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ACCELERATING EQUITY: OVERCOMING THE GENDER GAP IN VC FUNDING

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Accelerating Equity: Overcoming the Gender Gap in VC Funding

Chuan Chen* Michele Fioretti[†] Junnan He[‡] Yanrong Jia[§]

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Abstract

We examine the growing gender gap in venture capital funding, focusing on accelerator programs in the U.S. We collect a unique dataset with detailed information on accelerators and startups. Using a two-stage methodology, we first estimate a matching model between startups and accelerators, and then use its output to analyze the gender gap in post-graduation outcomes through a control function approach. Our results show that female-founded startups face a significant funding disadvantage, primarily due to relocation challenges tied to family obligations. However, larger cohorts and higher-quality accelerators help reduce this gap by offering female founders better networking opportunities and mentorship.

Keywords: venture capital, business accelerator, gender, startup, structural matching model

JEL Codes: L1, L26, J16, G24

*Washington University in St Louis, email: chuan.chen@wustl.edu

[†]Bocconi University, Department of Economics, email: fioretti.m@unibocconi.it

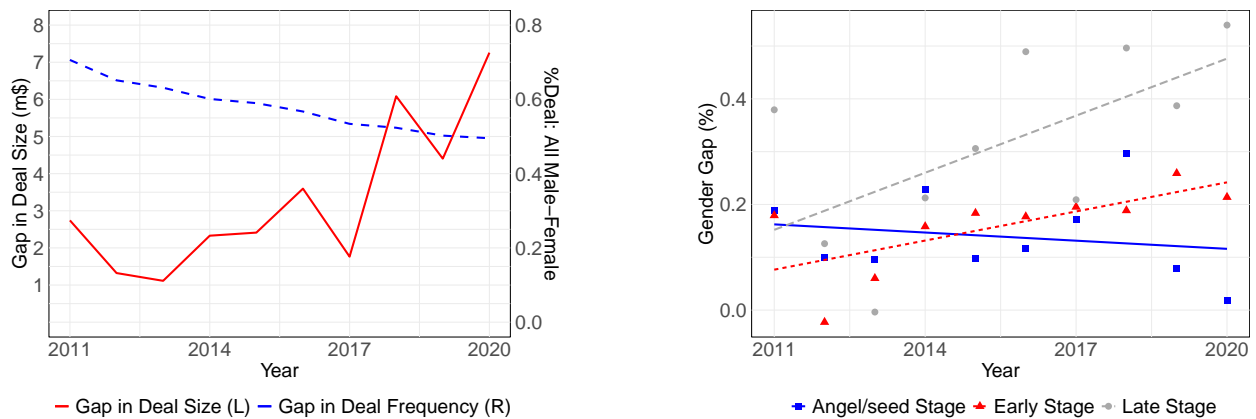
[‡]Sciences Po, Department of Economics, email: junnan.he@sciencespo.fr

[§]Baruch College, Zicklin School of Business, email: yanrong.jia@baruch.cuny.edu

1 Introduction

Over the past decade, the share of venture capital (VC) deals involving women-founded startups in the U.S. has steadily increased. However, the funding gap has widened in dollar terms, with women-founded startups receiving smaller average investments. Panel (a) of Figure 1 illustrates that while the gender gap in deal frequency has narrowed (blue dashed line), the disparity in funding amounts has grown (red solid line). This funding gap appears to be driven by late-stage investments (gray dashed line), which tend to be larger in size than earlier-stage funding (Panel b). In this paper, we explore the trend in the funding gap, discuss its underlying causes, and examine potential solutions.

Figure 1. The gender gap in venture capital funding



(a) The gap in US\$ is widening

(b) The gap rises in early and late stage

Notes: Using data from Pitchbook (2021, 2022), we compute VC deal counts and average deal sizes by gender from 2011 to 2020. Panel (a) shows two measures of the gender gap in VC funding: the red line represents the dollar-valued gap in deal size between male- and female-founded startups, while the blue dotted line plots the difference in deal frequency between all-male and women-founded startups (left vertical axis). Panel (b) plots the relative funding gap across VC stages, computed as $1 - \frac{\text{avg. funding for women-founded}}{\text{avg. funding for all-men founded}}$. Lines are regression fits by group. A startup is “women-founded” if at least one founder is a woman but results are qualitatively similar with other classifications.

Collecting detailed data on startups is challenging. Startups are inherently difficult to track compared to publicly listed firms, and, more importantly, there is often limited information on their operations. Who are the founders? What are their gender and background? How much funding have they raised? These challenges complicate productivity comparisons between startups led by female and male founders, as it becomes nearly impossible to control for the quality of a startup. Controlling for both observed and unobserved quality is crucial to identify discrimination in venture capital funding.

We address these problems by studying startups graduating from accelerators. Accel-

erators can be seen as colleges for startups, as they provide services (e.g., legal support) and mentorship. Similar to college admissions, startups apply to multiple accelerators before enrolling in one of them. We hand-collected information on the *universe* of startups “graduating” from *all* U.S. accelerators from their respective websites and other sources (e.g., LinkedIn). For each startup, we observe demographic information regarding its founders, funding outcomes over different horizons since graduation, as well as whether they were acquired or went public. We observe various characteristics for accelerators as well, such as their yearly cohort.

Our approach to investigating the gender gap is divided into two steps. In the first step, we build and estimate a one-to-many matching model with non-transferable utility between startups and accelerators. The model estimates the degree of assortative matching, so that high-quality startups and accelerators are more likely to match during the admission process. It is also flexible enough to allow startups to match with accelerators from other states. The second step takes advantage of the breadth of our dataset and estimates outcomes at the startup level, treating the gender of the startup founders and other covariates as factors in a control function approach. This method uses the matching probabilities between accelerators and startups—estimated in the first step—to control for unobserved endogenous quality.

We find strong evidence of a significant gender penalty. As shown in Figure 1, startups with a female founder have a -3.8 percentage point lower probability of reaching the five-million-dollar funding milestone one year after graduation, with the gap widening to -16 percentage points within five years. Since later VC rounds tend to be larger than earlier ones, this widening probability gap translates into an even larger gap in U.S. dollar terms. This result is particularly concerning because attending an accelerator serves as a signal of quality, meaning the quality heterogeneity among the startups in our sample should be smaller than the heterogeneity underlying Figure 1.

The mechanism behind this disparity seems to be related to the age of female founders when attending accelerators. We find that the gender gap is driven by startups where female founders are at an age when they are likely to have young children. These founders face significant challenges in relocating to other states to match with their preferred accelerators, resulting in a lower probability of securing funding. In contrast, female-founded startups that do relocate, while still trailing in early achievements, manage to close most of the gap by the fifth year post-graduation. Network externalities, such as the size of the cohort and the quality of the accelerators, help close the gap. This finding opens new research avenues, suggesting that accelerators not only foster firm growth but may also alleviate the frictions contributing to the gender gap in VC funding. For example, while

cohort size may be influenced by the overall structure of the accelerator, access to data on accelerator operations could help researchers understand the services and mentorship they offer, potentially applying these insights to lower-quality accelerators.

Previous research has primarily focused on the probability of securing any investment or smaller amounts, with less attention given to the gender gap in larger VC deals. Understanding this gap is crucial, as biases in larger investments may discourage early-stage investors from funding women-founded startups, perpetuating statistical discrimination (e.g., [Ewens and Townsend, 2020](#); [Gafni et al., 2021](#); [Gornall and Strebulaev, 2024](#); [Zhang, 2023](#)). Addressing this issue is important not only for ethical reasons, as reducing the gender gap can foster a more equitable environment for women entrepreneurs, but also because doing so generates economic value: despite raising less funding than qualitatively comparable firms, they are no more likely to go bankrupt in the first five years.¹ Moreover, they have the same likelihood of being acquired as their male counterparts, potentially indicating a more efficient use of funds. Therefore, closing the gender gap in financing is crucial not only for promoting fairness but also for sustaining innovation and fostering the entry of new firms into highly innovative sectors, such as the technology industry, which is the focus of our study.

Our approach emphasizes the link between accelerator evaluations and VC investment decisions. Investor-led accelerators, such as Y Combinator, are for-profit programs managed by successful VC investors and entrepreneurs ([Cohen and Hochberg, 2014](#)). Funded by venture investors, these accelerators select high-growth potential startups and take equity stakes ([Clarysse et al., 2016](#)). Graduates from these programs often attract significant VC interest, with accelerator alumni receiving about one-third of Series A funding in the U.S.² in 2018. By 2021, Y Combinator's top 30 graduates were valued at 575 billion US\$, while TechStars and 500 Startups had portfolios worth 71 billion US\$ and 49 companies valued at over 1 billion US\$.

This link is crucial for controlling unobserved startup and accelerator quality. If men-founded startups generally have higher quality during accelerator admission, women-founded startups securing admission to high-quality programs would inherently possess higher, unobservable quality. This unobserved quality can affect startup performance in the VC market, creating endogeneity by correlating gender with the error term in venture performance. To address this, we adopt the modeling approach of [Sørensen \(2007\)](#), where

¹Relatedly, a growing literature studies the role of women as directors and executives on corporate economic and social outcomes ([Adams and Ferreira, 2009](#); [Ferrari et al., 2022](#); [Field et al., 2020](#); [Huang and Kisgen, 2013](#); [Kenneth and Dittmar, 2012](#)).

²See reports by Ian Hathaway. <https://www.ianhathaway.org/blog/2019/4/9/accelerated-companies-at-series-a>.

accelerator assessments correlate with post-accelerator performance. The key assumption is that accelerator outcomes depend on the presence of other participants, while post-program performance is driven by the startup and its associated accelerator.

We estimate the model in two stages. In the first stage, accelerators and startups match based on maximizing expected startup value (e.g., NPV) at graduation. The expected value depends on accelerator characteristics (program quality), startup characteristics, complementary factors (e.g., location), and potentially unobserved qualities. The matching process is competitive and capacity-constrained, with equilibrium determined by pairwise stability, as in (Roth and Sotomayor, 1990).³

In the second stage, fundraising depends on observable variables and an unobserved match quality term, reflecting the tendency of better startups to pair with better accelerators. Drawing from the control function literature (Heckman, 1974), we show that this unobserved term correlates with observable matching outcomes obtained from the estimation of the matching model. Thus, a contribution of our paper is to account for unobserved heterogeneity in future outcomes related to the matching stage by leveraging the structure of the matching process, an approach that can be exported to study other questions (Akkus et al., 2020; Lu and Rui, 2018).

A common explanation for gender differences is relocation preferences, where women may face location constraints or family obligations that limit their ability to contact investors or fully dedicate themselves to their startups (e.g., Barbanchon et al., 2021; Bertrand et al., 2010; Jayachandran et al., 2024; Zandberg, 2021). These make female entrepreneurs more likely to locate their businesses in more segregated areas, with shorter commuting times and smaller networks (Rosenthal and Strange, 2012). Our results point to similar mechanisms in place for accelerator-startup matches, as accelerators with more enrolled startups and thus greater networking opportunities record smaller gender gaps in funding.⁴

Our results also indicate that the gender gap is unlikely to be explained by differences in pitch styles or networking abilities (Brooks et al., 2014; Exley and Kessler, 2022; Hu and Ma, 2021). Accelerators assess pitch styles during the admission process (Hallen et al., 2020; Stross, 2012) and provide pitch training (Clingsmith et al., 2022), which mitigates gender-based differences. However, our analysis shows that a gender gap per-

³This approach differs substantially from the standard discrete choice approach. In a discrete choice model where startups select accelerators, accelerators do not face capacity constraints. As a result, the market competition encountered by startups is not accounted for, which can lead to biased estimates.

⁴Risk aversion is another common explanation of gender differences (Buser et al., 2014; Croson and Gneezy, 2009), but prior research suggests limited evidence linking risk preferences to funding outcomes (Ewens, 2023), with Gafni et al. (2021) showing that gender differences in risk aversion disappear when accounting for industry factors.

sists in larger investments even after controlling for accelerator quality. Additionally, while female investors may offer better support to women founders (Hebert, 2023; Raina, 2021), female founders still face challenges breaking the glass ceiling in accelerators led by women.

Finally, this paper broadly relates to the extensive literature on the gender gap in the labor market (e.g., Biasi and Sarsons, 2022; Campa et al., 2011; Dahl et al., 2021; Ghazala and Ferrer, 2017; Kawaguchi, 2007) and in the sciences, as most of the founders in our datasets have STEM backgrounds (Ahn et al., 2024; Galasso and Profeta, 2024; Iaria et al., 2024). It relates to the literature on the “glass ceiling”—an invisible but persistent barrier that prevent certain groups—particularly women and minorities—from advancing to the highest levels of their professions, despite having the necessary qualifications and abilities (Albrecht et al., 2003; Bertrand et al., 2018; Matsa and Miller, 2011).

The paper is structured as follows. Section 2 explains the dataset and the data collection process. Section 3 describes the role of accelerators and compares our data to the broader venture capital market. Section 4 presents the matching model and its estimation, with the results detailed in Section 5. Section 6 explores relocation as a key driver of the gender gap, discussing the implications of our findings. Finally, Section 7 concludes the paper.

2 Data

We construct a novel dataset covering all U.S. accelerators from 2008 to 2011. Collecting startup data is inherently challenging. We began by identifying accelerators from `seed-db.com`, a well-known public repository of accelerator programs. However, its lists of accelerator participants can be incomplete, particularly for less prominent programs. To address this, we supplemented our data using Google News and platforms like TechCrunch, retrieving press releases and announcements from the relevant cohort years. To our knowledge, we have covered all participants of these cohorts.

Most accelerators during this period were investor-led programs focused on IT industries, with many well-known accelerators emerging at this time. We exclude non-profit-driven accelerators, including those with community restrictions, government or non-profit funding, or no equity stake. This ensures our dataset consists only of accelerators maximizing expected returns. We also omit startups with missing characteristics.⁵

⁵Most omitted startups had already ceased operations. However, they do not appear systematically different from other failed startups, and their exclusion, representing about 5% of the dataset, is unlikely to impact our results significantly.

We collect program and participant details from CrunchBase, AngelList, CapitalIQ, CBInsights, VentureXpert, and LinkedIn. Data on private firms often suffer from self-reporting bias, as successful startups are more likely to disclose information. To mitigate this, we cross-check firms using news articles and press releases. However, self-reporting bias is minimal in our dataset, as most startups had publicly available information due to the prominence of accelerators.

We define a “program” as a cohort of startups. Some accelerators operate multiple programs across different locations and time periods. In total, we identify 74 programs from 27 accelerators, covering 736 startup graduates.

Table 1 presents summary statistics for the accelerators in our dataset. Around 37% of the programs were located in startup hubs (CA, MA, NY), closely reflecting the broader geographic distribution of U.S. accelerators, with approximately 40% concentrated in major tech hubs such as Silicon Valley, Boston-Cambridge, and New York.

Table 1. 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 2 presents summary statistics for accelerator participants.⁶ Overall, gender differences are small, with differences across most variables being not statistically significant at the 10% level. However, women-founded startups have fewer founders with Engineering or Science degrees, smaller founding teams, older founders, and are less likely to operate in Software. We control for these differences in our analysis.

⁶Industries are classified using the six-digit 2012 NAICS codes: IT Service (519190), Software (511210), Data Processing and Hosting (518210), Internet and Web (519130), and Others (e.g., Healthcare, Mobile Devices).

Table 2. Startup profiles

	All		Women Founded		Men Founded	
	Mean	St. dev.	Mean	St. dev.	Mean	St. dev.
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 Ph.D. 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
By industry:						
- IT services	0.382	0.486	0.317	0.469	0.388	0.488
- Software	0.186	0.389	0.222	0.419	0.183	0.387
- Data processing&hosting	0.268	0.443	0.317	0.469	0.263	0.441
- Internet&web	0.092	0.290	0.032	0.177	0.098	0.298
- Others	0.072	0.259	0.111	0.317	0.068	0.253
Observations	736		63		673	

Notes: This table present summary statistics for the startups in our sample. The term “serial founder” indicates a founder who had already founded at least another startup before the focal one.

3 Background

3.1 What are accelerators?

Accelerators, also known as “seed accelerators” or “startup accelerators,” primarily target early-stage, high-tech startups, especially in IT-related industries. During our data period, most accelerators admitted startups ready to raise VC, typically taking a 5% equity stake.⁷ See Appendix A.1 for details on accelerator operations.

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 accelerator 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

⁷Accelerators also provided seed funding, often considered a stipend for participating entrepreneurs ([Cohen and Hochberg, 2014](#)).

Kauffman Foundation Survey—a panel study of 4,928 businesses founded in 2004 and tracked over their early years of operation through 2011.

Table 3 compares the funding received by accelerator graduates with that of comparable startups in the VC market. Panel A reports the average deal size across years. For each cohort from 2008 to 2011, the table shows the average funding received one year after graduation and compares it to that of similarly aged startups in the “seed” or “angel” stages of the VC market for the corresponding year (i.e., firms in the very first stages of the VC market). We find that accelerated startups secure slightly more funding in their first year post-graduation, suggesting they are of higher quality than the broader VC market.

Panel B examines their average yearly fundings over a longer horizon of five years. Each year, reports the total five-year funding divided by the number of years in operation for either the accelerated startups in our sample, or a sample of Pitchbook startups in the “seed” to “late” stages of the VC market. Also in this longer horizon, accelerated startups generally receive more funding than the average startup in the VC market, showing that their higher quality is maintained over time.

This comparison highlights the importance of controlling for variation in startup quality in our analysis.

Table 3. Accelerated startups receive more funding than other startups in the VC market

Average Yearly Funding for Cohort:	Graduation Year			
	2008	2009	2010	2011
<i>Panel A: In the first year since graduation</i>				
Accelerator graduates	0.82	1.37	1.36	1.45
Comparable startups (Seed and Angel stages)	1.06	1.00	0.86	0.87
<i>Panel B: In the first five years since graduation</i>				
Accelerator graduates	1.55	6.70	2.42	2.06
Comparable startups (same age)	2.64	2.05	1.96	1.95

Values in US\$ millions.

Notes: This table compares funding received by accelerator graduates with comparable startups in the VC market. Panel A reports the average deal size for accelerator graduates from 2008 to 2011 in their first year post-graduation, alongside startups of similar age in the “seed” or “angel” stages of the VC market for the corresponding year. Panel B presents the average yearly funding over a five-year horizon, calculated as total funding over five years divided by years in operation. The comparison sample consists of startups in the “seed” to “late” stages from PitchBook. Funding amounts are inflation-adjusted to constant dollars.

3.2 Accelerators' Admission of Women-Founded Startups

This section shows that: (1) there is no evidence that accelerators favored women-founded startups during our data period, (2) accelerators did not admit more women than VCs, and (3) women-founded accelerator participants performed similarly to their male-founded counterparts. These results corroborate our modeling assumptions in the next section.

Accelerators were relatively new in the venture market, with approximately 800 graduates by the end of 2011. Gender diversity was not a selection criterion at the time. For instance, [Stross \(2012\)](#) notes that Y Combinator focused solely on startup growth potential and did not attempt to balance gender in applications. Criticism for admitting too few women only emerged post-2012. Y Combinator, often scrutinized for its low admission rate of women-founded startups, faced such criticism in 2013.⁸

To confirm that public opinion had little influence on accelerator admissions during our data period, we follow [Giuli and Kostovetsky \(2014\)](#) and regress the likelihood of admitting women-founded startups on the political preferences of the local public during the 2008 presidential election. As shown in Appendix Table [A1](#), we find no significant association between state-level political preferences and the admission of women-founded startups.

3.3 The Gender Gap in Startup Performance

Table [4](#) summarizes startup performance post-accelerator. Women-founded startups had a similar likelihood of securing VC funding within one year of graduation compared to men-founded startups (0.429 vs. 0.443) but raised smaller amounts on average (\$0.352 m vs. \$0.633 m). In terms of performance, women-founded startups had lower failure rates within one year but higher failure rates in the long run.⁹

Table [5](#) breaks down fundraising performance by VC funding amount. While women-founded startups performed similarly at lower funding levels, significantly fewer raised more than \$2 million.

A bootstrapping test (Appendix Table [A2](#)) shows that among funded startups, the difference in mean log-investment size between men- and women-founded startups is not significantly greater than zero (p-values: 0.293 within one year, 0.160 within five years). However, the log-investment size distribution for men-founded startups exhibits

⁸See: <http://www.paulgraham.com/ff.html>.

⁹The patterns in Figure [1](#) hold also with different definition of women-funded startup, as we show in Appendix [A.2](#).

significantly higher variance and right skewness. This suggests that male founders are more likely to secure exceptionally large funding amounts, whereas female founders face greater challenges in obtaining substantial investments.

Table 4. startup performance post graduation

	All		Women Founded		Men Founded	
	Mean	St. dev.	Mean	St. dev.	Mean	St. dev.
<i>VC Investments</i>						
Fraction of VC funded startups (1 yr since grad)	0.442	0.497	0.429	0.499	0.443	0.497
Fraction of VC funded startups (5 yr since grad)	0.510	0.500	0.429	0.499	0.517	0.500
Investment size (m\$) (1 yr since grad)	0.609	1.442	0.352	0.540	0.633	1.497
Investment size (m\$) (5 yr since grad)	6.544	34.406	1.341	2.769	7.031	35.935
<i>Operation Status</i>						
Fractions of startups that failed (1 yr since grad)	0.045	0.207	0.032	0.177	0.046	0.210
Fractions of startups that failed (5 yr since grad)	0.345	0.476	0.444	0.501	0.336	0.473
Fractions of startups that were acquired (5 yr since grad)	0.228	0.420	0.206	0.408	0.230	0.421
Observations	736		63		673	

Notes: This table presents the performance of startups after graduating from an accelerator. By investment size, we denote the average amount of capital received from VCs.

4 A Matching Model for VCs and Startups

We build a model to discern accelerator and startup quality and to measure the extent of discrimination in this industry (Sørensen, 2007). The model features assortative matching, so that high-quality startups and accelerators are more likely to match during admission. We also allow other types of complementarties (e.g., geographic proximity) to affect a match probability.¹⁰ Thus, part of a startup’s unobserved quality can be inferred from the quality of the accelerator it attends.

Importantly for our purposes, our identification strategy allows to separate gender-based sorting across accelerators from gender effects on future startup performances. Suppose a woman-founded startup s and a man-founded startup s' are otherwise identical. If gender-based sorting occurs, s and s' are unlikely to enter the same accelerator (or those of similar quality) within the same admission market. However, due to market-level variation in competing applicants, they may still end up in the same accelerator.

¹⁰Hallen et al. (2020) provide evidence for assortative matching between startups and accelerators.

Table 5. VC funding by gender of the founder

	Funded Startups		Funded Amount			Number of Startups
	Yes	No	>1m	>2m	>5m	
<i>One year after graduation</i>						
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)
<i>Five years after graduation</i>						
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)

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

By accounting for other agents in the market, the matching model allows us to compare the unobserved quality of s and s' . The key identifying assumption is that market composition is exogenous, meaning the unobserved quality of s in a potential match is independent of other agents' characteristics.

4.1 A Matching Model with Non-transferable Utility

We model accelerator admissions as a two-sided matching game with non-transferable utility, following [Roth and Sotomayor \(1990\)](#). Each accelerator-startup match generates a joint match value, which is split according to a fixed equity share. This value depends on observed and latent characteristics of both accelerators and startups, including quality measures and complementarities. The equity share is exogenous and identical across matches. This assumption is supported by the data: the average accelerator equity share is 6.2% with a standard deviation of 1%, and all matches within an accelerator have the same equity share.

Agents maximize payoffs by selecting partners on the other side, and equilibrium is defined by pairwise stability, ensuring no agent has a profitable deviation. The equilibrium exists and is unique under stable matching. We estimate the model parameters using a maximum simulated likelihood algorithm.

Market definition. Our market definition is quite flexible as each market comprises all U.S. accelerators and their program participants within a six-month period, beginning in January 2008 and ending in June 2011. This definition imposes fewer geographical constraints than [Sørensen \(2007\)](#)—who uses smaller regional areas—given the prevalence of out-of-state matches.

We adopt a semiannual market frequency to align with accelerators that run two programs per year, such as Y Combinator. This avoids self-overlapping while ensuring market independence. Sensitivity checks confirm that adjusting market windows does not alter qualitative results. We treat consecutive markets as independent, following [Sørensen \(2007\)](#) and [Fox \(2018\)](#), and omit dynamic considerations, as startups typically attend accelerators only once.

The information structure. We assume that all startups seeking accelerator programs are aware of all available programs within the same market. This is a standard assumption in the literature, justified by the widespread availability of public announcements online months before admissions begin. However, we do not assume that accelerators have complete knowledge of all potential startups in the market.

Complementarities in portfolio selection. To ensure the existence of a stable match, we abstract from complementarities in accelerator portfolio selection, assuming that an accelerator’s preference for one startup is independent of its preference for others.¹¹ This assumption is standard in empirical two-sided matching models (e.g., [Akkus et al., 2016, 2020](#); [Fox, 2018](#); [Honoré and Ganco, 2020](#); [Mindruta et al., 2016](#); [Pan, 2017](#)). In practice, accelerators face competition, making deliberate portfolio construction difficult, and it is not uncommon for direct competitors to be admitted to the same cohort ([Stross, 2012](#)).

4.1.1 Setup of the Theoretical Model

Our model has two stages. The first-stage relates to the matching problem between accelerators and startups. The second stage involves startup performances post graduation.

First stage (matching). 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_{as}^a and U_{as}^s be the payoffs for a and s from match

¹¹The evidence in Section 3 suggests that accelerators’ and VCs’ evaluations of startups are closely aligned, thus supporting our assumption that both VCs and accelerators view startup characteristics, those that are unobserved by researchers, in a similar way. Therefore, we can infer accelerator preferences via admission outcomes to approximate VC assessments of these unobserved characteristics.

(a, s) , respectively. We have:

$$\begin{aligned} U_{as}^s &= (1 - E) \times U_{as} \\ U_{as}^a &= E \times U_{as} \end{aligned}$$

where E is the (exogenous) equity share of a and is not match-specific. Given E , 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 μ 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 μ . The solution concept relies on the “no-blocking condition:” A pair (a, s) is blocking for μ 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 μ , 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 μ , and a prefers s to at least one of its current matches in $\mu^{-1}(a)$. A matching μ is “stable” if there is no blocking pair. Proposition 1 in [Sørensen \(2007\)](#) applies to our framework and ensures the existence of a unique stable matching μ .¹²

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

$$U_{as} = X^{as}\beta + \epsilon^{as}. \quad (1)$$

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

Second stage (longer-term performance). In the second stage, post-matching performance, Y^{as} , is modeled as

$$Y^{as} = X^{as}\alpha + \eta^{as}. \quad (2)$$

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 α .

The second-stage error term is η^{as} correlated with ϵ^{as} . This is because the VC’s decision Y is also correlated with the unobserved match quality ϵ^{as} , which is observed by the accelerator managers and the startups during the admission process. For each potential

¹²Without a unique equilibrium, the statistical likelihood function lacks a well-defined structure, and without a straightforward equilibrium condition, the empirical model becomes intractable ([Bresnahan and Reiss, 1991](#)).

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

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

4.2 Model Estimation

We first estimate the first stage of the matching model and impute the unobservables ϵ using the estimated parameters. We then control for these unobservables in the second-stage performance equations, enabling the analysis of various outcome variables. This approach also allows us to examine matching patterns independently of second-stage outcomes, including also those startups with no second-stage outcomes (i.e., failed ones).

4.2.1 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 μ 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 ϵ^{as} for $s \in \mu^{-1}(a)$ and $\epsilon^{a's'}$ for $a' = \mu(s')$. Therefore, given the unobservables ϵ^{as} for each observed pair (a, s) that satisfies $a = \mu(s)$, the probability that μ is the equilibrium is

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

where Φ 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 μ is therefore

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

By considering ϵ^{as} as latent for all matched pairs (a, s) where $a = \mu(s)$, we can obtain the maximum likelihood estimates for the parameters β using a simulated likelihood approach. The confidence intervals for the parameters are obtained through bootstrapping (500 repetitions) because, in this matching framework, it is theoretically unclear whether the number of accelerators or the number of startups must go to infinity for the standard asymptotic result to hold.

4.2.2 Second Stage: Estimating the Performance of Startup Graduates

In the second-stage analysis, we study ex post outcomes Y^{as} through (2). However, η^{as} is not independent of X^{as} due to its correlation with ϵ^{as} . For example, when a and s are distant from each other, they can still form a match if the realized ϵ^{as} is large enough. Therefore, among the realized matches, distance correlates with ϵ^{as} . As a result, since ϵ^{as} correlates with η^{as} , η^{as} correlates with X^{as} .

To have consistent results, we must control for $\mathbb{E}[\eta^{as}|\mu, X]$, the conditional expectation of each η^{as} given the realized matching with all observable characteristics X in the market. In other words, suppose that we observed $\mathbb{E}[\widehat{\eta^{as}}|\mu, X]$, we could use it in (2) to correct for endogeneity problems through a control function approach:

$$Y^{as} = X^{as}\alpha + \mathbb{E}[\widehat{\eta^{as}}|\mu, X] + \delta \quad (3)$$

where $\delta := \eta^{as} - \mathbb{E}[\widehat{\eta^{as}}|\mu, X]$. Since the error term δ 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, according to:

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

Proof. See Appendix section A.4. \square

The proposition finds that we can use the observed $\mathbb{E}[\epsilon^{as}|\mu, X]$ in place of the unobserved $\mathbb{E}[\eta^{as}|\mu, X]$ in (3) to obtain an unbiased least squares estimate for α . We estimate $\mathbb{E}[\epsilon^{as}|\mu, X]$ by taking the average of the simulated conditional distribution of $\mathbb{E}[\epsilon^{as}|\mu, X]$ from the matching model. The standard errors for α is obtained through bootstrapping.¹³

¹³In the case where the outcome of interest is a binary variable, we simplify the computation using the linear probability model in the regression. We check whether the estimates from a probit model are qualitatively similar.

4.3 Observables

Gender gap. To examine the gender gap, we define *Female Founder* as an indicator for whether at least one startup founder is female. While analyzing all-women founding teams is of interest, the limited number of such cases constrains our analysis. This measure aligns with the divergence trend observed in Pitchbook data, where gender disparities are likely more pronounced for all-women teams (Box and Segerlind, 2018).

Team member characteristics. We collect other characteristics of the founding members with information collected from LinkedIn and their personal websites. To capture prior entrepreneurship experience, we define *No Serial Founder* as an indicator equal to one if no founder has prior startup experience. General work experience, proxied by age, serves as a quality signal, which we examine through *Average Age of Founding Team*. We also include indicators for educational background: *At least One Graduate Degree*, *At least One PhD Degree*, and *At least One Engr/Sci Degree*. Additionally, *Founding Team Size* captures the number of founders. Industry differences are accounted for using six-digit 2012 NAICS codes.

Startup characteristics. Longer-established startups differ from newly founded ones, as they are more likely to have a defined business model, customer base, and experienced founders, all of which facilitate investor attraction. To account for this, we include *Startup Age*, defined as the number of years since founding prior to accelerator admission.

Accelerator characteristics. We capture accelerator quality variation with $\log(\text{Cohort Size})$, while *Accelerator Experience* measures the years an accelerator has operated before the current cohort. *Accelerator in Startup Hubs* indicates whether the accelerator is in MA, CA, or NY.¹⁴ To account for potential gender-related differences, *'All-Men' Accelerator* equals 1 if the accelerator has no female founder.

Second-stage performance variables. We measure startup performance using total VC investment received within one year and five years after demo day. Following the literature, we also track survival status (failed or still operating) and acquisition status (acquired or not) by the fifth year (Ewens and Rhodes-Kropf, 2015; Gompers et al., 2010; Hockberg et al., 2007). Since very few accelerator graduates have completed an IPO, we do not consider IPOs as a measure of performance.

¹⁴Data limitations prevent controlling for detailed location fixed effects.

5 Results

Since the first stage is not the primary focus of our analysis, we describe its estimation routine in Appendix A.5, while Appendix A.6 reports the estimation result. The model fits the data well, explaining 78% of the observed and unobserved variation in match qualities. In this section, instead, we focus on the second-stage estimates and the gender gap.

5.1 Post-Accelerator Performance

The first four columns of Table 6 present the OLS regression results for startup VC fundraising performance one year after the demo day.¹⁵ We begin with the one-year horizon because such funding is typically initiated during or shortly after the demo day, as the process from signing the initial contract to receiving the investment often takes several months.¹⁶ Within this short period, the quality of startups changes minimally following graduation, providing us with sufficient control over the startup qualities that are observable to accelerators and investors but not to researchers.

Column (1) uses “*Funded*” as the dependent variable, an indicator equal to one if the startup secured any VC funding. Columns (2)-(4) examine progressively larger funding thresholds, using indicators for whether a startup raised more than one million, two million, and five million US\$, respectively.

All models control for graduation year effects and include a correction term for unobserved startup-accelerator match quality from Proposition 1. The results in columns (1) and (2) show that the coefficients on “*Female Founder*” are not statistically significant, suggesting no significant gender differences in the likelihood of receiving any VC funding or amounts below two million US\$. However, in columns (3) and (4), the coefficients on “*Female Founder*” become significantly negative, indicating that women-founded startups are significantly less likely to raise larger amounts of funding.

The remaining four columns of Table 6 extend the horizon to funding in the first five years since graduation and find a similar pattern, with large deals being less likely. In

¹⁵Across tables we always include the set of regressors discussed in Section 4.3. The independent variables in the regression include founder characteristics such as *Female Founder*, *Female Founder* \times “*All Men*” *Accelerator*, *No Serial Founder*, *At least One Graduate Degree*, *At least One PhD Degree*, *At least One Engineering/Science Degree*, *Average Age of Founding Team*, and *Founding Team Size*. Additionally, startup and accelerator characteristics include *Startup Age*, *Startup Relocated*, *Accelerator in Startup Hubs (CA, NY, MA)*, *Accelerator Experiences (years)*, *Log(Cohort Size)*, and “*All Men*” *Accelerator*. The regressions also control for, the *Correction Term* ($\mathbb{E}[\eta^{as}|\mu, X]$), *Year Fixed Effects*, and *Industry Fixed Effects*.

¹⁶<https://www.forbes.com/sites/alejandrocremades/2019/01/03/how-long-it-takes-to-raise-capital-for-a-startup/?sh=1129c4a37a41>

Table 6. Second-stage estimation: Performance at one and five years post graduation

Linear Probability Model:	(1) (2) (3) (4)				(5) (6) (7) (8)			
	Funding Within One Year Since Graduation				Funding Within Five Years Since Graduation			
	Funded?	Funding Exceeds (0/1)			Funded?	Funding Exceeds (0/1)		
	(0/1)	One Million	Two Millions	Five Millions	(0/1)	One Million	Two Millions	Five Millions
Female Founder	0.053 (0.130)	-0.049 (0.102)	-0.082*** (0.029)	-0.038* (0.021)	-0.029 (0.123)	-0.156 (0.124)	-0.109 (0.116)	-0.160** (0.073)
"All Men" Accelerator	0.049 (0.062)	0.051 (0.052)	-0.023 (0.034)	-0.009 (0.025)	0.085 (0.064)	0.055 (0.067)	0.051 (0.061)	0.007 (0.053)
Female Founder × "All Men" Accelerator	-0.097 (0.149)	0.068 (0.113)	0.066* (0.039)	0.017 (0.024)	-0.097 (0.145)	0.168 (0.143)	0.068 (0.133)	0.103 (0.090)
Startup Relocated	-0.068 (0.052)	-0.105*** (0.038)	-0.043** (0.022)	-0.033** (0.016)	-0.046 (0.057)	-0.084 (0.053)	-0.081* (0.045)	-0.034 (0.042)
Other Control Variables	✓	✓	✓	✓	✓	✓	✓	✓
Correction Term $E[\eta^{as} \mu, X]$	✓	✓	✓	✓	✓	✓	✓	✓
Year Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓
Industry Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓
<i>N</i>	736	736	736	736	736	736	736	736
<i>R</i> ²	0.093	0.117	0.055	0.034	0.097	0.087	0.056	0.048

* - $p < 0.1$; ** - $p < 0.05$; *** - $p < 0.01$

Notes: This table presents linear probability estimates from (3), where the dependent variables measure performance within one year and cumulatively by year five after graduation. They indicate whether a startup received VC funding, more than \$1 million, more than \$2 million, or more than \$5 million. All specifications include controls (see Section 4.3 for details), correction terms, and fixed effects as indicated. Bootstrapped standard errors are in parentheses.

particular, the magnitude of the probability of raising at least US\$ 5 million in the first five years is four times larger (in absolute value) than that in column (4), indicating that very few female-founded startups reach this level of financing.

Across columns, we also examine whether “all-man” accelerators further decrease the chances of female entrepreneurs obtaining funding, as prior studies have shown that female investors do not display bias against female entrepreneurs and can help mitigate the gender gap (Hebert, 2023; Raina, 2021). The coefficients of “Female Founder × ‘All Men’ Accelerator” are generally not significant for the probability of being funded (columns 1 and 5). However, it is surprisingly positive and significant in column (3) for the probability of receiving funding of more than 2 million US\$. Taken together, this evidence does not support the idea that startups with women founders are more likely to match with accelerators with a mixed (or all-women) gender composition.

Finally, the last row of Table 9 highlights the significant costs associated with relocation. Moving to a new state reduces the probability of reaching the one-million and five-million funding milestones by approximately 3.3 to 10 percentage points. To the extent that startups securing five million in funding are of higher quality, their superior capabilities may help them better absorb these relocation costs. Over the five-year horizon, however, the negative impact of relocation diminishes substantially.

In the next section, we further dissect the gender gap to assess the extent to which it

stems from relocation costs.

6 What Drives the Gender Gap in Funding?

Thus far, our evidence indicates that a gender gap exists, with female founders having lower chances of receiving large amounts of funding. In the following section, we relate this result to relocation costs.

A significant difference highlighted in the literature is that women face higher relocation costs than men (Bielby and Bielby, 1992; Jayachandran et al., 2024). In particular, women founders may be less likely to move their startups to a different state even if they expect a better match for their startup with an accelerator in that state. If this factor explains the observed funding gap, women-founded startups that relocated to a different state to join accelerators should raise more funding after graduation.

In Table 7, we include the interaction of “*Female Founder*” and “*Startup Relocated*.” As in the previous table, the first four columns report startups’ performance one year after graduation, while the remaining columns extend the analysis to five years. Importantly, because of our control function approach (Proposition 1) we can consider startup relocation as exogenous as relocation was controlled for in the matching utilities (1)—as for all the other covariates in (3)—ensuring a causal interpretation of our findings.

Across columns, the estimated coefficients for “*Female Founder*” closely align with those in Table 6. For example, female-founded teams have a 7.6 percentage point lower probability of securing at least two million US\$ in the first year after graduation and a 17.9 percentage point lower probability of raising five million US\$ within five years. However, this gap narrows for startups willing to relocate.

The second row presents the estimates for the interaction term. Despite large standard errors due to the small sample, the coefficients are generally positive, suggesting that relocation mitigates the gender gap in funding.

To further assess this mechanism, the table reports a two-sided test for whether the sum of the gender gap coefficient and its interaction term with “*Startup Relocated*” equals zero. Across columns, we fail to reject the null hypothesis in all cases except column (3), where the dependent variable is the probability of securing two million US\$ within one year of graduation.

Higher-quality startups may be more likely to relocate, raising the concern that our analysis captures unobserved aspects of startup quality correlated with female-founded teams rather than the actual match quality and complementarity between startups and accelerators.

Table 7. The role of relocation

Linear Probability Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Funding Within One Year				Funding Within Five Years			
	Funded? (0/1)	Funding Exceeds One Mil.	Funding Exceeds Two Mil.	Funding Exceeds Five Mil.	Funded? (0/1)	Funding Exceeds One Mil.	Funding Exceeds Two Mil.	Funding Exceeds Five Mil.
Female Founder (α_1)	-0.014 (0.135)	-0.078 (0.101)	-0.076** (0.030)	-0.041* (0.023)	-0.087 (0.132)	-0.195 (0.129)	-0.111 (0.126)	-0.179** (0.086)
Female \times Startup Relocated (α_2)	0.238* (0.143)	0.102 (0.116)	-0.022 (0.034)	0.010 (0.019)	0.209 (0.143)	0.139 (0.146)	0.007 (0.129)	0.065 (0.106)
Other Controls	✓	✓	✓	✓	✓	✓	✓	✓
Correction Term $E[\eta^{as} \mu, X]$	✓	✓	✓	✓	✓	✓	✓	✓
Year Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓
Industry Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓
Test								
$H_0 : \alpha_1 + \alpha_2 = 0$	0.225 (0.149)	0.024 (0.150)	-0.098** (0.039)	-0.031 (0.029)	0.122 (0.144)	-0.056 (0.164)	-0.104 (0.140)	-0.113 (0.103)
N	736	736	736	736	736	736	736	736
R^2	0.097	0.118	0.055	0.034	0.100	0.088	0.056	0.048

* - $p < 0.1$; ** - $p < 0.05$; *** - $p < 0.01$

Notes: This table presents linear probability estimates from (3) adding the interaction term between Female \times Startup Relocated, where the dependent variables measure performance within one year and cumulatively by year five after graduation. They indicate whether a startup received VC funding, more than \$1 million, more than \$2 million, or more than \$5 million. The Test panel tests the null hypothesis that the sum of the coefficients for Female Founder (α_1) and Female \times Startup Relocated (α_2) is zero. All specifications include controls (see Section 4.3 for details), correction terms, and fixed effects as indicated. Bootstrapped standard errors are in parentheses.

To address this issue, we replicate the previous analysis using a restricted sample that includes only startups that survived their first year. This approach removes the lowest-quality startups, creating a more homogeneous sample at the cost of a smaller dataset and larger standard errors. Appendix Table A3 presents the results.

Across columns, the point estimates for the gender gap (first row) are even larger than those in Table 7. Meanwhile, the estimated benefits of relocating appear smaller. Although the test never rejects the null hypothesis that the sum of the two coefficients is zero, this result may be driven by the larger standard errors due to the smaller sample. Notably, the point estimate for the sum of “*Female Founder*” and “*Female Founder* × *Startup Relocated*” is larger in magnitude than in Table 7.

Since, if higher-quality startups were to be more likely to relocate we would have expected larger gains from relocation, this analysis reinforces the presence of a gender gap in funding and suggests that female-founded startups willing or able to relocate can partially close this gap.

6.1 Mechanism

Costs for mother founders. To understand the mechanism, we replicate the analysis above, focusing on the probability of observing fundings exceeding two and five million US\$ at either horizon, as the previous analyses highlight that the gender gap is especially pronounced for these funding levels.

Relocation may be particularly costly for mother entrepreneurs. Relocating with a newborn or a young child may be particularly difficult, regardless of the quality of the startup. To understand whether the gender gap is particularly severe in these cases, we subset the data to include only startups whose teams’ average age is between 28 and 40 years old. We chose this range because there is evidence that women with a degree tend to have their first child later than other mothers, with a median age of first childbirth at 28. This age further increases for women in STEM fields, as is relevant to our sample of startup founders (Lappegard et al., 2020; Livingston, 2015; Schweizer and Guzzo, 2020).

The results in Table 8 indicate a larger gender gap (row 1) compared to the estimates obtained from the full sample. The gender gap appears particularly large over the five-year horizon (columns 3 and 4). For instance, female founders who do not relocate are 34 percentage points less likely to reach both the two- (non-significant) and the five-million funding milestones. This result comes as no surprise, as parenting may take significant resources from mother entrepreneurs, and the time they allocate away from their startups has a substantial economic cost five years after graduation.

However, the second line provides new insights into the benefits of relocation. While there seems to be no advantage over short horizons (columns 1 and 2), there are substantial gains from (successfully) relocating over the five-year horizon. Here, relocating female founders improve their odds of reaching the two-million milestone by 26.5 percentage points and the five-million milestone by 41 percentage points. We show that this effect compensates for the gender gap, opening up possibilities for policy solutions that support young women in relocating. We turn to what accelerators can do to ease relocation costs next.

Table 8. The role of relocation for female entrepreneurs in motherhood age

Linear Probability Model:	(1)	(2)	(3)	(4)
	Funding Within One Year		Funding Within Five Years	
	Exceeds (0/1)		Exceeds (0/1)	
	Two Millions	Five Millions	Two Millions	Five Millions
Female Founder (α_1)	-0.113** (0.057)	-0.077* (0.045)	-0.335 (0.212)	-0.344*** (0.117)
Female \times Startup Relocated (α_2)	-0.062 (0.077)	0.015 (0.045)	0.265 (0.255)	0.410* (0.229)
Other Control Variables	✓	✓	✓	✓
Correction Term $E[\eta^{as} \mu, X]$	✓	✓	✓	✓
Year Fixed Effects	✓	✓	✓	✓
Industry Fixed Effects	✓	✓	✓	✓
Test				
$H_0 : \alpha_1 + \alpha_2 = 0$	-0.175** (0.085)	-0.062 (0.064)	-0.070 (0.260)	-0.067 (0.229)
Sample	Average Age in [28-40] years			
N	337	337	337	337
R^2	0.086	0.077	0.109	0.132

* - $p < 0.1$; ** - $p < 0.05$; *** - $p < 0.01$

Notes: This table presents linear probability estimates from (3) adding the interaction term between Female \times Startup Relocated, where the dependent variables measure performance within one year and cumulatively by year five after graduation. They indicate whether a startup received VC funding, more than \$1 million, more than \$2 million, or more than \$5 million. The Test panel tests the null hypothesis that the sum of the coefficients for Female Founder (α_1) and Female \times Startup Relocated (α_2) is zero. Only startup whose founders' average age is between 28 and 40 are considered. All specifications include controls (see Section 4.3 for details), correction terms, and fixed effects as indicated. Bootstrapped standard errors are in parentheses.

Can accelerators level the gap? We leverage variation across accelerators to examine whether higher-quality accelerators either exhibit a smaller gender gap or help close it through the relocation channel.

Table 9 presents regression results on another subsample. The first four columns focus on networking effects: we restrict the sample to accelerators with cohorts larger than the median, under the assumption that larger accelerators—such as Y Combinator—have more resources, can host more startups, and generate stronger network externalities among participants.

Once again, our findings reveal a stark contrast between short- and long-term funding outcomes. The estimated gender gap (row 1) is similar to the full-sample estimates from columns (3) and (4) of Table 7. Moreover, the benefits of relocation appear limited, particularly in column (1). However, columns (3) and (4) offer a different perspective over the five-year horizon: the gender gap narrows substantially, shrinking by approximately 60% in column (3) $\left(\frac{-0.044+0.111}{-0.111}\right)$ and by 39% in column (4) $\left(\frac{-0.110+0.179}{-0.179}\right)$. The gender gap among relocating female founders decreases even further, to about one-fourth and half of the values observed in Table 7.

These results suggest that one key advantage of larger cohorts is that by engaging with a broader group of founders, relocating female entrepreneurs build a support network that fosters their startups' growth. Further research could explore the underlying mechanisms driving this effect. For instance, female founders may not only exchange knowledge on managing a startup but also on balancing entrepreneurial and household responsibilities. Additionally, a stronger network may allow them to overcome time constraints (as the coefficients on the first row remain negative) by providing access to trusted individuals who can assist with specific business challenges. Enhanced networking opportunities may also facilitate strategic partnerships between startups or among key individuals within the ecosystem.

The remaining columns of Table 9 examine a sample of more experienced accelerators. While the gender gap persists for one-year funding milestones (columns 5 and 6), it fully disappears over the five-year horizon (columns 7 and 8). Experienced accelerators may offer structured mentorship programs tailored to female founders, equipping them with the skills necessary to successfully scale their startups.

We acknowledge that the confidence intervals for these estimates are quite large, reflecting the small sample size.¹⁷ This limitation prevents us from further expanding the sample to explore additional mechanisms at play. Nevertheless, our findings underscore the importance of complementarities between startups and accelerators, pointing to promising avenues for future research. In particular, leveraging datasets that track in-

¹⁷To the extent that the population of interest consists of firms matching with accelerators in the U.S. during our study period, we observe the entire population. In this case, our standard errors are conservative (Sancibrián, 2024).

Table 9. The role of accelerators at closing the “relocation” gap

Linear Probability Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	
	Accelerators with larger cohorts				More experienced accelerators				
	Funding Within One Year Exceeds (0/1)		Funding Within Five Years Exceeds (0/1)		Funding Within One Year Exceeds (0/1)		Funding Within Five Years Exceeds (0/1)		
	Two Mil.	Five Mil.	Two Mil.	Five Mil.	Two Mil.	Five Mil.	Two Mil.	Five Mil.	
Female Founder (α_1)	-0.072* (0.043)	-0.044 (0.033)	-0.044 (0.149)	-0.110 (0.103)	-0.093** (0.043)	-0.036 (0.031)	0.000 (0.303)	0.125 (0.297)	
Female \times Startup Relocated (α_2)	0.018 (0.055)	0.037 (0.039)	0.069 (0.217)	0.053 (0.162)	-0.063 (0.126)	-0.041 (0.081)	0.262 (0.429)	0.342 (0.406)	
Other Control Variables	✓	✓	✓	✓	✓	✓	✓	✓	
Correction Term $\mathbb{E}[\eta^{as} \mu, X]$	✓	✓	✓	✓	✓	✓	✓	✓	
Year Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓	
Industry Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓	
Test									
$H_0 : \alpha_1 + \alpha_2 = 0$	-0.053 (0.062)	-0.006 (0.050)	-0.025 (0.196)	-0.056 (0.137)	-0.156 (0.141)	-0.076 (0.096)	0.262 (0.515)	0.466 (0.493)	
Sample		Large cohorts (above median)				Experienced accelerator (above median)			
N	408	408	408	408	326	326	326	326	
R ²	0.082	0.061	0.060	0.071	0.076	0.060	0.098	0.088	

* - $p < 0.1$; ** - $p < 0.05$; *** - $p < 0.01$

Notes: This table presents linear probability estimates from (3) adding the interaction term between Female \times Startup Relocated, where the dependent variables measure performance within one year and cumulatively by year five after graduation. They indicate whether a startup received VC funding, more than \$1 million, more than \$2 million, or more than \$5 million. The Test panel tests the null hypothesis that the sum of the coefficients for Female Founder (α_1) and Female \times Startup Relocated (α_2) is zero. Columns 1 to 4 focus on startups in accelerators with cohorts above the median cohort size. Columns 5 to 8 focus on startups in accelerators with more than the median number of years of activity. All specifications include controls (see Section 4.3 for details), correction terms, and fixed effects as indicated. Bootstrapped standard errors are in parentheses.

teractions between founders within an accelerator, as well as the specific programs available, could provide deeper insights into how accelerators help reduce the gender gap in VC financing.

6.2 Economic Benefits of Bridging the Gender Gap

In this section, we document that policies aimed at reducing the gender gap in financing are beneficial not only from a fairness perspective but also in economic terms. This is because startups founded by women are not less productive than comparable startups. Although measuring productivity in startups is challenging due to the lack of reliable revenue and employment data, we use the probability of failure in the early years after graduation as a proxy for productivity.

To assess this, we analyze the first three columns of Table 10. Column (1) examines failure within the first year, while column (2) considers failure within the first five years. The results indicate that female-founded startups are not significantly more likely to fail

than their counterparts. While these measures capture the “lack of productivity,” column (3) presents a complementary perspective, showing that female-founded startups are equally likely to be acquired or go public (IPO) within five years—an indicator of high productivity, as these outcomes often signal successful and profitable exits.

The remaining columns further investigate these findings by conditioning on surviving startups. Columns (4) to (6) confirm that female-founded startups receive less funding, particularly struggling to reach the five-million milestone. Despite this funding gap, female-founded startups are just as likely to survive or successfully exit within five years as other startups. This suggests that female-founded startups can achieve similar outcomes as male-founded or mixed-gender startups with fewer financial resources, highlighting their high productivity.

As a result, further bridging the gender gap in financing could not just merely increase the number of startups but also create more successful ones. While additional research is needed to better understand the specific policies implemented by higher-quality accelerators, our findings suggest that accelerators sustaining diversity among startup founders can grow the pie, being beneficial for both firms and society.

Table 10. Operating status

Linear Probability Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Failed in its First		Acquired	Funding Exceeds (0/1)			Failed	Exited
	1 Year	5 Years	in 5 Years	One Million	Two Millions	Five Millions	(0/1)	(0/1)
Female Founder	0.068 (0.128)	0.029 (0.137)	0.068 (0.134)	-0.185 (0.186)	-0.133 (0.184)	-0.213* (0.129)	-0.026 (0.141)	-0.015 (0.162)
Other Controls	✓	✓	✓	✓	✓	✓	✓	✓
Correction Term $\mathbb{E}[\eta^{as} \mu, X]$	✓	✓	✓	✓	✓	✓	✓	✓
Year Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓
Industry Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓
Sample	All	All	All	Conditional on surviving in the first year since graduation				
<i>N</i>	736	736	736	325	325	325	325	325
<i>R</i> ²	0.044	0.108	0.044	0.091	0.061	0.091	0.072	0.055

* - $p < 0.1$; ** - $p < 0.05$; *** - $p < 0.01$

Notes: This table presents linear probability estimates from (3) of startup outcomes, including failure, acquisition, and funding milestones. The first three columns analyze failure within one and five years, as well as acquisition within five years. Columns (4)–(6) examine whether a startup raised more than \$1 million, \$2 million, or \$5 million, conditional on surviving the first year. The last two columns report failure and exit probabilities. Bootstrapped standard errors are in parentheses. All specifications include controls (see Section 4.3 for details), correction terms, and fixed effects as indicated. Bootstrapped standard errors in parentheses.

7 Conclusions

This study provides insights into the gender gap in venture capital funding, focusing on how gender-based disparities persist in larger funding rounds despite similar early-stage performance. By analyzing data from accelerator graduates, we highlight that female-founded startups face significant challenges, particularly due to the relocation constraints often associated with family responsibilities. Our findings suggest that while accelerators play a crucial role in fostering startup growth, they also have the potential to mitigate the gender gap in funding. Reducing this gap is important not only for fairness but also for maximizing the economic potential of women entrepreneurs.

The methodology used in this paper combines a one-to-many matching model with non-transferable utility and a control function approach to estimate startup outcomes. By first modeling the matching process between startups and accelerators, and then using this information to control for unobserved startup quality, we provide a robust analysis of funding disparities. This approach allows us to account for the endogenous factors that may affect venture outcomes and offers a nuanced understanding of the gender funding gap in the venture capital landscape.

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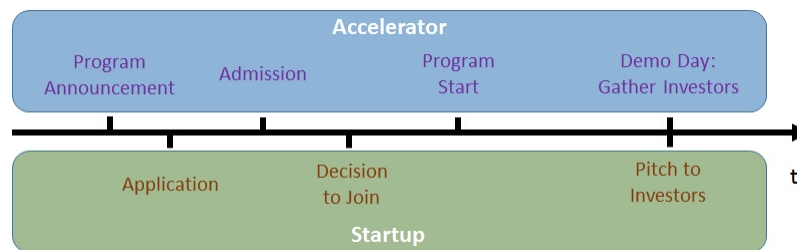
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A Online Appendix

A.1 Accelerator Process

As shown in Figure A1, 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 A1. Accelerator Process

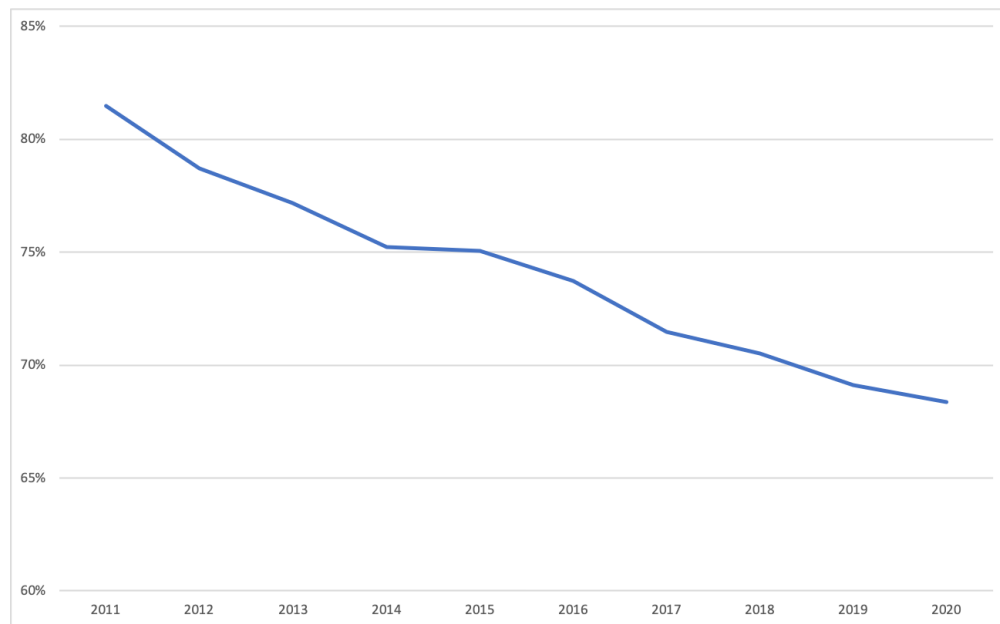


A.2 Gender Gaps in the VC Market

Figure A2 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 A3 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

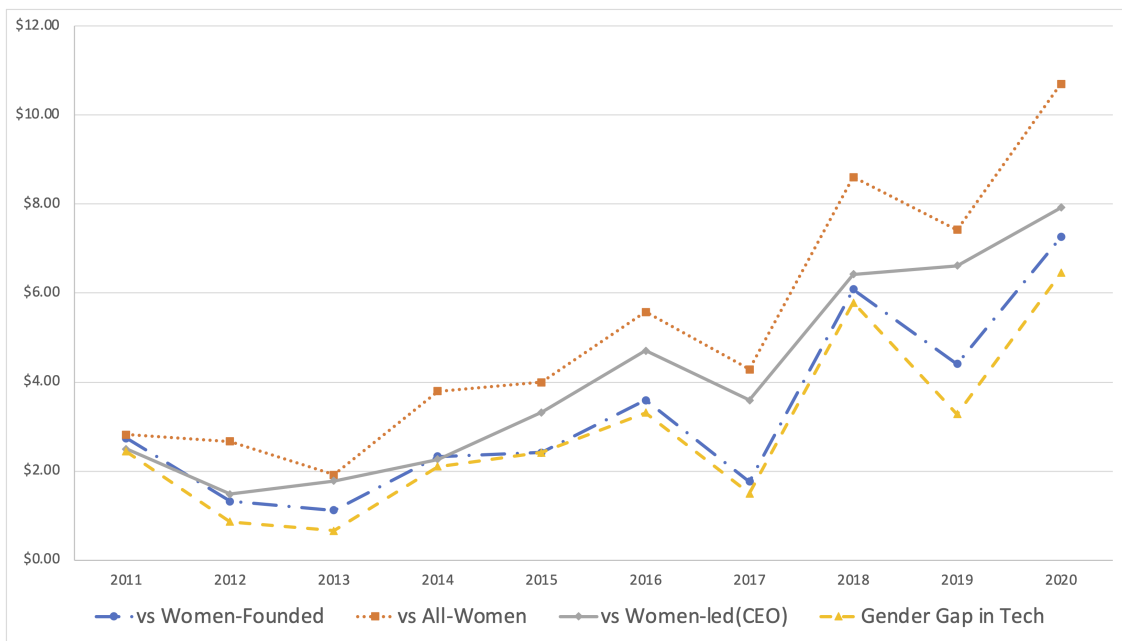
Figure A2. Gender gap in the relative number of VC deals



Note: The figure shows, with the vertical axis in percentages, $(\frac{\# \text{ deals all-men founded}}{\# \text{ all deals}} - \frac{\# \text{ deals all-women founded}}{\# \text{ all deals}})$.

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.

Figure A3. Diverging gender gap in average investment sizes of VC deals



Note: 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 US\$.

A.3 Omitted Tables

Table A1. Accelerator admission and political environment

	(1)	(2)	(3)	(4)
Acc in Democratic State	0.007 (0.032)	0.012 (0.032)	0.025 (0.032)	0.028 (0.033)
Year Fixed Effects		Y		Y
<i>N</i>	736	736	74	74
<i>R</i> ²	0.000	0.002	0.009	0.022

* - $p < 0.1$; ** - $p < 0.05$; *** - $p < 0.01$

Notes: 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 startups are founded by women. The dependent variables for the last two models are the percentages of women-founded startups.

Table A2. Startup VC funding

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

Notes: This table shows the $\log(\text{InvestSize})$ 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.

Table A3. The role of relocation for surviving startups

Linear Probability Model:	(1)	(2)	(3)	(4)	(5)	(6)
	Funding Within One Year			Funding Within Five Years		
	Exceeds (0/1)			Exceeds (0/1)		
	One Mil.	Two Mil.	Five Mil.	One Mil.	Two Mil.	Five Mil.
Female Founder (α_1)	-0.125 (0.182)	-0.130* (0.076)	-0.065 (0.053)	-0.174 (0.202)	-0.044 (0.198)	-0.206 (0.165)
Female \times Startup Relocated (α_2)	0.113 (0.202)	-0.022 (0.086)	0.041 (0.048)	-0.026 (0.206)	-0.214 (0.230)	-0.018 (0.188)
Other Control Variables	✓	✓	✓	✓		
Correction Term $\mathbb{E}[\eta^{as} \mu, X]$	✓	✓	✓	✓		
Year Fixed Effects	✓	✓	✓	✓		
Industry Fixed Effects	✓	✓	✓	✓		
Test						
$H_0 : \alpha_1 + \alpha_2 = 0$	-0.012 (0.220)	-0.152 (0.088)	-0.024 (0.066)	-0.199 (0.215)	-0.257 (0.207)	-0.223 (0.159)
Sample	Conditional on surviving in the first year since graduation					
N	325	325	325	325	325	325
R^2	0.161	0.103	0.062	0.091	0.064	0.091

* - $p < 0.1$; ** - $p < 0.05$; *** - $p < 0.01$

Notes: This table presents linear probability estimates from (3) adding the interaction term between Female \times Startup Relocated, where the dependent variables measure performance within one year and cumulatively by year five after graduation. They indicate whether a startup received VC funding, more than \$1 million, more than \$2 million, or more than \$5 million. The Test panel tests the null hypothesis that the sum of the coefficients for Female Founder (α_1) and Female \times Startup Relocated (α_2) is zero. Only startup that survived the first year after graduation are considered. All specifications include controls (see Section 4.3 for details), correction terms, and fixed effects as indicated. Bootstrapped standard errors are in parentheses.

A.4 Proof of proposition 1.

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

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

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

A.5 Simulated Maximum Likelihood Algorithm

The steps taken to perform the maximum simulated likelihood estimation are detailed below. Suppose that there are K markets $\{1, \dots, K\}$ 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 ϵ^{as} from an i.i.d normal distribution of dimension m_k . Independently simulate a large number T of such ϵ -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 ϵ^{as} .
3. Choose β to maximize the objective

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

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

A.6 The Matching Model Estimates

Table A4 reports the estimates of the matching model. Column *Coef* is the β as in the match value function of Equation 1. We also report the standard errors, obtained from bootstrapping, of our point estimates. In addition to all of the empirical controls discussed in Section 4.3, 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.

Table A4. First-stage results: Admission matching

	Coefficient	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

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 variance 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%.