underline{U}_{as'} \right) \right) \prod_{a = \mu(s)} d\epsilon^{as}.$$

By considering $\epsilon^{as}$ as latent for all matched pairs $(a, s)$ where $a = \mu(s)$, we can obtain the maximum likelihood estimates for the parameters $\beta$ using a simulated likelihood approach. The confidence intervals for the parameters are obtained through bootstrapping.

### 5.3.2 Second Stage: Estimating Ex Post Startup Performance

In the second-stage analysis, we study ex post outcomes $Y^{as}$ through

$$Y^{as} = X^{as} \alpha + \eta^{as}.$$

However, $\eta^{as}$ is not independent of $X^{as}$ due to its correlation with $\epsilon^{as}$. For example, when $a$ and $s$ are distant from each other, they can form a match when $\epsilon^{as}$ is large enough. Therefore, among the realized matches, the distance (controlled for in $X^{as}$) correlates with $\epsilon^{as}$. Since $\epsilon^{as}$ correlates with $\eta^{as}$, $\eta^{as}$ correlates with $X^{as}$. To perform an unbiased regression analysis, we must control for $\mathbb{E}[\eta^{as}|\mu, X]$, the conditional expectation of each $\eta^{as}$ given the realized matching with all observable characteristics $X$ in the market. In other words, suppose that we have $\mathbb{E}[\eta^{as}|\mu, X]$, estimate the regression

$$Y^{as} = X^{as}\alpha + \mathbb{E}[\eta^{as}|\mu, X] + \delta$$

where $\delta := (\eta^{as} - \mathbb{E}[\eta^{as}|\mu, X])$. Since the error term $\delta$ now has expectation zero given $X^{as}$ (i.e., $X^{as}$ is controlled for in $X$), this regression can be estimated with no bias through the ordinary least squares (OLS) method.

Based on the following proposition, we find that to control for $\mathbb{E}[\eta^{as}|\mu, X]$, it suffices to control for $\mathbb{E}[\epsilon^{as}|\mu, X]$.[21]

**Proposition 1** *$\mathbb{E}[\eta^{as}|\mu, X]$ is a scalar multiple of $\mathbb{E}[\epsilon^{as}|\mu, X]$, i.e., they are collinear.*

Therefore, to obtain an unbiased least squares estimate for $\alpha$, we can simply regress $Y^{as}$ on $X^{as}$ while controlling for $\mathbb{E}[\epsilon^{as}|\mu, X]$. We obtain the latter by taking the average of the simulated conditional distribution of $\mathbb{E}[\epsilon^{as}|\mu, X]$. The standard error for $\alpha$ is obtained through bootstrapping.[22]

## 5.4 Empirical Characteristics

To examine the gender gap, we construct a control "*Female Founder*," an indicator for whether at least one member of the startup founding team is female. While it is also

[21] The proof is provided in the Appendix.

[22] In the case where the outcome of interest is a binary variable, we simplify the computation using the linear probability model in the regression. We can check whether the point estimate from a probit model is qualitatively similar.

interesting to study startups with only female founders, we have limited observations of all-women founding teams. This measure is also consistent with the divergence trend that we found using Pitchbook data. The gender difference is likely to be more severe for startups founded by all-women teams (Box & Segerlind, 2018).

Other than gender, we obtain characteristics of the founding members with information collected from Linkedin and their personal websites. To capture the impact of prior entrepreneurship experience, we control for "*No Serial Founder*," an indicator that is equal to one if no member of the founding team has prior entrepreneurship experience. Furthermore, a founder's general work experience, as may be captured by the entrepreneur's age, is also a signal of startup quality. We explore this feature by studying the effect of the average age, *Average Age of Founding Team*, of the startup founding team. In addition, we have "*At least One Graduate Degree*," an indicator for whether at least one team member has a graduate degree;[23] "*At least One PhD Degree*," an indicator for whether at least one team member has a PhD degree; "*At least One Engr/Sci Degree*," an indicator for whether at least one team member has a degree in science or engineering; and "*Founding Team Size*" the number of entrepreneurs on the founding team. To control for startup variation across industry, we coded them into categories according to 6 digit level of 2012 North American Industry Classification System (NAICS).

Startups that have survived for years tend to differ from their newly founded counterparts. For early-stage startups, those with longer operating histories are more likely to have an established business model and customer base, which are helpful in attracting potential investors. Moreover, their founders are also more likely to have a better idea of how to run the company. We control for this variation by including the variable "*Startup Age*," which is defined as the number of years since the startup was founded before joining an accelerator.

On the accelerator side, cohort structure is an essential feature of accelerators, and

[23] Of the founders in our dataset, 99% have BA degrees.

we capture part of the accelerator quality variation with the variable "*log(Cohort Size)*." We also control for the number of years that the accelerator had been operating prior to the current cohort with "*Accelerator Experience*" and whether the accelerator is located in a "startup hub" (defined as MA, CA, and NY) with "*Accelerator in Startup Hubs*."[24] As accelerators with a female founder may be more friendly to female entrepreneurs, we capture such variation through "*'All-Men' Accelerator*" that equals "1" if there is no female founder.

### 5.5 Startup Performance Measures

We obtain the total amounts of VC investment the startups received within one year after the demo days and by the end of the fifth year after the demo days.

Following the literature (Ewens & Rhodes-Kropf, 2015; Ewens & Townsend, 2020; Gompers, Kovner, Lerner & Scharfstein, 2010; Hockberg, Ljungqvist & Lu, 2007; Raina, 2021), we collected two other startup performance measures: startup survival status (failed or still in operation) and acquisition status (acquired by other companies or not) by the end of the fifth year after the demo day.[25]

## 6 Results

We estimate the first-stage matching model using maximum simulated likelihood. As the first stage is not the focus of our analysis, we report the detailed results in Appendix A.5. We also examine the goodness of fit of the model, and find that the $R^2$-type measure is approximately 78%.

[24] The limited amount of data restricted our ability to control for detailed location fixed effects.

[25] Very few accelerator graduates have carried out an IPO.

## 6.1 Post-accelerator Performance

In the second stage, we examine the startups' fundraising performance after graduation. We first report the VC deals received within one year after graduation. Such funding is likely initiated during or shortly after the demo day because it can take several months from the original contract for investment to the actual investment being made.[26] Within this short period, startup qualities have limited changes following graduation. As a result, our approach offers good control over the startup qualities that are observed by accelerators and investors but not researchers.

Table VIII reports the OLS regression results for startup VC fundraising performance one year after the demo day. The first model has as its dependent variable, *Funded*, an indicator that is equal to one if the startup received any funding from VCs. The second to the last models have as dependent variables indicators of whether the startup received more than one million USD (*One Mil+*), more than two million USD (*Two Mil+*), and more than five million USD (*Five Mil+*). For all of the analyses, we included a control for graduation year effects and a correction (*Correction*) for the unobserved startup-accelerator match quality. While there are no significant gender differences in the probability of receiving any VC deals or deals of less than two million USD, women-founded startups are significantly less likely to receive a large amount of funding.

We examine the longer-term funding performance in Table IX. The analysis is similar to that of one-year fundraising, and we still find that women-founded startups are substantially less likely to receive a large amount of venture funding.[27]

[26] https://www.forbes.com/sites/alejandrocremades/2019/01/03/how-long-it-takes-to-raise-capital-for-a-startup/?sh=1129c4a37a41

[27] Appendix A.6 provides Tobit estimation results as a robustness check. The results are consistent.

TABLE VIII. **Second-stage OLS Result: One-year VC Funding**

This table presents the linear probability estimates with dependent variables as indicators of, within one year of graduation, the VC funding, funded more than 1 million USD, funded more than 2 million USD, and funded more than 5 million USD.

| | (1) Funded | (2) One Mil+ | (3) Two Mil+ | (4) Five Mil+ |
|---|---|---|---|---|
| Female Founder | 0.053 | -0.049 | -0.082 | -0.038 |
| | (0.130) | (0.102) | (0.029) | (0.021) |
| Female Founder*"All Men" Accelerator | -0.097 | 0.068 | 0.066 | 0.017 |
| | (0.149) | (0.113) | (0.039) | (0.024) |
| No Serial Founder | -0.052 | -0.078 | -0.041 | -0.018 |
| | (0.036) | (0.030) | (0.019) | (0.014) |
| Startup Age | 0.068 | 0.041 | 0.013 | 0.004 |
| | (0.020) | (0.017) | (0.011) | (0.007) |
| At least One Graduate Degree | -0.017 | 0.034 | 0.022 | 0.009 |
| | (0.043) | (0.032) | (0.023) | (0.015) |
| At least One PhD Degree | 0.034 | -0.039 | -0.031 | -0.021 |
| | (0.077) | (0.054) | (0.037) | (0.024) |
| At least One Engr/Sci Degree | -0.072 | -0.062 | -0.005 | -0.010 |
| | (0.038) | (0.030) | (0.020) | (0.014) |
| Average Age of Founding Team | 0.361 | -0.000 | -0.091 | -0.007 |
| | (0.356) | (0.240) | (0.148) | (0.098) |
| Founding Team Size | 0.061 | 0.044 | -0.006 | 0.005 |
| | (0.024) | (0.018) | (0.012) | (0.008) |
| Accelerator in Startup Hubs (CA,NY,MA) | 0.050 | 0.052 | 0.003 | 0.001 |
| | (0.057) | (0.042) | (0.026) | (0.017) |
| Accelerator Experiences (yrs) | -0.018 | 0.017 | 0.003 | 0.001 |
| | (0.013) | (0.009) | (0.006) | (0.005) |
| log(Cohort Size) | 0.181 | 0.095 | 0.024 | 0.013 |
| | (0.048) | (0.034) | (0.018) | (0.014) |
| "All Men" Accelerator | 0.049 | 0.051 | -0.023 | -0.009 |
| | (0.062) | (0.052) | (0.034) | (0.025) |
| Startup Relocated | -0.068 | -0.105 | -0.043 | -0.033 |
| | (0.052) | (0.038) | (0.022) | (0.016) |
| Correction | 0.075 | 0.045 | 0.027 | 0.019 |
| | (0.035) | (0.025) | (0.017) | (0.014) |
| Intercept | -0.261 | -0.165 | 0.089 | 0.021 |
| | (0.188) | (0.152) | (0.092) | (0.070) |
| Year Fixed Effects | Y | Y | Y | Y |
| Industry Fixed Effects | Y | Y | Y | Y |
| $N$ | 736 | 736 | 736 | 736 |
| $R^2$ | 0.093 | 0.117 | 0.055 | 0.034 |

bootstrapped standard errors in parentheses

TABLE IX. **Second-stage OLS Result: Five-year VC Funding**

This table presents the linear probability estimates with dependent variables measuring cumulatively by year five of graduation, the indicators of VC funding, funded with more than 1 million, more than 2 million, and more than 5 million USD.

| | (1) Funded | (2) One Mil+ | (3) Two Mil+ | (4) Five Mil+ |
|---|---|---|---|---|
| Female Founder | -0.029 | -0.156 | -0.109 | -0.160 |
| | (0.123) | (0.124) | (0.116) | (0.073) |
| Female Founder*"All Men" Accelerator | -0.097 | 0.168 | 0.068 | 0.103 |
| | (0.145) | (0.143) | (0.133) | (0.090) |
| "All Men" Accelerator | 0.085 | 0.055 | 0.051 | 0.007 |
| | (0.064) | (0.067) | (0.061) | (0.053) |
| Startup Relocated | -0.046 | -0.084 | -0.081 | -0.034 |
| | (0.057) | (0.053) | (0.045) | (0.042) |
| Year Fixed Effects | Y | Y | Y | Y |
| Industry Fixed Effects | Y | Y | Y | Y |
| Other Controls | Y | Y | Y | Y |
| Correction | Y | Y | Y | Y |
| $N$ | 736 | 736 | 736 | 736 |
| $R^2$ | 0.097 | 0.087 | 0.056 | 0.048 |

bootstrapped standard errors in parentheses

# 7 Potential Explanations

## 7.1 Gender Difference in Startup Development

It is possible that women-founded startups develop in a systematically different way from their men-founded counterparts after graduation despite being similar in accelerators. For example, women might be more risk-averse (Buser et al., 2014; Croson & Gneezy, 2009; Sapienza, Zingales & Maestripieri, 2009). Therefore, they might prefer to develop startups more conservatively/safely and require less money. However, there is also evidence suggesting that women and men are not substantially different in risk-taking and development in entrepreneurship after controlling for industry (Gafni et al., 2021). In general, there are only limited evidence to support that risk preferences play a significant role in explaining funding outcomes (Ewens, 2023). Another possibility is that women face more constraints from family responsibilities (Core, 2022; Zandberg, 2021) and therefore cannot fully devote themselves to startup development.

These differences are unlikely to be important explanations for our findings. First, such differences, if they exist, are likely to have been captured by the accelerators during the admission process. Since the accelerator managers are experienced in the VC industry, it is unlikely that they would systematically miss such gender differences that are then immediately discovered by VCs after graduation, causing a glass ceiling in the short term.

Second, if there is a gender difference in risk-preferences and it causes women to choose low-risk, low-return projects, we would expect women-founded startups perform differently on other measures such as the survival rate and exit rate. To examine these aspects, we report in Table X the OLS results for startups' one-year failure rates, five-year failure rates and the five-year probability of being acquired.[28] Furthermore, in Table XI, we analyze the five-year failure rates and acquisition rates for startups received funding within one year after graduation. We do not find any significant gender differences across any of these measures. These findings conflict with the hypothesis that the difference in funding amounts is due to variation in the riskiness of projects.

TABLE X. **Second-stage OLS Result: Operating Status**

This table presents the linear probability estimates with dependent variables as indicators of: startups that failed within one year after graduation, failed within five years after graduation, and exited within five years after graduation.

| | (1)<br>Failed 1Yr | (2)<br>Failed 5Yr | (3)<br>Exited 5Yr |
|---|---|---|---|
| Female Founder | 0.068 | 0.029 | 0.068 |
| | (0.128) | (0.137) | (0.134) |
| Year Fixed Effects | Y | Y | Y |
| Industry Fixed Effects | Y | Y | Y |
| Other Controls | Y | Y | Y |
| Correction | Y | Y | Y |
| $N$ | 736 | 736 | 736 |
| $R^2$ | 0.044 | 0.108 | 0.044 |

bootstrapped standard errors in parentheses

Another related potential gender difference is that women might prefer not to relocate (Bielby & Bielby, 1992), which can restrict the startup's ability to find more VC. If this

[28]Few acquisitions happened within one year after graduation.

TABLE XI. **Startup 5yr Performance Conditional on 1yr Funded**

This table presents the linear probability estimates with dependent variables as indicators of the following five-year startup performance: VC funded more than 1 million USD, funded more than 2 million USD, funded more than 5 million USD, Failed, and Exited.

| | (1) One Mil+ | (2) Two Mil+ | (3) Five Mil+ | (4) Failed | (5) Exited |
|---|---|---|---|---|---|
| Female Founder | -0.185 | -0.133 | -0.213 | -0.026 | -0.015 |
| | (0.186) | (0.184) | (0.129) | (0.141) | (0.162) |
| "All Men" Accelerator | -0.005 | 0.029 | 0.010 | -0.125 | 0.034 |
| | (0.098) | (0.095) | (0.102) | (0.069) | (0.089) |
| Female Founder*"All Men" Accelerator | 0.438 | 0.189 | 0.165 | 0.019 | 0.031 |
| | (0.214) | (0.215) | (0.171) | (0.168) | (0.203) |
| Year Fixed Effects | Y | Y | Y | Y | Y |
| Industry Fixed Effects | Y | Y | Y | Y | Y |
| Other Controls | Y | Y | Y | Y | Y |
| Correction | Y | Y | Y | Y | Y |
| $N$ | 325 | 325 | 325 | 325 | 325 |
| $R^2$ | 0.091 | 0.061 | 0.091 | 0.072 | 0.055 |

bootstrapped standard errors in parentheses

difference is the explanation, women-founded startups that relocated to a different state to join accelerators should have better performance after graduation. In Table XII, we include as a control the interaction of *Female Founder* and *Startup Relocated*. We find that women-founded startups that relocated have a significantly higher probability of raising VC in the short term. However, even those startups are less likely to secure funding over two million USD. Table XIII shows a similar analysis as Table XII but with the startup funding performance within five years after graduation. The results are consistent with each other.

## 7.2 Gender Differences in Resources

Women-founded startups may have fewer available resources because the current venture market is male-dominated. Women may prefer to work with female investors and face greater challenges in networking with men (Brooks et al., 2014; Howell & Nanda, 2023). How women pitch and communicate with investors could also be less preferred by male investors (Hu & Ma, 2021).

TABLE XII. **Second-stage OLS Result: One-year Funding (Relocated Startups)**

This table presents the linear probability estimates with dependent variables as indicators of the following: VC funding, funded more than 1 million USD, funded more than 2 million USD, and funded more than 5 million USD.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Funded | One Mil+ | Two Mil+ | Five Mil+ |
| Female Founder | -0.014 | -0.078 | -0.076 | -0.041 |
| | (0.133) | (0.100) | (0.030) | (0.022) |
| Startup Relocated | -0.088 | -0.113 | -0.041 | -0.034 |
| | (0.054) | (0.038) | (0.025) | (0.017) |
| Female*Startup Relocated | 0.238 | 0.102 | -0.022 | 0.010 |
| | (0.142) | (0.115) | (0.036) | (0.019) |
| Year Fixed Effects | Y | Y | Y | Y |
| Industry Fixed Effects | Y | Y | Y | Y |
| Other Controls | Y | Y | Y | Y |
| Correction | Y | Y | Y | Y |
| $N$ | 736 | 736 | 736 | 736 |
| $R^2$ | 0.097 | 0.118 | 0.055 | 0.034 |

bootstrapped standard errors in parentheses

Similar to the argument in the previous section, these gender differences are likely to have been captured during accelerator admission. Furthermore, the assistance during accelerator programs, such as networking opportunities and training on pitching skills, should mitigate the gender gap. Last, these differences should also be reflected in a startup's fundraising performance in general, such as a lower probability of raising any money, rather than only in large-amount funding.

Furthermore, previous studies have shown that female investors do not display bias against female entrepreneurs and can help mitigate the gender gap (Hebert, 2023; Raina, 2021). However, we did not find evidence supporting the idea that women are more likely to join accelerators with female founders, nor did we find that such a match leads to better startup performance after graduation.

We cannot exclude the possibly that female founders might ask for less from investors. In the context of the labor market, there have been observations that women may shy away from negotiation and may ask for less in terms of salary. However, as noted by Bertrand (2011), there is a lack of consistent patterns for such a gender difference, and

TABLE XIII. **Second-stage OLS Result: Five-year Funding (Relocated Startups)**
This table presents the linear probability estimates with dependent variables as indicators of the following: VC funding, funded more than 1 million USD, funded more than 2 million USD, and funded more than 5 million USD.

| | (1) Funded | (2) One Mil+ | (3) Two Mil+ | (4) Five Mil+ |
|---|---|---|---|---|
| Female Founder | -0.087 | -0.195 | -0.111 | -0.179 |
| | (0.144) | (0.120) | (0.121) | (0.082) |
| Startup Relocated | -0.063 | -0.095 | -0.081 | -0.039 |
| | (0.058) | (0.054) | (0.046) | (0.041) |
| Female*Startup Relocated | 0.209 | 0.139 | 0.007 | 0.065 |
| | (0.155) | (0.151) | (0.129) | (0.104) |
| Year Fixed Effects | Y | Y | Y | Y |
| Industry Fixed Effects | Y | Y | Y | Y |
| Other Controls | Y | Y | Y | Y |
| Correction | Y | Y | Y | Y |
| $N$ | 736 | 736 | 736 | 736 |
| $R^2$ | 0.100 | 0.088 | 0.056 | 0.048 |

bootstrapped standard errors in parentheses

the variation depends on the situational or contextual factors of the negotiation. There is no clear evidence that female entrepreneurs ask for less investment after controlling for industry differences. Gafni et al. (2021) shows that, within the same industry, women do not ask for less in their crowdfunding campaigns on Kickstarter.com.

Even if women ask for less in negotiations, it can still be a consequence of the gender or stereotypical bias in the market. The VC market is male-dominated. It has been shown that women who self-promote and negotiate in a male-dominated field are perceived to be less competent and receive fewer rewards (Bertrand, 2011). Therefore, if women ask for less from investors and it is not because of risk aversion (as discussed above), it may be due to their anticipation of the extra resistance due to gender stereotypes in the market.

# 8 Concluding Discussion

This study examines the widening disparity in average fundraising amounts for high-tech, high-growth startups. Using a novel dataset and a structural estimation method, we discover that women-founded startups receive less funding, even when their quality and performance are similar. Common explanations from the startup side, such as risk aversion or relocation preferences, do not find support in our analysis. Our findings suggest gender bias among certain VC investors but only present in large investments.

With the growing societal awareness of gender equality in the past decade, recent literature more focused on explaining the remaining gap with gender differences in preferences and choices. Our paper demonstrated another possibility that the investor- or employer-side bias may still exist or even increase in areas that are difficult for outsiders to verify.[29]

# References


Akkus, O., Cookson, A. & Hortacsu, A. (2016). The determinants of bank mergers: A revealed preference analysis. *Management Science*, *62*(8), 2241-2258.

Akkus, O., Cookson, A. & Hortacsu, A. (2020). Assortative matching and reputation in the market for first issues. *Management Science*, *67*(4), 2049-2074.

Albrecht, J., Bjorklund, A. & Vroman, S. (2003). Is there a glass ceiling in sweden? *Journal of Labor Economics*, *21*(1).

Alesina, A., Giuliano, P. & Nunn, N. (2013). On the origins of gender roles: Women and the plough. *The Quarterly Journal of Economics*, *128*(2), 469-530.

*All In: Female Founders in the US VC Ecosystem* (Tech. Rep.). (2021, 11). Pitchbook.com.

Arulampalam, W., Booth, A. & Bryan, B. (2007). Is there a glass ceiling over europe? exploring the gender pay gap across the wage distribution. *Industrial and Labor Relations Review*, *60*(2), 539-72.

Barbanchon, T., Rathelot, R. & Roulet, A. (2021). Gender differences in job search: Trading off commute against wage. *The Quarterly Journal of Economics*, *136*(1), 381-426.

Bertrand, M. (2011). *New perspectives on gender*. Elsevier.

Bertrand, M. (2018). Coarse lecture - the glass ceiling. *Economica*, *85*, 205-231.

Bertrand, M. (2020). Gender in the twenty-first century. *AEA Papers and Proceedings*, *110*, 1-24.

Bertrand, M., Black, S., Jensen, S. & Lleras-Muney, A. (2018). Breaking the glass ceiling? the effect of board quotas on female labour market outcomes in norway. *The Review of Economic Studies*, *86*(1), 191-239.

Bertrand, M., Goldin, C. & Katz, L. (2010). Dynamics of the gender gap for young professionals in the financial and corporate sectors. *American Economic Journal: Applied Economics*, *2*, 228-255.

Bertrand, M. & Mullainathan, S. (2004). Are emily and greg more employable than lakisha and jamal? a field experiment on labor market discrimination. *American Economic Review*, *94*(4), 991-1013.


[29] Our findings are similar to those of Bian, Li and Li (2023), demonstrating that mandating women on corporate boards can lead to decreased demand for female labor in the same companies.

Bian, B., Li, K. & Li, J. (2023). Does mandating women on corporate boards backfire? *Working paper*.
Biasi, B. & Sarsons, H. (2022). Flexible wages, bargaining, and the gender gap. *The Quarterly Journal of Economics*, *137*(1), 215-266.
Bielby, W. & Bielby, D. (1992). I will follow him: Family ties, gender-role beliefs, and reluctance to relocate for a better job. *American Journal of Sociology*, *97*(5), 1241-1267.
Booth, A. & Leigh, A. (2010). Do employers discriminate by gender? a field experiment in female-dominated occupations. *Economics Letters*, *107*(2), 236-238.
Box, M. & Segerlind, L. (2018). Entrepreneurial teams, gender, and new venture survival: Contexts and institutions. *SAGE Open*, *8*(2).
Brooks, A., Huang, L., Kearney, S. & Murray, F. (2014). Investors prefer entrepreneurial ventures pitched by attractive men. *PNAS*, *111*(12).
Buser, T., Niederle, M. & Oosterbeek, H. (2014). Gender, competitiveness, and career choices. *The Quarterly Journal of Economics*, *129*(3), 1409-1447.
Carlsson, M. (2011). Does hiring discrimination cause gender segregation in the swedish labor market? *Feminist Economics*, *17*(3), 71-102.
Choo, E. & Siow, A. (2006). Who marries whom and why. *Journal of Political Economy*, *114*(1), 175-201.
Clarysse, B., Wright, M. & Van Hove, J. (2016). *A look inside accelerators in the united kingdom: Building technology business*. Imperial College Press.
Clingingsmith, D., Drover, W. & Shane, S. (2022). Examining the outcomes of entrepreneur pitch training: an exploratory field study. *Small Business Economics*.
Cohen, S., Bingham, C. & Hallen, B. (2018). The role of accelerator designs in mitigating bounded rationality in new ventures. *Administrative Science Quarterly*, 1-45.
Cohen, S., Fehder, D., Hochberg, Y. & Murray, F. (2019). The design of startup accelerators. *Reseach Policy*, *48*(7), 1781-1797.
Cohen, S. & Hochberg, Y. (2014). Accelerating startups: The seed accelerator phenomenon. *Working paper*.
Coleman, S. & Robb, A. (2014). Access to capital by high-growth women-owned businesses. *National Women' s Business Council*.
Core, F. (2022). Female innovative entrepreneurship and maternity risk. *Working Paper*.
Croson, R. & Gneezy, U. (2009). Gender differences in preferences. *Journal of Economic Literature*, *47*(2), 448-74.
Dahl, G., Kotsadam, A. & Rooth, D. (2021). Does integration change gender attitudes? the effect of randomly assigning women to traditionally male teams. *The Quarterly Journal of Economics*, *136*(2), 987-1030.
Da Tin, M., Hellmann, T. & Puri, M. (2013). *A survey of venture capital research*. Elsevier.
Ewens, M. (2023). *Race and gender in entrepreneurial finance*. Elsevier.
Ewens, M. & Rhodes-Kropf, M. (2015). Is a vc partnership greater than the sum of its partners? *Journal of Finance*, *70*(3), 1081-1113.
Ewens, M. & Townsend, R. (2020). Are early stage investors biased against women? *Journal of Financial Economics*, *135*(3), 653-677.
Exley, C. & Kessler, J. (2022). The gender gap in self-promotion. *The Quarterly Journal of Economics*, *137*(3), 1345-1381.
Fehder, D. & Hochberg, Y. (2019). Spillover effects of startup accelerator programs: Evidence from venture-backed startup activity. *Working paper*.
Fox, J. (2018). Estimating matching games with transfers. *Quantitative Economics*, *9*(1), 1-38.
Gafni, H., Marom, D., Robb, A. & Sade, O. (2021). Gender dynamics in crowdfunding(kickstarter): Evidence on entrepreneurs, backers, and taste-based discrimina-

tion. *Review of Finance*, *25*(2), 235-274.
Ghazala, A. & Ferrer, R. (2017). Gender gaps in performance: Evidence from young lawyers. *Journal of Political Economy*, *125*(5), 1306-1355.
Giuli, A. & Kostovetsky, L. (2014). Are red or blue companies more likely to go green? politics and corporate social responsibility. *Journal of Financial Economics*, *111*(1), 158-180.
Goldin, C. (2014). A grand gender convergence: Its last chapter. *American Economic Review*, *104*(4), 1091-1119.
Goldin, C., Katz, L. & Kuziemko, I. (2006). The homecoming of american college women: The reversal of the college gender gap. *Journal of Economic Perspectives*, *20*(4), 133-156.
Goldin, C. & Rouse, C. (2000). Orchestrating impartiality: The impact of "blind" auditions on female musicians. *American Economic Review*, *90*(4), 715-741.
Gompers, P., Kovner, A., Lerner, J. & Scharfstein, D. (2010). Performance persistence in entrepreneurship. *Journal of Financial Economics*, *96*, 18-32.
Gompers, P. & Wang, S. (2017). Diversity in innovation. *Working Paper*.
González-Uribe, J. & Leatherbee, M. (2018). The effects of business accelerators on venture performance: Evidence from start-up chile. *The Review of Financial Studies*, *31*(4), 1566-1603.
González-Uribe, J. & Reyes, S. (2021). Identifying and boosting "gazelles" : Evidence from business accelerators. *Journal of Financial Economics*, *139*(1), 260-287.
Gornall, W. & Strebulaev, I. (2020). Gender, race, and entrepreneurship: A randomized field experiment on venture capitalists and angels. *Working Paper*.
Guzman, J. & Kacperczyk, A. (2019). Gender gap in entrepreneurship. *Research Policy*, *48*(7), 1666-1680.
Hallen, B., Cohen, S. & Bingham, C. (2020). Do accelerators work? if so, how? *Organization Science*, *31*(2), 378-414.
Hebert, C. (2023). Gender stereotypes and entrepreneur financing. *Working Paper*.
Hockberg, Y., Ljungqvist, A. & Lu, Y. (2007). Whom you know matters: Venture capitalnetworks and investment performance. *Journal of Finance*, *62*(1), 251-301.
Honoré, F. & Ganco, M. (2020). Entrepreneurial teams' acquisition of talent: Evidence from technology manufacturing industries using a two-sided approach. *Strategic Management Journal*.
Howell, S. & Nanda, R. (2023). Networking frictions in venture capital, and the gender gap in entrepreneurship. *The Journal of Financial and Quantitative Analysis*, 1-56.
Hu, A. & Ma, S. (2021). Persuading investors: A video-based study. *Working Paper*.
Kenneth, A. & Dittmar, A. (2012). The changing of the boards: The impact on firm valuation of mandated female board representation. *The Quarterly Journal of Economics*, *127*(1), 137-197.
Koning, R., Samila, S. & Ferguson, J. (2021). Who do we invent for? patents by women focus more on women's health, but few women get to invent. *Science*, *372*, 1345-1348.
Matsa, D. & Miller, A. (2011). Chipping away at the glass ceiling: Gender spillovers in corporate leadership. *American Economic Review*, *101*(3), 635-639.
Mindruta, D. (2013). Value creation in university - firm research collaborations: A matching approach. *Strategic Management Journal*, *734*, 644-665.
Mindruta, D., Moeen, M. & Agarwal, R. (2016). A two-sided matching approach for partner selection and accessing complementarities in partners' attributes in interfirm alliances. *Strategic Management Journal*, *37*, 206-231.
Niederle, M. & Vesterlund, L. (2007). Do women shy away from competition? do men compete too much? *The Quarterly Journal of Economics*, *122*(3), 1067-1101.

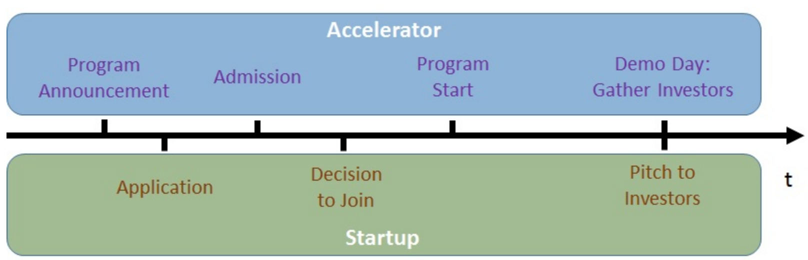
Pan, Y. (2017). The determinants and impact of executive-firm matches. *Management Science*, *63*(1), 185-200.
Pedro, B., Coffman, K., Gennaioli, N. & Shleifer, A. (2019). Beliefs about gender. *American Economic Review*, *109*(3), 739-773.
Piloto, C. (2023). *The gender gap in stem: Still gaping in 2023.* Retrieved from https://professionalprograms.mit.edu/blog/leadership/the-gender-gap-in-stem/
*PitchBook-NVCA Venture Monitor* (Tech. Rep.). (2022, 04). Pitchbook.com.
Proudfoot, D., Kay, A. & Koval, C. (2015). A gender bias in the attribution of creativity: Archival and experimental evidence for the perceived association between masculinity and creative thinking. *Psychological Science*, *26*(11), 1751-1761.
Raina, S. (2021). Vcs, founders, and the performance gender gap. *Working Paper*.
Roth, A. & Sotomayor, M. (1990). *Two-sided matching: A study in game-theoretic modeling and analysis*. Cambridge University Press.
Sapienza, P., Zingales, L. & Maestripieri, D. (2009). Gender differences in financial risk aversion and career choices are affected by testosterone. *PNAS*, *106*(36).
Sørensen, M. (2007). How smart is smart money? a two-sided matching model of venture capital. *The Journal of Finance*, *62*(6), 2725-2762.
Stross, R. (2012). *The launch pad: Inside y combinator*. Penguin Publishing Group.
Winston-Smith, S. & Hannigan, T. (2015). Swinging for the fences: How do top accelerators impact the trajectories of new ventures? *Working paper*.
*Women in the workplace study* (Tech. Rep.). (2022). Leanin.org.
Yu, S. (2020). How do accelerators impact high-technology ventures? *Management Science*, *66*(2), 503-1004.
Zandberg, J. (2021). Family comes first: Reproductive health and the gender gap in entrepreneurship. *Journal of Financial Economics*, *140*(3), 838-864.

# A Appendix

## A.1 Accelerator Process

As shown in Figure III, the accelerator procedure starts with a public announcement of the details and terms of the program, including information such as cohort size, location, and schedule. Once announced, these terms rarely change and are not subject to negotiation. Startups submit their applications to the accelerators that they would like to join, and the accelerators admit the strongest applicants based on predetermined cohort capacities. Admitted entrepreneurs start the program together at the same time and in the same location. The program lasts for a fixed period, often three months, during which the accelerator offers mentorship, network opportunities, and other business support. At the end of the program, the accelerator invites potential investors to join a "demo day" during which the graduating startups present their pitches. The graduating startups pitch to investors to secure funding. The participating firms are under no obligation to the accelerator after graduation, but they often remain involved in the community as alumni.

FIGURE III. **Accelerator Process**




## A.2 Gender Gaps in the VC Market

Figure IV shows the decreasing gender gap in terms of the number of VC deals. The curve shows a downward trend in the difference between the number of VC deals obtained by startups with all-men founders and the number of VC deals obtained by startups with all-women founders.

FIGURE IV. **Diverging Gender Gap in Average Investment Sizes of VC Deals**
The figure shows, with the vertical axis in percentages, ($\frac{\text{\# deals all-men founded}}{\text{\# all deals}}$ - $\frac{\text{\# deals all-women founded}}{\text{\# all deals}}$). The X axis is years.

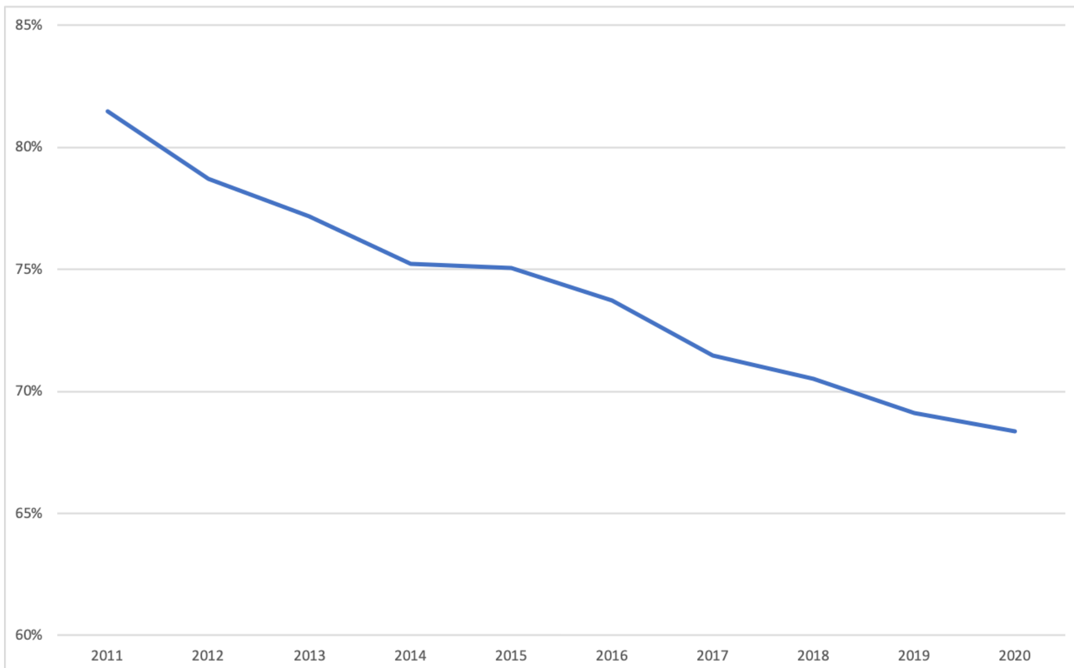


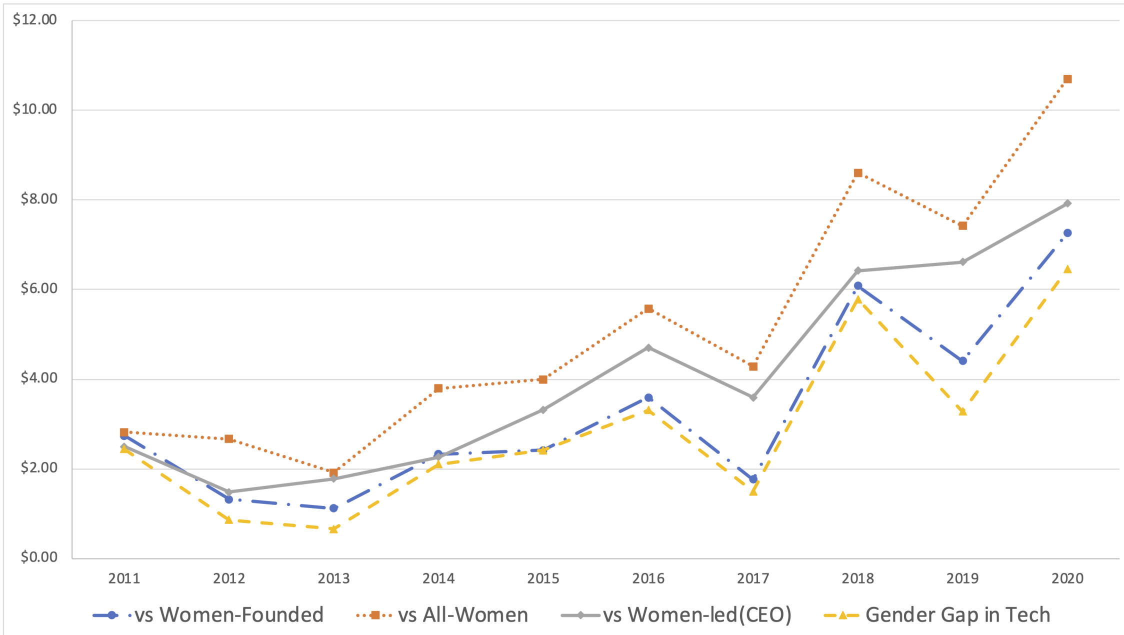

Figure V shows the increasing gender gap in terms of average funding size. In the figure, women-founded startups means there is at least one woman on the founding team; all-women startups is defined as startups with only female founders; women-led startups is defined as startups whose CEO is a woman; and women-founded startups in Tech is defined as startups in tech-industry whose founders include at least one woman.

## A.3 Simulated Maximum Likelihood Pseudocode

The steps taken to perform the maximum simulated likelihood estimation are detailed below. Suppose that there are $K$ markets $\{1, \ldots, K\}$ where the $k$th market has observed matching $m_k$ that contains $|m_k|$ number of matched pairs.

1. For the $k$th market with $|m_k|$ matched pairs $\{(a,s)_i\}_{i=1}^{|m_k|}$, simulate vectors $\epsilon^{as}$ from an

FIGURE V. **Diverging Gender Gap in Average Investment Sizes of VC Deals**
This figure shows the differences in the average VC investment sizes between all-men founded startups and 1) women-founded startups, 2) all-women startups, and 3) women-led startups (female CEO). In addition, it also shows the gap in average investment sizes between all-men and women-founded startups in Tech. The Y axis is in unit of million USD, and the X axis is years.




i.i.d normal distribution of dimension $m_k$. Independently simulate a large number $T$ of such $\epsilon$-vectors, e.g., $T = 10000$.

2. For the $k$th market, with observed matching $m_k$, $g_k(\beta, \epsilon^{as}) = \sum_{a' \neq m_k(s')} \ln \Phi(\underline{U}_{a's'})$. where $\underline{U}_{a's'}$ is defined as in the main text. Here, $g_k$ is a function of the parameters of interest and the $|m_k|$-dimensional vector $\epsilon^{as}$.

3. Choose $\beta$ to maximize the objective

$$LogSumExp\left(g(\beta, \epsilon_t^{as})\right) = \ln\left(\sum_{k=1}^{K}\sum_{t=1}^{T} \exp\left[g_k(\beta, \epsilon_t^{as})\right]\right).$$

The solution is our point estimate $\hat{\beta}$.

## A.4 Proof of proposition 1.

**Proof.** Observe that through law of iterated expectation, we have

$$\begin{aligned}
\mathbb{E}[\eta^{as}|\mu, X] =& \mathbb{E}\left[\mathbb{E}[\eta^{as}|\epsilon, \mu, X]|\mu, X\right] \\
=& \mathbb{E}\left[\mathbb{E}[\eta^{as}|\epsilon, X]|\mu, X\right] \\
=& \mathbb{E}\left[\mathbb{E}[\eta^{as}|\epsilon^{as}]|\mu, X\right] \\
=& \mathbb{E}\left[\rho\sigma\epsilon^{as}|\mu, X\right] \\
=& \rho\sigma\mathbb{E}\left[\epsilon^{as}|\mu, X\right]
\end{aligned}$$

The second inequality is due to the fact that the $\sigma$-field generated by $(\epsilon, X)$ determines $\mu$. The third inequality is due to the fact that $(\epsilon^{a's'}, X)$ are independent of $\eta^{as}$ when $a's' \neq as$. The fourth inequality follows from properties of bivariate normal distribution. Consider the product $\rho\sigma$ as a deterministic parameter; this completes the proof. ■

## A.5 The Matching Model Estimates

Table XIV reports the estimates of the matching model. Column *Coef* is the $\beta$ as in the match value function of Equation 3. We also report the standard errors, obtained from bootstrapping, of our point estimates. In addition to all of the empirical controls discussed in Section 5.4, we include an additional indicator *Startup Relocated* to capture whether the startup had to relocate to a different state to join the accelerator. Such relocation can be very costly for a startup, not only because the founding team needs to change its place of residence but also because the startup might lose its original local support, business partner(s), and customer base.

Our matching model estimates indicate that startups founded by women are less valued in the accelerator market, as indicated by the negative parameter for *Female Founder*. To measure the goodness-of-fit for the first-stage matching model, we compare the vari-

TABLE XIV. **First-stage Result: Admission Matching**

| | Coef | Std Err |
|---|---|---|
| Female Founder | -0.326 | 0.142 |
| No Serial Founder | -0.124 | 0.215 |
| Startup Age | -0.198 | 0.303 |
| At least One Graduate Degree | 0.119 | 0.210 |
| At least One PhD Degree | 0.196 | 0.163 |
| At least One Engr/Sci Degree | 0.700 | 0.230 |
| Average Age of Founding Team | 0.020 | 0.042 |
| Founding Team Size | -0.353 | 0.235 |
| Accelerator in Startup Hubs (CA, NY, MA) | -0.261 | 0.162 |
| Accelerator Experiences (yrs) | 0.060 | 0.040 |
| log(Cohort Size) | 0.652 | 0.119 |
| Accelerator w Female Founder | 0.132 | 0.160 |
| Accelerator w Female Founder*Female Founder | -0.006 | 0.165 |
| Startup Relocated | -2.692 | 0.113 |

ance of $X^{as}\hat{\beta}$ from the structural component of the matching value, to the variance of $\hat{\epsilon}^{as}$ from the imputed unobserved matching quality. Because the value of a match is determined according to the model as $U^{as} = X^{as}\beta + \epsilon$, this comparison provides a measure analogous to the multiple $R^2$ in a regression. We find that $Var[X^{as}\hat{\beta}]/Var[\hat{\epsilon}] = 4.63$, comparable to an $R^2$ of approximately 82%.

## A.6 Tobit Second-stage Regression

For robustness, we conduct a Tobit second-stage regression using log-investment size as the response variable. Table XV shows that the gender gap is larger over the five-year horizon that has more large-size investments, supporting our previous findings.

TABLE XV. **Second-stage Tobit Result: Fund Size**

This table presents the Tobit estimates with dependent variables as the *log(Invest$+1)* and the lower cutoff as zero (log(1)).

| | (1) log(Invest 1yr) | (2) log(Invest 1yr) | (3) log(Invest 5yr) | (4) log(Invest 5yr) |
|---|---|---|---|---|
| Female Founder | 0.255 | -0.736 | -1.182 | -2.205 |
| | (1.774) | (1.802) | (1.721) | (1.908) |
| "All Men" Accelerator | 0.708 | 0.706 | 1.233 | 1.233 |
| | (0.944) | (0.973) | (1.002) | (1.011) |
| Female Founder*"All Men" Accelerator | -1.051 | -0.904 | -1.042 | -0.877 |
| | (2.081) | (2.019) | (2.141) | (2.269) |
| Startup Relocated | -1.034 | -1.319 | -0.753 | -1.027 |
| | (0.779) | (0.832) | (0.820) | (0.905) |
| Female*Startup Relocated | | 3.172 | | 3.254 |
| | | (1.948) | | (2.229) |
| Year Fixed Effects | Y | Y | Y | Y |
| Industry Fixed Effects | Y | Y | Y | Y |
| Other Controls | Y | Y | Y | Y |
| Correction | Y | Y | Y | Y |
| *N* | 736 | 736 | 736 | 736 |

bootstrapped standard errors in parentheses