Financing The Next VC-Backed Startup: The Role of Gender

Camille Hebert[a]
[a]University of Toronto
Heather Tookes[b]
[b]Yale School of Management, Yale University
Emmanuel Yimfor[c]
[c]Columbia Business School, Columbia University
January 18, 2025

Abstract

Is there a gender gap in the serial founding of VC-backed startups? Despite robust evidence linking serial entrepreneurship to startup success, women comprise 13.3% of VC-backed founders but just 4% among those who found three or more startups. We introduce a novel empirical design that exploits within-startup variation and compares future funding outcomes for men and women who co-founded the same startup. This approach helps us control for unobservable differences in startup quality. We document substantial gender gaps, both on average and following failure or success of the current startup. Following failure, women are 22.5% less likely to found another VC-backed startup compared to their cofounders who are men. Among those who do found another VC-backed firm, women raise 53.3% less capital following failure of the current venture and 24.6% less capital following success. We investigate potential demand- and supply-side drivers of these gaps. Lower interest by women in founding new firms can partially explain our findings, however the gender gap attributable to this demand channel is modest. We find no evidence of gender differences in founder quality or to investor learning about the effectiveness of woman founders over time. Rather, we find strong evidence of unequal treatment of women by investors. In particular, consistent with theories of stereotyping, our analysis reveals striking negative spillovers following investors' experiences with failures of other (unrelated) women-founded startups but no positive spillovers following their successes.

JEL Codes: G24, G41, J16
Keywords: Serial entrepreneurship, Gender gap, Venture capital-backed startups

*Camille Hebert, camille.hebert@rotman.utoronto.ca Rotman School of Management, University of Toronto; Heather Tookes, heather.tookes@yale.edu Yale School of Management, Yale University; Emmanuel Yimfor, emmanuel.yimfor@columbia.edu Columbia Business School, Columbia University.
For helpful comments, we thank Mike Ewens, Sabrina Howell, Marlene Koffi, Ed Rieckelman, Valentina Rutigliano, Heather Sarsons, Merih Sevilir, Stephan Siegel, Rick Townsend, Ting Xu, and Ayako Yasuda, as well as participants at the UW Foster DEI workshop 2024, the University of Toronto, Frankfurt School of Finance, Halle IWH, ESMT Berlin, Indiana University, Carnegie Mellon University, SITE Psychology and Economics 2024, UBC Summer Finance Conference 2024, Northwestern Causal Inference Conference 2024, and NFA 2024. We also thank Ava Chae, Aytaj Damirchibayli, and Sophia Wang for excellent research assistance.

1. Introduction

We begin with two facts from the entrepreneurial finance literature. First, there is robust evidence linking serial entrepreneurship and startup success (e.g., Hsu, 2007; Gompers, Kovner, Lerner and Scharfstein, 2010; Lafontaine and Shaw, 2016; Shaw and Sørensen, 2019). Second, women are underrepresented among venture capital (VC)-backed entrepreneurs and those who achieve success (e.g., Ewens and Townsend, 2020; Raina, 2021; Hebert, 2024). These observations raise important questions about whether entrepreneurial experience shapes future venture outcomes differently for men and women.[1]

In this paper, we study the roles of gender and prior entrepreneurial outcomes in determining the ability of startup founders to raise VC for a future venture. Our analysis reveals a large gender gap in VC-backed financing for the next startup. We examine potential explanations for this gap. The strongest evidence points to the unequal treatment of women founders by investors. Using investor portfolio-level data, we show that failures by women-founded startups lead to negative spillovers for unrelated women founders, while successes generate no positive spillovers. In contrast, male founders benefit from larger deal sizes after successful exits, indicating that investor behavior toward women founders reflects bias rather than statistical updating.

We introduce a new empirical design that compares future funding outcomes for men and women who are cofounders of the same startup. In doing so, we address a fundamental challenge in understanding gender gaps in entrepreneurial financing: accounting for differences in founder quality that potential investors infer by observing the current business.[2] By comparing cofounders within the same current startup, we ensure that any identified gender gaps are not driven by variations in startup quality, industry focus, or shared team characteristics. This approach, akin to twin studies, allows us to control for factors that are typically unobservable to researchers. Our empirical design is, to our knowledge, new to the entrepreneurial finance literature.[3]

Starting with aggregate PitchBook data on VC-backed US startups, we find that 13.3% of founders are women. Hidden beneath the 13.3% figure is a meaningful variation in gender balance. Women founders comprise 16% of first-time VC-backed entrepreneurs. However, the representation of women declines to only 9% among those entrepreneurs

[1] In their recent literature review, Ibáñez and Guerrero (2022) highlight the relative absence of scholarly attention to the role of gender in serial entrepreneurship.

[2] For example, startups led by men and women often differ in industry focus, with men more likely to start technology firms and women more represented in consumer products. See Ewens (2023) for a review of the literature.

[3] Close to our approach, Sorkin (2023) identifies pairs of high-tenure workers at the same firm to quantify racial disparities in workers' earnings.

who have founded two VC-backed startups and further down to 4% among those who have founded three or more VC-backed startups. This declining representation is particularly puzzling given that success probabilities increase substantially with founder experience for both men and women. Among first-time founders, 17% of men and 12% of women achieve successful exits within five years. These success rates more than double for founders of multiple startups, reaching nearly 50% for both men and women who found three or more companies. Thus, while the data show that serial entrepreneurship is a powerful predictor of success and that women founders who persist achieve similar success rates to men, women are dramatically less likely to found subsequent VC-backed startups.

Using our novel empirical design, we document substantial gender gaps in VC-backed financing for the next venture that cannot be explained by differences in either the types or outcomes of the businesses that men and women start.[4] Relative to the men with whom they co-founded the current VC-backed startup, women are 28.1% less likely to be VC-backed for the next startup. When women do obtain VC funding for their next startup, they raise 53.3% less funding compared to their male cofounders. This gender gap in follow-on funding points to potential differences in how men and women experience and benefit from co-founding roles, even within the same startup, or to differential treatment by investors despite shared startup experience.

Given the strong relationship between serial entrepreneurship and future success, we repeat the same exercise for the subsamples of founders who have experienced failure or success with the current startup, as these transition points naturally lead to new entrepreneurial attempts.[5] Following the failure of the current startup, our estimates imply that women are 22.5% less likely to found another VC-backed startup compared to their cofounders who are men. Even following success, women are 26.9% less likely to found another VC-backed startup compared to their cofounders who are men (i.e., a gap that is similar to what we observe following failure).

We examine three key mechanisms that could explain the gender funding gap: (1) gender differences in preferences for launching another VC-backed venture, (2) differential accumulation of experience within the same startup, and (3) unequal treatment by investors, which might stem from biased priors about women entrepreneurs

[4]The literature suggests that the returns to entrepreneurship are low (Hamilton, 2000; Moskowitz and Vissing-Jørgensen, 2002), unless we consider the option to re-enter the workforce (Manso, 2016; Catherine, 2022). Amornsiripanitch, Gompers, Hu, Levinson and Mukharlyamov (2023) find that former VC-backed entrepreneurs re-entered the workforce without any penalty. However, Botelho, Fehder and Miric (2023) show that women get lower-ranked positions than men upon reentry.

[5]Following the literature (e.g., Yimfor and Garfinkel (2023); Ewens and Farre-Mensa (2020); Bernstein, Giroud and Townsend (2016); Hochberg, Ljungqvist and Lu (2007)), we categorize a startup as a success if it went public via an IPO or was acquired by December 2023. Failure is a business closure without such an exit. In addition, closure is associated with (i) an inactive website, (ii) a founder who left the company, and (iii) a company that did not raise a new round following the exit of its founder.

or from investor preferences. Our empirical tests examine each of these potential explanations.

The funding gap could reflect women's different preferences for serial entrepreneurship after exits. These preferences could be shaped by factors such as risk tolerance, family considerations, alternative career opportunities in the entrepreneurial ecosystem (e.g., venture capital or board roles), or subjective perceptions of failure (Puri and Robinson, 2013; Hvide and Panos, 2014). To test for evidence of different propensities to start new businesses, we collect data from founders' LinkedIn profiles to identify all of their newly launched firms (VC-backed or not). These data, combined with the information in Pitchbook, allow us to examine both the propensity to start another business and subsequent access to VC funding. Compared to their cofounders who are men, we find that women are 9.4% less likely to start another firm after failure and 8.9% less likely to do so following success. While these differences are statistically significant, they explain only a modest portion of the overall funding gap. Indeed, among those founders who do start another business, women are 30% less likely to raise VC following failure and 18% less likely following success. Differences in the propensity to start new businesses explain some of the VC funding gap following success (reducing it from 26.9% to 18%), but a substantial gender disparity remains in access to venture capital.

A second way to shed light on the possibility that women entrepreneurs have less interest in pursuing subsequent ventures is to examine the intensive margin of VC funding. If the gap is driven by women's lack of interest in a subsequent VC-backed business, we would expect significant gender differences at the extensive margin only. At the intensive margin, it is reasonable to assume that both men and women entrepreneurs would seek similar amounts of capital when raising funds for similar types of ventures.[6] Conditional on raising VC funding for a new startup, we find economically significant disparities between men and women cofounders, particularly following startup failure. Women founders of VC-backed startups raise 53.3% less capital than men following failure. Following success, the gap is smaller but still meaningful, at 24.6%. The evidence from both of the demand-side tests are inconsistent with a pure founder-demand side explanation for the gender gaps.

One potential alternative interpretation of our findings is that, even though we control perfectly for startup quality, men and women cofounders play different roles within their startups and accumulate different types of experience. The CEO role could be particularly important for future fundraising since CEOs typically lead investor relationships and

[6]Unlike the average women, who tend to negotiate less and ask lower salaries (Exley and Kessler, 2022; Roussille, 2024), serial VC-backed women entrepreneurs operating in high-stakes environments are likely to share similar motivations and preferences with their male counterparts (Adams and Ragunathan, 2017; Hebert, 2024).

financing rounds. All of our regressions include controls for whether the cofounder serves as CEO. Moreover, if the gender gap is driven by women having less exposure to fundraising, we would expect to see the gap to be eliminated when comparing men and women who served as CEOs. We do not find any evidence of this in the data. Differences in founder roles and their associated fundraising experience do not explain the gender gap in funding for subsequent startups.

While the founder-demand channel explains part of the gender gap, substantial disparities remain in both the likelihood and amount of VC funding for subsequent startups. We next examine potential supply-side explanations. Even within the stringent within-startup design, gender differences could reflect investors' correct beliefs about men's and women's relative capacities to build and scale profitable businesses. If there are systematic differences in founder effectiveness, we would expect suppliers of capital to respond accordingly.

We begin with an outcomes test that compares the exit outcomes of subsequent startups that men and women launch (Becker, 1993; Cook, Marx and Yimfor, 2024). If investors fund men's ventures more frequently because men are better at identifying and executing profitable opportunities, we would expect to see higher success rates for men's subsequent startups. However, we find no differences in the probability of a successful exit for the next startup, despite women raising less money compared to men. While this outcomes test provides the most direct evidence on founders' relative effectiveness at building successful ventures, sample size limitations lead us to take a second, complementary approach to understanding whether systematic differences between men and women explain our findings.

Our second approach exploits variation in local capital supply conditions to identify situations where startup outcomes are more likely to reveal founder quality. We use state pension fund assets as a plausibly exogenous source of local venture capital, as pension funds are major limited partners with documented local investment biases (Hochberg and Rauh, 2013; González-Uribe, 2020). When capital is abundant, even lower-quality startups can survive, meaning that failures during these periods are particularly informative about founder quality. Conversely, successes during abundant capital periods may include some lower-quality startups that benefited from easy funding conditions.

If women founders are systematically worse at building ventures, we would expect two patterns: First, a larger gender gap in follow-on funding among founders whose startups failed during periods of abundant capital, as these failures more strongly signal poor quality. Second, we would expect a larger gender gap among founders who succeeded during prior capital-rich periods, as investors correct for artificially inflated success outcomes. We find no evidence of either pattern. The gender gap in follow-on funding does not vary with capital supply conditions at the time of failure or success, inconsistent

with systematic quality differences between men and women founders. Given this evidence against quality-based explanations, we next examine investor bias as a potential mechanism.

Finally, we exploit the investor portfolio-level information in Pitchbook to examine whether their past experiences with women founders influence their funding decisions. We find that when an investor experiences a failure by a woman-founded startup, they become 7.8 percentage points less likely to fund other unrelated women founders over the next five years. This pullback in funding is incremental to the baseline 14 percentage points gender gap. We find no similar spillover effects when startups founded by men fail. This unequal response to failure could help explain why women face particular challenges in raising capital from investors after failure. While existing investors who have direct experience with founders show no gender gap in follow-on funding following failure, new investors appear to overweight negative experiences with women founders in their portfolio when evaluating new investment opportunities.

The negative spillovers that we document could be due to investors' attempts to learn about the abilities of women entrepreneurs through statistical updating. It could also be due to unequal treatment of women. To distinguish these explanations, we examine success. If investors are more likely to participate in deals with women founders following the success of another women-founded firm, then the evidence is consistent with statistical updating. If the failure and success results are asymmetric (i.e., if women entrepreneurs do not receive more financing following the success of other women), the evidence points to unequal treatment of women (Bertrand, Chugh and Mullainathan, 2005; Bordalo, Coffman, Gennaioli and Shleifer, 2016).

We find no evidence that investors increase funding to women founders after experiencing success with other women-founded companies in their portfolios. This is true even when we restrict our definition of success to extreme successes (IPOs and acquisitions at exit value to invested capital ratios that exceed the 90th percentile). In contrast, deal sizes for male founders are larger after an investor experiences success with other startups founded by men. This asymmetric pattern of negative spillovers after failure but no positive spillovers after success for women founders, suggests that investors' responses to women founders' performance cannot be explained by simple statistical updating about founder quality (Bohren, Imas and Rosenberg, 2019). Instead, the evidence points to bias in how investors interpret and apply their experiences with women founders.

This paper contributes to the literature in three important ways. First, it is well-known that women are underrepresented at different stages of the entrepreneurship pipeline (Guzman and Kacperczyk, 2019; Ewens, 2023); however, large-scale analyses that control for potential differences in entrepreneurial abilities and the quality of businesses that men

and women start are less common in the literature. Our empirical approach, in which we compare funding outcomes for men and women cofounders of the same firm, allows us to make substantial progress toward identifying true differences in outcomes for men and women. This allows us to build on previous research which has documented the existence of a gender gap in VC funding by comparing men and women within the same sector and geography and controlling for observable characteristics (e.g., Brush, Carter, Gatewood, Greene and Hart, 2003; Gompers and Wang, 2017; Ewens and Townsend, 2020; Raina, 2021).

Second, our paper uncovers potential mechanisms related to the demand and supply of capital that drive the gap. Existing studies have primarily focused on factors such as investor homophily and network effects to explain disparities in VC funding (Ewens and Townsend, 2020; Howell and Nanda, 2024; Gornall and Strebulaev, 2024).[7] Building on Sarsons (2017), who shows that women surgeons face fewer referrals after a negative patient outcome tied to another woman surgeon, we uncover a strikingly similar dynamic in venture capital. Failures by women-founded startups trigger a significant drop in funding for unrelated women founders, while their successes fail to generate any positive spillovers. In contrast, male founders benefit from larger deal sizes after successful exits. This stark asymmetry underscores that investor behavior toward women founders is shaped more by bias than by learning about founder quality.

Finally, our focus on serial entrepreneurship, which is linked to startup success (e.g., Hsu, 2007; Gompers, Kovner, Lerner and Scharfstein, 2010; Nahata, 2019; Shaw and Sørensen, 2019; Genc, 2024) reveals important gaps in women founders' ability to secure VC funding for their next startup and is new to the literature.[8] Overall, our results suggest that the observed gender gaps are not driven by the quality of businesses women entrepreneurs launch. And, although there is some evidence of differences in the propensities of women to start subsequent businesses, this demand-side mechanism alone does not explain our results. We find strong evidence of unequal treatment by investors, which suggests room for increased efficiency that might be achieved through initiatives to reduce frictions faced by experienced women founders of VC-backed businesses (i.e., later in the pipeline).

This paper proceeds as follows: Section 2 details the data that we use for the analysis.

[7] Ewens and Townsend (2020) find that investors who are men are less likely to target women-led firms, whereas women investors are more likely to do so. Even if the presence of homophily seems to help women, Ewens and Townsend (2020) conclude on the existence of investors' biases. Hebert (2024) suggests the existence of context-dependent stereotypes in male-dominated sectors, without providing direct evidence.

[8] Among the few papers that consider the intersection between gender and serial entrepreneurship, Shaw and Sørensen (2019) use administrative data from Denmark and find that men and serial entrepreneurs who start several small businesses have higher sales than women and novice entrepreneurs. However, they find that the productivity gains of women who start a series of businesses are higher than men.

Section 3 presents the results of the main empirical tests for evidence of a funding gap. Section 4 shows analyses of potential mechanisms driving the main results. Section 5 concludes.

2. Data and Summary Statistics

2.1. Data

Our analysis draws on PitchBook data from companies that have raised venture capital funding. The sample period begins in January 2010 and extends through December 2022. We follow funding outcomes through December 2023 to ensure at least one year of post-event observations for all startups. Following standard practice in entrepreneurial finance research, we define venture capital funding to include deals classified in PitchBook as "Early Stage VC," "Later Stage VC," "Seed Round," "Angel (individual)," or "Accelerator/Incubator." For each company in our sample, PitchBook provides information on funding rounds, including the amount raised and the identities of participating investors.[9]

For each company in our sample, PitchBook provides detailed founder information, including their identities and gender. PitchBook also provides information about startup outcomes, including whether a company is out of business, bankrupt, acquired, or went public. Following the literature (e.g., Yimfor and Garfinkel (2023); Ewens and Farre-Mensa (2020); Bernstein, Giroud and Townsend (2016)), we categorize a startup as a success if it went public via an IPO or was acquired by December 2023. Because failures are notoriously challenging to measure (Pollman (2023)), we use a more comprehensive approach to identify failed startups. We classify a startup as a failure if PitchBook flags it as closed or bankrupt by December 2023. In the absence of such a flag, we classify a startup as a failure if *all* of the following conditions hold: (i) a founder left the company; (ii) the company did not raise another round of financing following the founder's departure; (iii) the company did not exit via an IPO or acquisition; and (iv) the startup's website is inactive.

2.2. Gender and Serial Founding of VC-Backed Startups

In our dataset of VC-backed startup founders, 13.3% are women. This value is roughly in line with the literature (e.g., Gompers and Wang, 2017; Ewens, 2023). Hidden beneath the 13.3% figure is a meaningful variation in gender balance across serial entrepreneurship, failure, and success outcomes.

Figure 1, Panel A shows that women account for 16% of all first-time VC-backed company founders, but they represent only 4% of founders of 3 or more companies.

[9] PitchBook has been recognized as the most comprehensive database for private deals, particularly in the period following 2010 (Cook, Marx and Yimfor, 2024).

Figure 1, Panel B shows startup founder success (defined as an IPO or acquisition by December 2023) as a function of the number of VC-backed companies founded.[10] There are two important observations. First, success probabilities increase substantially with founder experience for both men and women. For men, 17% of one-time startup founders experience success within five years and 35% of men who are founders of two startups experience success within five years. For women, 12% of one-time startup founders experience success, and 32% of founders of two startups experience success. Second, although success probabilities are lower for one-startup women founders, the probabilities converge as the number of startups founded increases. Among both men and women, nearly half of all founders of 3 or more VC-backed firms experience success during the sample period. The sharp increase in success probabilities for women occurs along with sharp declines in representation across experience bins.

[INSERT FIGURE 1 ABOUT HERE.]

In Figure 1, Panel B, conditional on founding a second firm, the success gap between men and women is only 10 percent (0.32/0.35) and is nearly zero upon founding three or more firms. Still, there is a decline of more than 100 percent in the proportion of women founders among those who have founded three or more startups.

What can explain the differences in the data? There are several explanations. It could be that women are less interested in serial entrepreneurship due to differences in risk preference or other personal considerations; it could be that women are less talented entrepreneurs; it could be that suppliers of VC capital have incorrect initial beliefs about the quality of women founders or that they treat women differently from men (due to stereotypes or to discrimination).

The following analysis aims to uncover some of the mechanisms underlying the patterns that we observe in the data. Our main empirical approach compares the funding outcomes of men and women founders. Our most stringent tests compare outcomes of men and women cofounders of the same firm (i.e., within firm tests, where identification comes from mixed-gender teams with at least one man and one woman cofounder). Figure 2 shows the number of deals by founder team type during the sample period. Although founding teams comprised of all men are most common (75% in 2022), the number of mixed-gender teams that experience a failure or a success in every year of the sample is substantial (17% in 2022).

[10] IPOs alone are another measure of success, but since these exits are uncommon, this definition would cause us to miss a large number of successful exits. This is especially true in recent years, with the increasing importance of acquisitions as an exit in PE and VC. Gompers, Kovner, Lerner and Scharfstein (2010) define success as going public or filing to go public; however, they find similar results when they use our preferred definition as an alternative success measure.

[INSERT FIGURE 2 ABOUT HERE.]

In addition to analysis of the extensive margin (i.e., whether founders receive VC funding for a new startup), the intensive margin is also of interest. In our data, men raise substantially more funding than women, suggesting shorter runways for women-founded firms (see Appendix Figure A.1a).[11] We examine these patterns more formally later in the paper.

2.3. Failure and Success Events

Table 1 shows the sample of failure and success events for VC-backed startups by year. There are 11,062 startups that failed and 12,028 unique startups with successful exits during the sample period.[12]

[INSERT TABLE 1 ABOUT HERE.]

Table 1 decomposes the data according to whether the startup's founders are all men (*Men*), there is at least one woman and at least one man on the founder team (*Mixed*), and all founders are women (*Women*). *Year* is the year in which the startup failed or succeeded. Consistent with prior work, women founders of VC-backed startups are underrepresented in both the failure and success samples. Startups with founder teams that are all-men comprise 78 percent of failure events and 89 percent of success events. Mixed-gender teams account for 15 percent of failures and 13 percent of successes.

2.4. Summary Statistics

Table 2 reports summary statistics for the sample of VC-backed startups and founders. The level of observation for the data in Panels A through C is the startup-founder level. Panel A shows all VC-backed startups. On average, 6.3 percent of founders successfully raise funding for a new startup within 5 years of the last round for the current startup *I(Invested)*; however, this value masks large gender differences. Among founders who are men, 6.8 percent receive financing for a new startup within five years, compared to 3.1 percent of women founders. This difference is statistically significant.

[INSERT TABLE 2 ABOUT HERE.]

[11] Consistent with shorter runways, Appendix Figure A.1b shows that most startup failures (closures) happen between years 4 and 6 relative to founding, with women-founded firms closing 6-12 months earlier than men. Interestingly, Appendix Figure A.1d shows that, except in the early years, the path to success is shorter for women than for men, suggesting that they put their capital (smaller than that allocated to men, as shown in Appendix Figure A.1c) to work quickly to generate faster exits.

[12] The number of failures in our sample may appear small relative to the conventional wisdom that most startups fail; however, our analysis conditions on VC funding might be considered a measure of early success. Moreover, the definition of failure that we use is rather strict. We require several conditions to hold, including an inactive website and no other funding rounds following a founder's departure.

On average, startups with women on their founding teams receive about half of the VC funding relative to those founded by all men ($28.3 million versus $56.0 million). This difference is unlikely to reflect startup maturity, as the age at the last funding round of startups founded by all men is only 5 months older than those with women founders. Panel A of Table 2 also shows that the likelihood of serving as founder-CEO is similar for men and women. Still, women in the sample are considerably less likely to be serial founders compared to men, consistent with Figure 1.

Table 2 Panel B shows data for the subsample of failed startups.[13] Panel C shows the subsample of successes, defined as startups that exited via an IPO or acquisition. As noted earlier, these failure and success subsamples will be important for our empirical tests because these are times when founders are likely to begin to seek capital for new startups. Consistent with this, Panel B shows that 7.7% of founders of VC-backed firms that fail successfully raise capital for another VC-backed startup within 5 years following failure (this is higher than the base rate of 6.4% in Panel A). Panel C shows that 14.1% raise VC funding for a new firm following a successful exit event. These values vary significantly across men and women, with only 4% of women raising VC funding for a new startup following failure, compared to 8.2% of men. The success premium is substantial: founders are nearly twice as likely to raise VC funding following success versus failure (14.1% versus 7.7%). Yet women founders face persistent headwinds. After a successful exit, women raise VC funding for a new startup only 7.8% of the time, a rate even lower than that of men following failure (8.2%).

When they do raise capital, women founders raise substantially less capital than men following both failures and successes. Specifically, startups founded by women raised $18.5 million on average during the 5 years following failure, while new startups founded by men raised $61.5 million. The gap is even larger following success, where women raise $32 million for their new startups, while men raise $102.8 million.[14]

The data in Panel D of Table 2 are at the venture capital investor-deal level. These data are used in the spillover tests, where we examine how investors' past experiences with women-founded firms affect their future investments. The data are disaggregated according to the gender composition of startup founding teams. We find deal sizes are larger when founder teams consist of all men. We also observe some specialization according to the founder's gender. Investors in any deals where founder teams are all men

[13] Note that the number of observations is much larger in Panel B of Table 2 than the failures listed in Table 1 because Table 1 shows data at the startup level, while Table 2 Panel B is at the startup-founder level. There are often multiple founders for a given startup.

[14] Average deal sizes are driven by very large deals in the right tail of the distribution. The median deal size raised by new startups founded by men is $7.2 million, whereas the median deal size for women is $4.7 million. PitchBook's deal sizes reflect the commitments of all venture capitalists participating in a given deal instead of the individual venture capitalist's commitment (Hochberg, Ljungqvist and Lu, 2007).

have approximately 17% of deals in their portfolios allocated to firms founded by at least a woman (*P(Investments in Women)*). Investors in any deals with all-women founders have 27.1% of the deals in their portfolios allocated to teams where at least one founder is a woman. We also observe that most of the investors in our sample have experienced the failure of a startup in their portfolios at some point in the past. This is not surprising, given the risk of investing in startups and the number of years it takes for new investors to experience the failure or the success of their portfolio companies.

These descriptive statistics do not tell the whole story, but they provide a useful backdrop for the analysis that follows.

2.5. Methodology

We report the main tests in Table 3. The unit of observation is a founder-startup pair. We examine the role of gender in VC financing outcomes of new startups. We specify the regressions as follows:

$$\begin{aligned} \text{I(Invested)} = \quad & \beta_1 \text{I(Woman)} + \beta_2 \text{Serial Founder} \\ & + \beta_3 \text{I(CEO)} + \beta_4 \ln(\text{Funding Current Startup}) \\ & + \beta_4 ln(\text{Age}) \\ & + \lambda_j + \eta_t. \end{aligned} \tag{1}$$

The dependent variable, *I(Invested)*, is an indicator equal to one if the founder receives VC funding for a new startup within five years after the last round of funding for the current startup. The main explanatory variable of interest is *I(Woman)*, an indicator equal to one if the founder is a woman. To address the most obvious alternative explanations while maintaining parsimony, we include targeted controls for key differences across founders: whether they had founded other VC-backed startups prior to the current one (*Serial Founder*), which captures pre-existing differences in VC access and startup experience, and whether they served as CEO in the current startup (*I(CEO)*), which accounts for potentially different roles in fundraising and investor relationships. We also control for total funding the current startup has raised to date (*Ln(Funding Current Startup)*), and the current startup age (*Ln(Age)*). We also include year, state (where the startup is headquartered), and industry fixed effects for the cross-sectional analysis. In our most stringent specifications, we conduct a within-current startup analysis, including startup fixed effects. This allows us to compare fundraising outcomes for men and women cofounders of the same current startup for the next startup.

This empirical design tackles a fundamental challenge in understanding gender gaps in entrepreneurial financing. The startup fixed effects allow us to control for many

startup-level characteristics that are typically unobservable, including the quality of the business idea, the industry focus and the combined capabilities of the founding team. This approach is akin to twin studies and goes beyond simply matching entrepreneurs and their startups on observable characteristics. It provides a unique opportunity to hold constant the inherent network differences between men and women entrepreneurs, or unobserved abilities in cofounders' team formation (e.g., Bloom, Jones, Van Reenen and Webb, 2020; Cullen and Perez-Truglia, 2023). We rely on founders' endogenous matching to define the control group for women founders. Prior research shows that teams do not form randomly (Bloom, Jones, Van Reenen and Webb, 2020). In academia, men and women coauthors tend to sort on quality (Sarsons, Gërxhani, Reuben and Schram, 2021). Homophily seems to explain the team formation process, especially in entrepreneurship (e.g., Boisjoly, Duncan, Kremer, Levy and Eccles, 2006; Ductor, Goyal and Prummer, 2023; Gompers, Huang and Wang, 2022; Cullen and Perez-Truglia, 2023). Moreover, within our sample, we find evidence of shrinkage in observable differences between men and women among cofounders compared to the full sample. This empirical design is, to our knowledge, new to the entrepreneurial finance literature and helps to ensure that any results are not driven by unobservable differences in the businesses that men and women start.

3. Main Results

3.1. Financing the next startup

We begin with an analysis of the extensive margin. We estimate Equation 1 to test for potential gender differences in the likelihood that a founder will raise VC funding for a new startup within five years from the last recorded funding round of the current startup. The baseline percentage of founders who do so is 6.34%.

Table 3 reveals substantial gender gaps in serial entrepreneurship. The estimated coefficient on *I(Woman)* in Column 1, where we include only founding year fixed effects as controls, is -3.394. This implies a gender gap of 53.5 percent in serial entrepreneurship in VC-backed firms. In Column 2, we add controls for founder experience, whether the founder also serves as a CEO, the amount of funding raised by the current startup, and the startup's age. The specification in Column 3 is identical to Column 2 except that we add primary industry and state fixed effects to control for potential industry clustering and regional differences in startups founded by women. When we add these controls, the estimated gender gaps are smaller but still economically meaningful and statistically different from zero. The estimated coefficients of -1.619 (Column 2) and -1.784 (Column 3) imply a gender gap of between 25.5 and 28.1 percent.

[INSERT TABLE 3 ABOUT HERE.]

The specifications in Columns 1 through 3 provide results from cross-sectional tests, where we compare all founders of startups founded in the same year. We use variation from all startups, including those that are founded by single founders, and by founder teams that are all men and all women. The control variables, including the state and industry fixed effects, are included to capture potentially important variations in the types of startups that men and women found, as well as potential regional differences in access to capital. Our results are consistent with the existing literature: women are less likely to raise VC funding for their current startup and future startups.

In Columns 4 and 5, we remove single-founder startups from the sample and conduct within-startup tests using startup fixed effects. In these specifications, *I(Woman)* is identified based on differences between men and women cofounders of the *same startup*. Under the assumption that execution, performance, and skills gained from launching a given startup are major observables that potential investors use when making future funding decisions, the null hypothesis is that men and women on the same cofounder team are equally likely to secure VC-backed funding for a future startup. In Column 5, we add founder experience variables to address potential concerns about important gender differences in experience within a startup (e.g., CEO-founders may have more valuable experience than other cofounders).

Our results imply economically large gender gaps that are similar in magnitude to what we observe in the between-firm tests. The estimated coefficient of -2.926 on *I(Woman)* in Column 4 implies a gender gap of 46.2% and the coefficient of -1.891 in Column 5 implies a gender gap of 28.1%. Overall, the results in Table 3 reveal a large gender gap in the likelihood of receiving VC funding for a new startup. Women are less likely to raise VC funding for a new startup, even relative to men with whom they co-founded a startup.

The estimated coefficients on the control variables shown in all of the specifications in Table 3 line up with what one might expect: serial founders and those associated with startups that have raised more funding to date are more likely to launch another VC-backed startup within five years; founders who are CEOs (likely involved with running the current startup) and those founders associated with older startups are less likely to do so. It is also useful to note that we observe large increases in R-squared values once we include startup fixed effects in the specifications. The R-squared values increase more than threefold, from 1–7% in the between-startup analysis (columns 1-3) to 19–21% in the within-startup analysis (columns 4-5). These increases underscore the importance of startup-level unobservables in cofounder matching.

3.2. Financing the next startup following failure and success

Given the strong relationship between serial entrepreneurship and future success, we present results of regressions that are identical to those in Table 3, but we condition on

failure and success events. Not only are these times when founders are more likely to need capital for a new startup, but the fate of the last startup is also salient to investors making funding decisions. Table 4 presents the results.[15]

[INSERT TABLE 4 ABOUT HERE.]

One immediate observation from Table 4 is that the mean *I(Invested)* is larger than the unconditional full-sample mean of 6.34% following both failure and success events. From the table, 7.66% of founders go on to found another VC-backed startup following failure, and 14.19% of founders do so following success of the previous startup. Both of these values are higher than the mean of 6.34% when we do not condition on these events, consistent with the assumption that the years following success and failure are times when founders are likely to search for funding for new startups. The fact that the likelihood of receiving funding for a new startup is 80% higher following success compared to failure is expected since one would expect investors to make positive inferences about founder ability from observed successes. This increases our confidence that we are capturing true failures and successes, despite the empirical challenge associated with observing these outcomes (see Section 2.3).

Table 4 Panel A shows results from the analysis of failure events. As in Table 3, we find significant gender gaps across all specifications. Focusing on the within-firm specifications with the full set of controls in (Column 5), the results imply a gender gap of 22.5%. Thus, following the failure of a previous startup, women are less likely to successfully raise VC again for a new startup compared to men with whom they started the failed startup. This unequal funding following startup failure can limit innovation, employment, and growth in the economy.[16]

In Table 4 Panel B, we examine success events, defined as an exit via an IPO or acquisition. Consistent with the raw summary statistics in Table 2, we find that the reward for success is lower for women. Within startup, the estimate in Column 5 implies a gap of 26.9%. Thus, even following success, women founders of firms are less likely to receive VC funding for a subsequent startup relative to men in the same industry geography and also relative to their cofounders with whom they successfully exited a previous startup.

[15] Since the identification relies on mixed-gender teams (comprising approximately 17% of the main sample), we replicate the main test on this subsample in Appendix Table A.1. The results remain consistent, confirming that the variation originates from this type of firm.

[16] As Pollman (2023) writes: "[T]he ability of startups, and their participants, to fail efficiently and 'with honor' helps sustain the system out of which also grows some of the largest successes in the history of US business." For venture capital firms, the investment strategy is often to identify a few portfolio firms that deliver out-sized returns. Failure of at least some startups is expected.

4. Potential Mechanisms

What drives the funding gaps that we observe in Tables 3 and 4? The patterns we observe could come from founder demand, investor supply, or both. On the demand side, women founders might have different preferences for serial entrepreneurship or accumulate different types of experience within their startups, particularly around fundraising. On the supply side, it is possible that VC investors rationally provide less capital to women entrepreneurs due to quality differences between men and women. Alternatively, the funding gap could be due to investors' incorrect beliefs about women entrepreneurs or to their preferences for startups founded by men. We examine each of these potential explanations in turn.

4.1. Founder Demand

4.1.1. Gender Differences in Experience Accumulation Within Startups

A potential alternative interpretation of our findings is that men and women cofounders accumulate different types of experience within startups due to their roles. This could be particularly important for fundraising experience, as CEOs typically lead investor relationships and financing rounds. If the gender gap we observe were driven by women having less exposure to fundraising in their co-founding roles, we would expect to see the gap concentrated among non-CEO founders and eliminated when comparing men and women who served as CEOs. In Table 5, we repeat the analysis of Table 4 but add an interaction between the gender and CEO indicator variables. The main findings are almost identical to those in Table 4 and the coefficients on the interaction *I(Woman)* X *I(CEO)* are insignificant in all specifications. Thus, differences in founder roles and their associated fundraising experience do not explain the gender gap in follow-on funding.[17]

[INSERT TABLE 5 ABOUT HERE.]

4.1.2. Gender Differences in the Propensity to Launch Another Startup

The VC funding gap could reflect fundamental differences in men's and women's preferences for serial entrepreneurship. After exiting a VC-backed startup through either failure or success, women might be less interested in launching subsequent ventures due to factors such as risk tolerance, family considerations, alternative career opportunities in the entrepreneurial ecosystem (e.g., venture capital or board roles), or subjective perceptions of failure (Puri and Robinson, 2013; Hvide and Panos, 2014). To examine whether differences in the propensity to start new businesses can explain the gender gaps

[17] In Appendix Tables A.2 we add to the specification other roles in the founding team, including CTO, COO, CMO and CFO. The results are similar.

we observe, we depart from Pitchbook data and use founders' LinkedIn profiles to collect information on newly launched firms, including those that are not VC-backed.

In Panel A of Table 6, we test for gender differences in the propensity of women to found new firms after failure and success of the current startup. The specifications are the same as those in Panel B of Table 6, except we replace the dependent variable (indicator for launching a new VC-backed startup) with an indicator equal to one if the founder reports being the founder of a new firm in their LinkedIn profile. After failure, we find that 26% of founders from VC-backed startups go on to launch a new firm. By contrast, this figure rises to 35% following a successful exit.

Panel A of Table 6 reveals that, following both the failure and success of the current VC-backed startup, women are indeed less likely to start a new business compared to their male cofounders. Focusing on the within-startup specifications in Columns (2) and (4), the estimates imply that women are 9.4% and 8.9% less likely to found another firm relative to their male cofounders. These gaps are significant statistically but they are much smaller in magnitude than what we find for VC-backed businesses.

[INSERT TABLE 6 ABOUT HERE.]

To test formally whether the VC funding gap is due to women starting fewer businesses, we repeat the Table 6 Panel A analysis using only the subsample of founders who actually start new firms. Results are in Panel B of Table 6. Again focusing on the most stringent tests in Columns (2) and (4), the estimates imply that, conditional on founding another business, women are still 30% less likely (compared to their cofounders who are men) to raise VC for the next firm following failure and 18% less likely following success. Thus, the VC funding gap following failure and success cannot be explained solely by differences in men's and women's propensities to start new businesses.

4.1.3. Gender Differences at the Intensive Margin

The intensive margin provides another way to shed light on the possibility that the VC funding gaps that we observe are due to founder demand. If gender differences in demand are important, we would expect significant gender differences at the extensive margin. However, a founder demand-side explanation would not imply meaningful gender differences in funding at the intensive margin. That is, conditional on founding a VC-backed business, we would not expect women to systematically demand less (or more) capital compared to men.

In Table 7, the dependent variable is the natural log of total funding raised in a new startup in the 5 years following an exit event (*Ln(Funding Amount)*). The number of observations is smaller than in the previous tables because the analysis conditions on a founder raising VC funding for a new startup (and in Columns 4 and 5, the regressions

require more than one cofounder of the same startup to raise VC funding for the next startup).

[INSERT TABLE 7 ABOUT HERE.]

Panel A shows the analysis of VC funding for a new startup post-failure. The estimated coefficients on *I(Woman)* are negative and significant, both statistically and economically, across all specifications. The cross-sectional tests in Columns 1 through 3 imply a gender gap of between 37.6% and 51.8% following failure. The most stringent within-firm tests (Column 5), which capture gender differences in funding for cofounders of the same firm, imply a gender funding gap of 53.3% for the subsample of startups that fail $(1 - e^{-0.759} \approx 0.533)$. The average woman raises $31.03 million less over the next five years than men who exited the same failed startup (sample mean = $58.56 million). We view the within-startup specification in Column 5 to provide the most powerful test.

Following success, the magnitude of the gap is still significant statistically, but it is smaller. The estimated coefficient of -0.283 on *I(Woman)* in Column 5 implies a funding gap of 24.6%. Thus, even successful women founders who manage to attract VC funding for their next startup appear to face headwinds in the amount of capital that they raise. Given the larger amounts raised following success, the average successful woman raises $28.08 million less over the next five years than men who exited the same successful startup (sample mean = $99.22 million). [18]

We interpret the evidence in Table 7 as inconsistent with a founder-demand side explanation for the gender gap that we observe at the extensive margin. The within-startup results in Column 5 bolster this interpretation since one might expect cofounders to have similar aspirations and entrepreneurial interests.

Taken together, the results in Tables 6 and 7 show that the demand channel is not the main driver of the results. Although women are less likely to start new businesses, the magnitude of this difference is modest relative to the gender gap in VC financing for the next startup that we document. In the next section, we consider the supply side. We begin with the hypothesis that VC investors are less likely to supply capital to women entrepreneurs because of quality differences between men and women.

4.2. Subsequent Startup Quality

4.2.1. Lower Quality Entrepreneurs? Comparing Observable Characteristics

Our startup fixed effects model perfectly controls for the quality differences between men and women founders' businesses. Because inference about founder ability is likely

[18] Appendix Figure A.2 presents regression results illustrating the cumulative funding differences between male and female founders in each year following success and failure events. The funding gap emerges as early as Year 1 and becomes statistically significant in subsequent years.

to come from observing the current business, the fixed effects specification improves our ability to identify potential gender gaps in VC financing for subsequent ventures. That said, we do not claim that men and women cofounders are identical. Still, our approach should improve on existing approaches to understanding gender gaps if men and women cofounders are more similar than men and women founders more generally. To examine potential gender differences in founder experience, we begin with a descriptive analysis of gender differences in observable characteristics. If founders are more similar to their cofounders in terms of observable characteristics than to other startup founders within the same industry, they are also likely to be more similar to their cofounders in terms of unobservable characteristics (Altonji, Elder and Taber, 2005; Oster, 2019).

In Table 8, we investigate the estimated relationship between various work experience and educational background characteristics and the likelihood that a founder is a woman. We compare cofounders of the same startups and as well as founders within the same industry. All variables are standardized so that comparisons across variables are straightforward.

[INSERT TABLE 8 ABOUT HERE.]

There are two important observations from the regressions in Table 8. First, although there are some differences between men and women founders, they are not large. Men do not dominate on every observable characteristic, nor do women (men tend to have more experience; women tend to have more and higher-status education credentials). Second, and more importantly, as we move from the between-startup comparisons to the within-startup specifications, we observe significant shrinkage in the estimated coefficients. That is, men and women cofounders are more similar than men and women founders within the same industry. For example, differences between men and women cofounders' tech experience shrinks by 22.2% relative to same-industry comparisons. Gender differences in past startup experience are 57.1% smaller within startups. The only observable where differences widen in the within startup specification are PhD/MD degrees. In addition to coefficient shrinkage, Table 8 shows an increase in Adjusted R^2 as one moves from the between-startup to the within-startup specifications. This provides further validation for our empirical design of comparing cofounders within the same startup. For example, consider technology experience, adding startup fixed effects not only explains 16 times more variation (Adjusted R^2 from 0.015 to 0.247), the gender coefficient also shrinks by 22.2%. Taken together, the results suggest homophily among cofounders.

4.2.2. Lower Quality Startups? Comparing Startup Outcomes

Although Table 8 suggests that men and women cofounders of the same VC-backed startups are more similar than other VC-backed founders, the analysis considers only

observable characteristics. For a formal test of gender differences in founder quality, we conduct an outcome test where we examine potential differences in the outcomes of the subsequent VC-backed startups that men and women cofounders launch following success or failure of the current startup (Becker, 1993; Hebert, 2024; Cook, Marx and Yimfor, 2024). We view the outcomes test as the ideal test of differences in quality. One important caveat, however, is that the sample size for the test is limited because it requires founders in the sample to have raised venture capital for at least two startups, exited the first one, and then raised financing and also exited the second one during the 2010-2023 sample period. Still, the sample of 588 founders provides a useful lens for analysis and the straightforward interpretation of the test allows us to shed at least some light on what is (and is not) likely to be the main driver of our findings.

Results of the outcome test are in Table 9. The unit of observation in these tests is a person-startup for the startup-person pairs from Tables 3 and 4 that started a new VC-backed startup following an exit. The outcome variable in Columns 1 and 2 is an indicator equal to one if the next VC-backed startup went public or was acquired. The control group are new VC-backed startups that failed. In Columns 3 and 4, we focus on IPOs only.

[INSERT TABLE 9 ABOUT HERE.]

Across all columns, the estimated coefficients on *I(Woman)* are positive (suggesting better outcomes for subsequent startups founded by women), and they are significant statistically in all columns except Column (1) where we do not control for pre-exit funding. In Column (2), when we control for pre-exit funding, we find that women-founded startups are significantly more likely to exit successfully. Thus, the evidence points to women founders having better outcomes while having access to fewer resources.

Thus, we do not find any evidence to support the hypothesis that women start lower-quality startups compared to their male cofounders following their exit from the current startup. If anything, the evidence suggests that subsequent startups founded by serial women enjoy higher rates of success, consistent with a higher bar for women entrepreneurs.

4.2.3. Lower Quality Startups? Exogenous Contributors to Startup Outcomes

Because there are potential limitations due to the small sample in the outcomes tests analysis, we conduct a second test for potential quality differences as a driver of the gender gaps following both failure and success. We exploit a plausibly exogenous driver of success and failure: the supply of capital from local pension funds. State pension funds are among

the most important limited partners in the venture capital industry.[19] Moreover, pension funds exhibit local biases in their venture capital portfolios (Hochberg and Rauh, 2013; González-Uribe, 2020).[20] The availability of this local capital for financially constrained startups is an important and arguably exogenous determinant of success and failure.

The tests that follow assume that startups that fail following periods of abundant capital are more likely to have poor quality ideas or execution (see e.g., Ljungqvist and Wilhelm Jr, 2003; Janeway, Nanda and Rhodes-Kropf, 2021). Under the hypothesis that the funding gap is due to unobservable differences in quality of women we then expect an even larger gender gap in funding following failures that occur during favorable capital supply conditions.

We measure local capital supply conditions as *Ln(Capital Supply)*, the natural log of the average pension fund assets in the state in which the startup is located during the four years preceding a deal. Before adding *Ln(Capital Supply)* as an exogenous supply shift variable, we first confirm the hypothesized relationship between local capital supply and startup outcomes. Table 10 Panel A shows that increases in local funding supply from state pension funds (*Ln(Capital Supply)*) are associated with decreased failure probabilities and increases in the likelihood of follow-on funding, as well as exit via IPO or acquisition.

[INSERT TABLE 10 ABOUT HERE.]

In Table 10 Panel B, we repeat the analysis of funding following failure shown in Table 4 Panel A, but we use supply of capital conditions to help identify failures of firms that are more likely to be of low quality, as opposed to those that fail due to financial constraints. If the *I(Woman)* variable captures poor quality, then the penalty to women founders of failed startups should be particularly severe when they fail following abundant capital supply conditions. In other words, if women are over-represented among low-quality entrepreneurs, then we would expect a significant and negative interaction between *I(Woman)* and *Ln(Capital Supply)*. We do not observe this. Women who fail following periods of abundant capital are penalized no more than men exposed to the same conditions. Instead, the negative and significant coefficient on the direct effect (*I(Woman)*) across all specifications shows that all women founders, regardless of capital supply conditions, face a funding gap.

[19] According to González-Uribe (2020), in 2011, they accounted for 28% of new funds committed to venture capital, almost twice the 13% accounted for by the industry's second most important capital provider, fund of fund managers.

[20] For example, González-Uribe (2020) estimates that after the adoption of "Prudent Investment Rules", local state pension funds' capital commitments to the local venture capital firms increased by 175 million USD (relative to pension funds located elsewhere), possibly because of home bias in state pension funds' venture capital investments.

In Table 10 Panel C, we examine "lucky successes." When startups succeed following periods of abundant capital, chances are greater that the observed successes include firms that are of lower quality ("lucky"). Thus, if the *I(Woman)* variable captures poor quality, then the penalty to poor-quality founders of successful startups should be particularly severe when they succeed following abundant capital supply conditions (i.e., as in Panel B, we would expect a negative and significant interaction between *I(Woman)* and *Ln(Capital Supply)*). We fail to find any significance. The evidence suggests that women are not of worse quality relative to men exposed to the same favorable conditions nor are they worse than other women who do not benefit from the supply of capital from the state's pension funds.

To summarize, we fail to find empirical support that the funding gap is due to differences in the quality of women founders.

4.3. Supply-side and Potential Role of Investors

4.3.1. Existing investors

Given the importance of networks and relationships in venture capital (Gompers, Gornall, Kaplan and Strebulaev, 2020; Howell and Nanda, 2024), one might expect current investors to be especially likely to invest in subsequent startups. These are also the investors that have more information about the individual founders of startups currently in their portfolios. Despite this potential informational advantage, repeat investing in multiple startups with the same founder is not common (Bengtsson, 2005; Gompers, Kovner, Lerner and Scharfstein, 2010). In our sample, only 1.13% of founders who fail receive future funding in new startups from the same VC investors. This value is much higher following success, with 4.06% of successful founders receiving funding from repeat investors for their new VC-backed startups. But in both cases, outside investors are the primary source of capital for startups.

Despite the relatively small sample of repeat current investors, we can test for evidence of a funding gap among this group of investors. In Appendix Table A.3, we repeat the Table 4 regressions, but we focus only on investments by current investors after a failure (Panel A) or success (Panel B). We do not detect evidence of a funding gap following failure (Panel A). However, this is not enough to close the overall gender gap because current investors are not the primary sources of funding for subsequent ventures. Interestingly, the gap remains following successful exits (Panel B).

4.3.2. Investment in new Startups

New investors are the main source of capital for subsequent VC-backed businesses. New investors might be more likely to rely on data from other investment experiences or even heuristics to evaluate unfamiliar startups and their founders. We therefore use portfolio dynamics over time to understand whether unequal funding from this group stems from

incorrect initial beliefs about women founders or to investor preferences for men. These are natural questions to ask in light of the gaps exist between same-startup founders and our findings that neither founder demand nor quality appear to be the primary drivers.

Investor beliefs and preferences are generally difficult to distinguish without observing their decision-making processes directly. However, we can use our dynamic setting, where we observe investors' participation in deals over time, to help. If investors simply prefer to avoid women founders or they do not use data from their experiences with same-gender founders to make inferences about other women (i.e., they do not stereotype), then the gender gap within their portfolios would be invariant to prior experiences with other women founders. Alternatively, if investors form their beliefs about women founders through statistical updating, then prior experiences with other women founders will impact future investment decision-making.[21]

In this section, we analyze investor-deal dynamics to examine spillovers. Building on the approach of Sarsons (2017), we investigate how investors' recent, plausibly exogenous positive or negative experiences with founders influence funding outcomes for other, unrelated founders of the same gender. We test whether the success or failure of a woman-founded portfolio company affects the funding decisions for unrelated women founders. We interpret sensitivity of initial disparities (i.e., the direct *I(Women)* effect) to prior experience with other women founders as consistent with stereotyping. Stereotypes can develop through statistical updating, which would result in both positive and negative spillovers. Different from statistical updating, stereotyping due to biased investor preferences would result in negative spillovers but not positive ones.

4.3.2.1 Portfolio Spillovers Following Failure

Table 11 shows the relationship between investor experience with a failed startup founded by a woman and deal size for new investments in other women-founded startups in the years following the failure event. We include all investors who have experienced a failure of any portfolio company in the past five years (defined as in the earlier tables). This failure experience filter allows us to ensure that any observed differences in funding following the failure of a woman-founded firm are not due to an experience of failure more generally.

The dependent variable is *Ln(Deal Size)*, the natural log of the deal size (in millions). We focus on the intensive margin rather than the extensive margin in the investor-level regressions for two reasons. First, deal size is of first-order importance to startups. Higher levels of funding provide more resources and longer runways during which startups can accelerate their growth. The second reason is a practical one based on data availability.

[21] (Bohren, Imas and Rosenberg, 2019) also use dynamics to distinguish between discrimination due to statistical updating versus preferences.

Because we do not observe all founder teams that *could* have received funding but did not, any tests at the extensive margin would be difficult to interpret.[22]

Because the regressions are at the investor-deal (rather than founder-deal level, as in the earlier tables, the gender variables are modified to capture the gender of a given startup's founding team. *I(Women-Founded)* is an indicator equal to one if at least one member of the founding team of the current investment is a woman. *I(Recent Failure)* is an indicator equal to one if the investor backed at least one startup over the previous five years that failed. *I(Failure Women)* is an indicator equal to one if the investor backed at least one startup with at least one woman founder that also failed over the previous five years. This variable captures the potential role of a recent experience with a failed startup founded by women. The main interaction of interest for the spillover test is *I(Women-Founded) X I(Failure Women)*, which captures the potential funding gap for startups with women founders following a recent failure by another firm in the investor's portfolio that also has women founders.[23]

We include a separate control variable to capture for specialization in women-founded firms to ensure that the interaction of interest captures spillovers rather than specialization. *P(Investments Women)* is defined as the size of deals in the VC firm's portfolio that fund startups with women founders over the previous five years, divided by the total size of all deals in which the investor participated. Similarly, we include a control for investors' propensity to invest with experienced founders. *P(Serial Founder)* represents the proportion of startup founders who have launched at least one other startup prior to the current one. Other controls include startup age and VC firm age. We also include time, industry, and state-fixed effects. Finally, our more rigorous specifications include investor fixed effects, which account for investors' fixed characteristics such as gender and enable comparisons of their behavior over time.

[INSERT TABLE 11 ABOUT HERE.]

Across all specifications, the results in Table 11 imply that, following the experience of the failure of a startup with a woman founder, the investor participates in smaller

[22]Moreover, note that PitchBook (and other VC-deal-level datasets) does not provide an individual investor's allocations in a given deal, nor does it consistently identify lead investors. In fact, our sample would be 90% smaller if we focused only on deals where PitchBook explicitly identifies the lead investor. While our results are directionally similar when we focus on this subset, they are not statistically significant due to the much smaller sample size. The underlying assumption in the interpretation is that an investor's willingness to participate is roughly proportional to deal size. Most VC investors target minority stakes. Even if their investments are not exactly proportional to deal size, their willingness to supply capital could impact the total amount raised.

[23]In Appendix Figure A.3, we plot the results of the spillover tests using difference-in-differences estimators, where the post-period corresponds to the first failure an investor experiences within their portfolio. The results are similar. However, a limitation of this specification is that investors may encounter multiple failures successively, potentially confounding the post-treatment period.

subsequent deals with women founders. The negative estimated coefficients on the *I(Women-Founded) X I(Failure Women)* interaction are not only significant statistically, but they are economically meaningful, implying funding gaps due to spillovers of between 7.4 and 17.9 percent. In fact, after controlling for investor fixed effects, we find that all of the deal size penalties associated with experiencing a recent failure are from deals to startups with women founders. Focusing on the Column 4 specification, the estimated coefficients of -0.147 on *Women-Founded* and -0.091 on the interaction of *I(Women-Founded)* with *I(Failure Women)* imply a funding gap of 14.0 percent $(1 - e^{-0.147} \approx 0.14)$ for all startups with women founders and an additional gap of 8.7 percent $(1 - e^{-0.091} \approx 0.087)$ when the investor has experienced a failure of at least one startup with a woman founder in the last five years. We interpret the results as evidence that unequal treatment of women founders of VC-backed startups is a meaningful contributor to the funding gaps observed in the founder-level analysis. This is consistent with a form of statistical updating, where an investor uses an experience with a member of a given group to shape funding outcomes for other (unrelated) members of that group.

The evidence of negative spillovers that we observe in Table 11 shows up in funding outcomes for firms with any women founders, including mixed-gender teams. In Column 2 of Appendix Table A.5 we repeat the analysis of Table 11, but we change the definition of a *Women Founded* startup to include only those firms with all-women founders. The estimated magnitudes on the *I(Women-Founded) X I(Failure Women)* interaction are striking. Compared to the magnitudes in the Table 11 regressions, they imply much greater spillovers for startups with all-women founders.[24] Given the importance of serial entrepreneurship in eventual success and the ubiquity of failures among startup firms, negative spillovers of this type could be an important friction serving to stifle success probabilities for many women entrepreneurs.[25]

4.3.2.2 Potential Portfolio Spillovers Following Success

The results in Table 11 could show that investors, who might have limited experience with startups founded by women, use information from both negative and positive outcomes of portfolio firms to infer success probabilities of unrelated founders who share similar characteristics. Table 12 addresses this question. In Panel A, we repeat the Table 11

[24]Focusing on the Column 2 of Appendix Table A.4, the estimated coefficients of -0.326 on *Women-Founded* and -0.137 on the interaction of *I(Women-Founded)* X *I(Failure Women)* imply a funding gap of 27.8 percent for all startups with all-women founders, and an additional gap of 12.8 percent when the investor has experienced a failure of at least one startup with all-women founders in the last five years.

[25]We also distinguish between follow-on and first-time investments and find that the gap is driven entirely by first-time deals, suggesting that spillover effects are greatest for investments in new startups and their founders. See Appendix A.5 for failures and Appendix A.6 for successes by unrelated founders.

analysis, but we replace the failure variables with success indicators. As in Table 11, *I(Women-Founded)* is an indicator equal to one if at least one member of the founder team is a woman. *I(Recent Success)* is an indicator equal to one if the investor backed at least one startup over the previous five years that provided an exit via an IPO or acquisition. Similar to Table 11, all of the investors in the sample have experienced at least one success in the past. *I(Success Women)* is an indicator equal to one if the investor backed at least one startup with at least one woman founder that also succeeded over the previous five years. The main interaction of interest for the spillover test is *I(Women-Founded) X I(Success Women)*, which captures potential funding advantage (or gap) for startups with women founders following a recent success by another firm in the investor's portfolio that also has women founders.

The main results of the success analysis are in Table 12, Panel A. We find no evidence of positive spillovers of successful women to other women-founded startups. In fact, somewhat surprisingly, we find that women founders receive less funding following a successful exit in an investor's portfolio of another startup with women founders. It is possible that this reflects rationing over the course of a fund life (i.e., a strategy to target X percent of investments in women-founded startups). Although the definition of success that we use in Panel A of Table 12 is common in the literature, it is also possible that some acquisitions are actually failures (e.g., wind-downs at unfavorable prices) or they are successful but they generate expected but unremarkable returns for investors.[26] We therefore refine the definition of success in Panel B to include only significant successes: IPOs and any acquisitions where the ratio of exit valuation to all funding raised prior to the exit price exceeds the 90^{th} percentile value.

[INSERT TABLE 12 ABOUT HERE.]

In Panel B of Table 12, the evidence points to a more level playing field (but not additional reward, as would be the case if the results were symmetric with the failure results in Table 11). That is, any rewards via increased deal sizes following past significant success of women-founded startups in the portfolio woman are enjoyed equally by both men- and women-founded startups.

The asymmetric results of the negative and positive spillover analyses are inconsistent with pure statistical updating that would occur in a rational belief-based explanation. Under such updating, investors would attempt to learn about the success probabilities of women-founded startups based on the positive and negative outcomes of other startups founded by women. Instead, anything less than the significant success of a startup

[26] Appendix Table A.6 repeats the analysis for success for all-women founders and for follow-on versus first-time deals. Results are similar.

founded by women appears to result in negative spillovers to other women-founded firms. This one-way updating, along with the persistent and negative direct effect of gender for women-founded firms, suggests that both stereotyping and preferences play important roles in the gaps that we observe in the data.[27]

5. Conclusion

Repeat chances are an important ingredient for entrepreneurial success (e.g., Lafontaine and Shaw (2016), Gompers, Kovner, Lerner and Scharfstein (2010)). Founders gain valuable experience from their prior startup through both their successes and failures, increasing the chances of future success.

In this paper, we find that women founders of VC-backed firms face significant headwinds in obtaining second chances. They are less likely to secure VC financing for a future startup, and when they do, they raise substantially less capital relative to men. These frictions do not appear to be driven by quality differences between men and women. And, although women do have lower propensities to start subsequent firms, the differences are small relative to the VC funding gap that we document. The results are also inconsistent with bias that is simply due to incorrect initial beliefs about women entrepreneurs. Specifically, spillover tests reveal that investors are less likely to invest in women founders after they experience failures by other women-founded firms in their portfolios but they are not more likely to invest in women-founded firms following the success of other women-founded firms. We interpret this asymmetry as evidence of unequal treatment of women and not bias due to lack of familiarity. The results suggest room for increased efficiency initiatives aimed at improving access to capital for experienced women founders of VC-backed businesses.

[27] Appendix Figure A.3 shows the results of the spillover analyses in event time. We plot estimated coefficients of regressions where the dependent variable is the natural log of funding raised and the explanatory variable of interest is the failure or success of a same-gender founder in the investor's portfolio. We observe a decline in deal size for women-founded startups starting in year two following failure of a startup founded by a woman. We do not observe a similar decline for startups founded by men following the failure of a startup founded by another man. The patterns following success are even more striking: we observe increases in the amount of funding to startups founded by men following a same-gender success event within the investor's portfolio. Similar to the regressions in Table 12, the same is not true for startups founded by women.

References

Adams, Renée B, and Vanitha Ragunathan. 2017. "Lehman sisters." Working Paper. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3046451.

Altonji, Joseph G, Todd E Elder, and Christopher R Taber. 2005. "Selection on observed and unobserved variables: Assessing the effectiveness of Catholic schools." *Journal of Political Economy*, 113(1): 151–184.

Amornsiripanitch, Natee, Paul Gompers, George Hu, Will Levinson, and Vladimir Mukharlyamov. 2023. "Failing just fine: Assessing careers of venture capital-backed entrepreneurs via a non-wage measure." Working Paper.

Becker, Gary S. 1993. "Nobel lecture: The economic way of looking at behavior." *Journal of Political Economy*, 101(3): 385–409.

Bengtsson, Lars Ola. 2005. "Repeated Relationships Between Venture Capitalists and Entrepreneurs." Working Paper. Available at https://elibrary.ru/item.asp?id=9412438.

Bernstein, Shai, Xavier Giroud, and Richard R Townsend. 2016. "The impact of venture capital monitoring." *Journal of Finance*, 71(4): 1591–1622.

Bertrand, Marianne, Dolly Chugh, and Sendhil Mullainathan. 2005. "Implicit discrimination." *American Economic Review*, 95(2): 94–98.

Bloom, Nicholas, Charles I Jones, John Van Reenen, and Michael Webb. 2020. "Are ideas getting harder to find?" *American Economic Review*, 110(4): 1104–1144.

Bohren, J. Aislinn, Alex Imas, and Michael Rosenberg. 2019. "The dynamics of discrimination: Theory and evidence." *American Economic Review*, 109(10): 3395–3436.

Boisjoly, Johanne, Greg J Duncan, Michael Kremer, Dan M Levy, and Jacque Eccles. 2006. "Empathy or Antipathy? The Impact of Diversity." *American Economic Review*, 96(5): 1890–1905.

Bordalo, Pedro, Katherine Coffman, Nicola Gennaioli, and Andrei Shleifer. 2016. "Stereotypes." *Quarterly Journal of Economics*, 131(4): 1753–1794.

Botelho, Tristan L, Daniel C Fehder, and Milan Miric. 2023. "Moving forward or falling back: Gender differences in career advancement for former entrepreneurs re-entering the workforce." Working Paper.

Brush, Candida G, Nancy M Carter, EJ Gatewood, Patricia G Greene, and Myra Hart. 2003. "Venture capital access: Is gender an issue." In *The emergence of entrepreneurship policy: Governance, start-ups, and growth in the US knowledge economy*. 141–154. Cambridge University Press.

Catherine, Sylvain. 2022. "Keeping options open: What motivates entrepreneurs?" *Journal of Financial Economics*, 144(1): 1–21.

Cook, Lisa D, Matt Marx, and Emmanuel Yimfor. 2024. "Funding black high-growth startups." *Journal of Finance, Forthcoming*.

Cullen, Zoe, and Ricardo Perez-Truglia. 2023. "The Old Boys' Club: Schmoozing and the Gender Gap." *American Economic Review*, 113(7): 1703–1740.

Ductor, Lorenzo, Sanjeev Goyal, and Anja Prummer. 2023. "Gender and collaboration." *Review of Economics and Statistics*, 105(6): 1366–1378.

Ewens, Michael. 2023. "Gender and race in entrepreneurial finance." In *Handbook of the Economics of Corporate Finance*. Vol. 1, 239–296. Elsevier.

Ewens, Michael, and Joan Farre-Mensa. 2020. "The deregulation of the private equity markets and the decline in IPOs." *Review of Financial Studies*, 33(12): 5463–5509.

Ewens, Michael, and Richard R Townsend. 2020. "Are early stage investors biased against women?" *Journal of Financial Economics*, 135(3): 653–677.

Exley, Christine L, and Judd B Kessler. 2022. "The gender gap in self-promotion." *Quarterly Journal of Economics*, 137(3): 1345–1381.

Genc, Caroline. 2024. "Exploring the success of second-time entrepreneurs." Working Paper.

Gompers, Paul A, and Sophie Q Wang. 2017. "Diversity in innovation." Working Paper w23082.

Gompers, Paul A, Kevin Huang, and Sophie Q Wang. 2022. "Homophily in entrepreneurial team formation." Working Paper.

Gompers, Paul, Anna Kovner, Josh Lerner, and David Scharfstein. 2010. "Performance persistence in entrepreneurship." *Journal of Financial Economics*, 96(1): 18–32.

Gompers, Paul A, Will Gornall, Steven N Kaplan, and Ilya A Strebulaev. 2020. "How do venture capitalists make decisions?" *Journal of Financial Economics*, 135(1): 169–190.

González-Uribe, Juanita. 2020. "Exchanges of innovation resources inside venture capital portfolios." *Journal of Financial Economics*, 135(1): 144–168.

Gornall, Will, and Ilya A Strebulaev. 2024. "Gender, race, and entrepreneurship: A randomized field experiment on venture capitalists and angels." Management Science.

Guzman, Jorge, and Aleksandra Olenka Kacperczyk. 2019. "Gender gap in entrepreneurship." *Research Policy*, 48(7): 1666–1680.

Hamilton, Barton H. 2000. "Does entrepreneurship pay? An empirical analysis of the returns to self-employment." *Journal of Political Economy*, 108(3): 604–631.

Hebert, Camille. 2024. "Gender stereotypes and entrepreneur financing." Review of Financial Studies, Accepted.

Hochberg, Yael V, Alexander Ljungqvist, and Yang Lu. 2007. "Whom you know matters: Venture capital networks and investment performance." *Journal of Finance*, 62(1): 251–301.

Hochberg, Yael V, and Joshua D Rauh. 2013. "Local overweighting and underperformance: Evidence from limited partner private equity investments." *Review of Financial Studies*, 26(2): 403–451.

Howell, Sabrina T, and Ramana Nanda. 2024. "Networking frictions in venture capital, and the gender gap in entrepreneurship." *Journal of Financial and Quantitative Analysis*, 59(6): 2733–2761.

Hsu, David H. 2007. "Experienced entrepreneurial founders, organizational capital, and venture capital funding." *Research policy*, 36(5): 722–741.

Hvide, Hans K, and Georgios A Panos. 2014. "Risk tolerance and entrepreneurship." *Journal of Financial Economics*, 111(1): 200–223.

Ibáñez, María José, and Maribel Guerrero. 2022. "Women serial high-tech entrepreneurs: A literature review and research agenda." In *Developments in Entrepreneurial Finance and Technology*. 39–66. Edward Elgar Publishing.

Janeway, William H, Ramana Nanda, and Matthew Rhodes-Kropf. 2021. "Venture capital booms and start-up financing." *Annual Review of Financial Economics*, 13: 111–127.

Lafontaine, Francis, and Kathryn Shaw. 2016. "Serial Entrepreneurship : Learning by doing?" *Journal of Labor Economics*, 34(S2): 101–147.

Ljungqvist, Alexander, and William J Wilhelm Jr. 2003. "IPO Pricing in the Dot-Com Bubble." *Journal of Finance*, 58(2): 723–752.

Manso, Gustavo. 2016. "Experimentation and the Returns to Entrepreneurship." *Review of Financial Studies*, 29(9): 2319–2340.

Moskowitz, Tobias J, and Annette Vissing-Jørgensen. 2002. "The returns to entrepreneurial investment: A private equity premium puzzle?" *American Economic Review*, 92(4): 745–778.

Nahata, Rajarishi. 2019. "Success is good but failure is not so bad either: Serial entrepreneurs and venture capital contracting." *Journal of Corporate Finance*, 58: 624–649.

Oster, Emily. 2019. "Unobservable selection and coefficient stability: Theory and evidence." *Journal of Business & Economic Statistics*, 37(2): 187–204.

Pollman, Elizabeth. 2023. "Startup failure." *Duke Law Journal*, 73: 327.

Puri, Manju, and David T Robinson. 2013. "The economic psychology of entrepreneurship and family business." *Journal of Economics & Management Strategy*, 22(2): 423–444.

Raina, Sahil. 2021. "VCs, Founders, and the Performance Gender Gap." Working Paper.

Roussille, Nina. 2024. "The role of the ask gap in gender pay inequality." *Quarterly Journal of Economics*.

Sarsons, Heather. 2017. "Interpreting signals in the labor market: Evidence from medical referrals." University of British Columbia Working Paper. https://drive.google.com/file/d/1YQFZbY-YOiRtmHO6zOK6J9cSn9tgSVUi/view.

Sarsons, Heather, Klarita Gërxhani, Ernesto Reuben, and Arthur Schram. 2021. "Gender differences in recognition for group work." *Journal of Political Economy*, 129(1): 101–147.

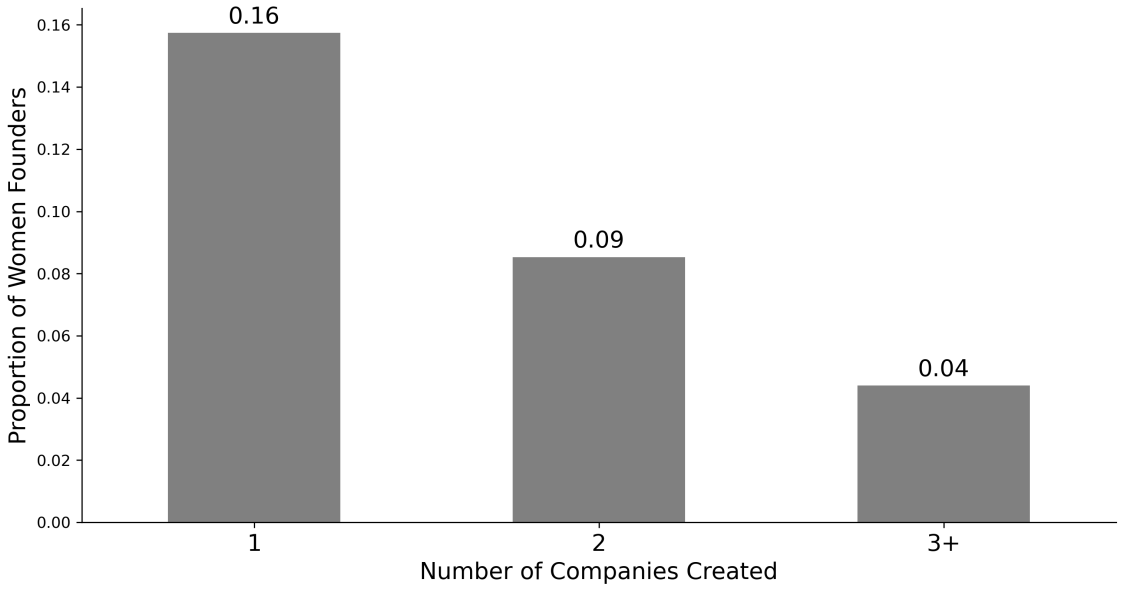
Shaw, Kathryn, and Anders Sørensen. 2019. "The productivity advantage of serial entrepreneurs." *ILR Review*, 72(5): 1225–1261.

Sorkin, Isaac. 2023. "Quantifying racial disparities using consecutive employment spells." Working Paper.

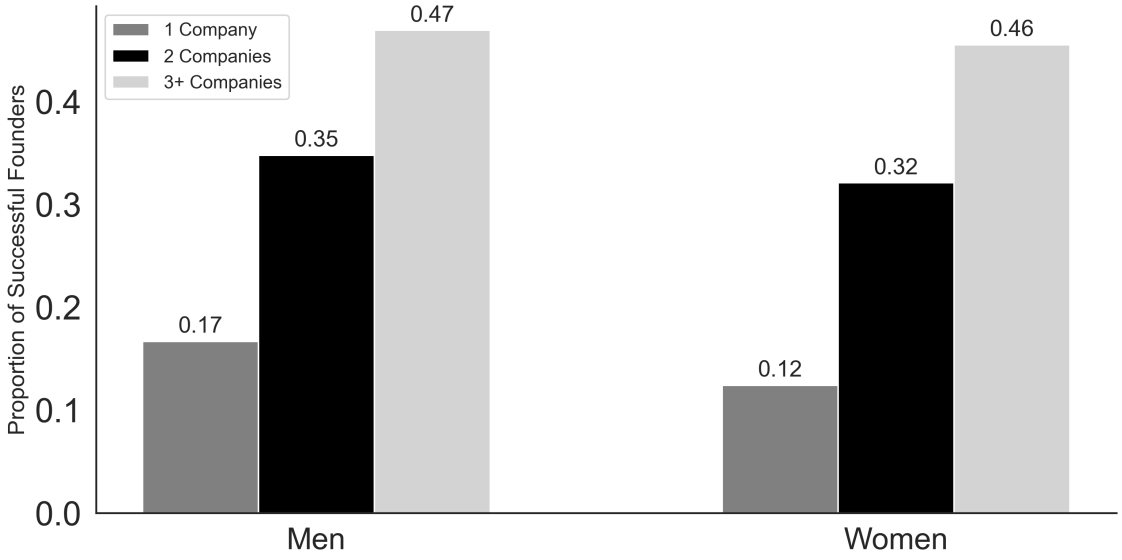
Yimfor, Emmanuel, and Jon A Garfinkel. 2023. "Predicting success in entrepreneurial finance research." *Journal of Corporate Finance*, 81: 102359.

Figure 1: **Serial Entrepreneurship by Gender**

The sample includes all founders of startups that raised at least one round of VC funding between 2010 and 2022. Founders are divided according to whether they have created 1, 2, or 3 or more unique VC-backed startups during the sample period. Panel A shows the proportion of women founders in the sample. Panel B shows the success rate of startups by how many VC-backed startups the founder has created, further split by founder gender. A startup is classified as successful if PitchBook classifies the firm as having exited through an IPO or an acquisition by December 2023.



(a) Serial Entrepreneurship, by Gender of Founder



(b) Serial Entrepreneurship by Gender and Success

Figure 2: **Single and Mixed Gender Teams**

The figure plots the number of VC-backed startups in the Pitchbook data over time, by gender of the founder team (Men Only, Women Only, and Mixed Gender teams). The unit of observation is a startup.

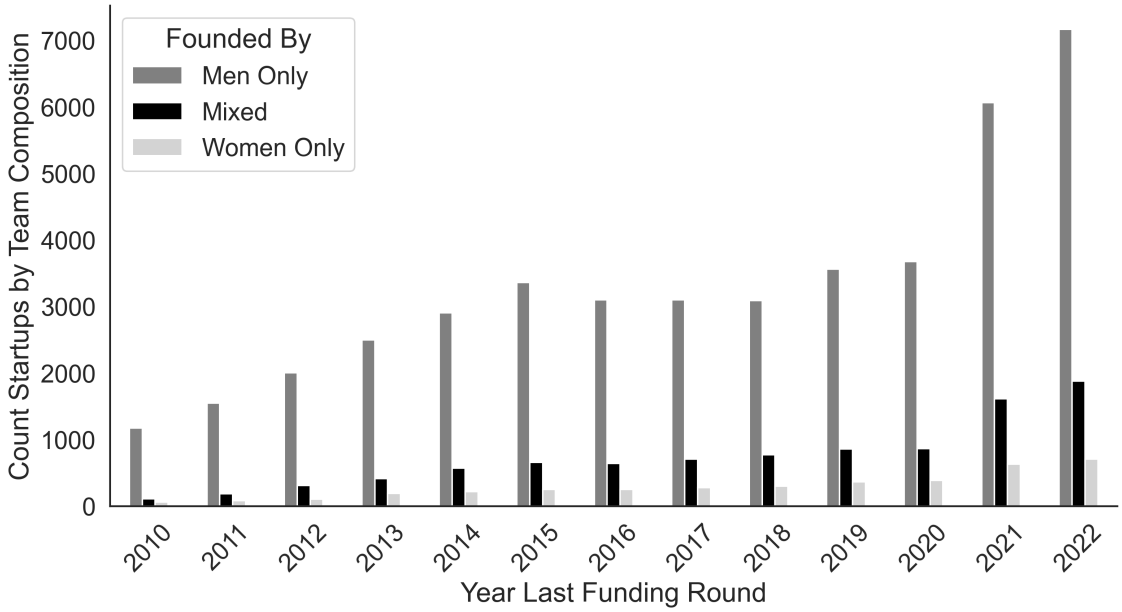


Table 1: **Sample of failure and success events by year**

This table shows the number of unique VC-backed startups that experienced successes or failures in each year of the sample. The data are also sorted according to whether: the startup's founders are all men (*Men*); there is at least one woman and at least one man on the founder team (*Mixed*); all founders are women (*Women*). *Year* is the year in which the startup failed or succeeded. We classify a VC-backed startup as a failure if Pitchbook flags the startup as closed or bankrupt by December 2023. The company is also classified as a failure (without the Pitchbook designation) if all of the following conditions hold: (i) the founder left the company; (ii) the company did not raise another round of financing following the founder's departure; (iii) the company did not provide an exit via an IPO or acquisition; and (iv) the startup's website is inactive. A startup is considered a success (*Success*) if it went public in an IPO or was acquired by December 2023. All startups in the sample raised at least one round of venture capital funding before the success or failure event.

Year	Failure				Success			
	Total	Men	Mixed	Women	Total	Men	Mixed	Women
2010	103	89.3%	6.8%	3.9%	389	90.7%	5.7%	3.6%
2011	150	87.3%	5.3%	7.3%	443	92.6%	3.8%	3.6%
2012	261	87.7%	8.4%	3.8%	544	89.9%	6.6%	3.5%
2013	401	85.5%	9.0%	5.5%	609	91.3%	5.9%	2.8%
2014	549	82.1%	12.9%	4.9%	793	88.1%	8.2%	3.7%
2015	895	81.5%	13.1%	5.5%	894	83.9%	12.3%	3.8%
2016	1202	79.7%	14.9%	5.4%	862	85.7%	10.8%	3.5%
2017	1117	79.1%	15.2%	5.7%	971	82.7%	13.1%	4.2%
2018	1347	77.1%	14.9%	7.9%	1111	81.9%	14.4%	3.7%
2019	1414	78.0%	15.6%	6.4%	1160	79.8%	15.1%	5.1%
2020	1020	73.8%	19.3%	6.9%	1168	81.7%	15.2%	3.2%
2021	1294	75.2%	16.2%	8.6%	1861	79.7%	16.1%	4.2%
2022	1309	74.0%	17.8%	8.2%	1223	78.3%	16.6%	5.1%
Total	11062	78%	15%	7%	12028	89%	13%	4%

Table 2: **Summary Statistics**

This table reports summary statistics for the full sample of VC-backed startups and founders (Panel A), the subsample of startups that failed within five years of receiving their last round of VC funding (Panel B), and the sample of startups that succeeded within five years of receiving their last round of VC funding (Panel C). The unit of observation in Panels A through C is a founder-startup pair. The table shows data for men and women founders separately, with p-values of the mean differences across men and women. *I(Invested)* is an indicator equal to one if the founder receives VC funding for a new startup within 5 years after the last round of funding for the current startup. *Funding Raised* is the total VC funding the startup has raised to date. *I(Invested Same Investors)* is an indicator equal to one if the founder receives funding for new startup (within 5 years) from the current startup's investors. *I(CEO)* is an indicator equal to one if the founder is listed as the current startup's CEO during any funding round. *I(Serial Founder)* is an indicator equal to one if the founder is already experienced, defined as founding another startup prior to the founding of the current startup. *Age Startup* is the startup's age (in years). *Pre-Failure funding* (*Pre-Exit*) is the amount of funding raised in the round immediately preceding the failure (success). Panel D shows summary statistics for the dataset used for the investor-level spillover tests. The unit of observation is an investor-deal pair. *All Men* refers to startups where founder teams are all men. *Mixed* refers to startups with men and women on their founder teams. *All Women* refers to teams with only women founders. *I(Women-Founded Startup)* is an indicator equal to one if there is a woman on the startup's founder team. *I(Invested in Women Founder)* is an indicator equal to one if the investor is invested in any firm with a woman founder. *P(Investments in Women)* represents the average proportion of a VC firm's investment dollars allocated to startups with at least one female founder, calculated over the previous five years. Panel D shows the mean, median, and standard deviation by gender of the founding teams. It also shows p-values of the mean differences between startups with all-men and all-women founder teams. $^{***}p < 0.01$ denotes significance at the 1% level, $^{**}p < 0.05$ denotes significance at the 5% level, and $^{*}p < 0.10$ denotes significance at the 10% level.

Founder's gender	Total	Men			Women			Difference
Variables	Mean	Mean	Median	Std. Dev	Mean	Median	Std. Dev	M-W
Panel A. All Startups that raise funding for a new startup								
I(Invested)	0.063	0.068	0.000	0.252	0.031	0.000	0.173	0.04***
Funding Raised ($M)	54.219	56.030	7.262	286.157	28.312	4.733	68.995	27.72***
Funding Raised New Startup ($M)	27.014	28.897	3.100	148.806	14.797	1.621	50.347	14.10***
I(CEO)	0.438	0.436	0.000	0.496	0.455	0.000	0.498	-0.02***
I(Serial Founder)	0.121	0.130	0.000	0.336	0.059	0.000	0.236	0.07***
Age Startup	5.343	5.406	4.000	4.764	4.933	4.000	4.107	0.47***
Observations	122,716	106,330			16,386			
Panel B. Founders from startups that failed								
I(Invested)	0.077	0.082	0.000	0.274	0.040	0.000	0.196	0.04***
Funding Raised New Startup ($M)	58.558	61.491	7.600	420.282	18.530	4.475	42.690	42.96***
I(Invested Same Investors)	0.011	0.012	0.000	0.109	0.007	0.000	0.083	0.01***
I(CEO)	0.457	0.456	0.000	0.498	0.461	0.000	0.499	-0.01
I(Serial Founder)	0.090	0.098	0.000	0.297	0.037	0.000	0.190	0.06***
Age Startup at Failure	7.139	7.213	6.000	4.663	6.644	6.000	3.580	0.57***
Pre-Failure Funding ($M)	7.097	7.461	0.650	44.581	4.665	0.325	29.557	2.80***
Observations	22,386	19,470			2,916			
Panel C. Founders from startups that succeeded								
I(Invested)	0.141	0.148	0.000	0.355	0.078	0.000	0.268	0.07***
Funding Raised New Startup ($M)	99.219	102.826	12.000	646.858	32.023	6.279	68.562	70.80***
I(Invested Same Investors)	0.041	0.043	0.000	0.202	0.019	0.000	0.137	0.02***
I(CEO)	0.402	0.404	0.000	0.491	0.383	0.000	0.486	0.02**
I(Serial Founder)	0.123	0.128	0.000	0.335	0.065	0.000	0.247	0.06***
Age Startup at Exit	8.831	8.879	8.000	5.086	8.356	7.000	5.483	0.52***
Pre-Exit Funding ($M)	41.061	42.876	8.220	222.834	23.183	4.570	57.202	19.69***
Observations	25,710	23,340			2,370			

Table 2 **(Continued)**

Panel D. Spillover dataset											
Team's gender	Total	All Men			Mixed (At least one Woman)			All Women			Difference
Variables	Mean	Mean	Median	Std. Dev	Mean	Median	Std. Dev	Mean	Median	Std. Dev	M-W
Deal Size ($M)	31.301	35.243	8.000	127.630	20.579	5.218	45.627	11.795	3.000	27.459	16.50***
I(Women-Founded Startup)	0.239	0.000	0.000	0.000	1.000	1.000	0.000	1.000	1.000	0.000	-1.00
I(Invested in Women Founder)	0.243	0.229	0.000	0.420	0.278	0.000	0.448	0.318	0.000	0.466	-0.06***
I(Recent Failure)	0.604	0.598	1.000	0.490	0.626	1.000	0.484	0.622	1.000	0.485	-0.03***
Age VC Investor	15.393	15.714	10.000	17.747	14.526	10.000	16.548	13.784	9.000	15.059	1.34***
Age Startup	5.081	5.207	4.000	3.740	4.683	4.000	3.103	4.658	4.000	3.164	0.53***
P(Investments in Women)	0.189	0.175	0.142	0.155	0.224	0.181	0.195	0.271	0.211	0.236	-0.06***
Observations	183,042	139,320			34,562			9,160			

Table 3: **Financing the next startup: Likelihood of VC funding for a new startup within five years**

This table examines the relationship between the founder's gender and the probability of securing funding for a new startup within five years after the last funding round for the current startup. The unit of observation is a startup-founder pair. The sample includes all startups that received their last funding between 2010 and 2022. This period allows all founders at least one year to raise funding as part of a new company by the end of our sample in December 2023. The dependent variable is *I(Invested)*, an indicator equal to one if the founder receives VC funding for a new startup within 5 years after the last round of funding for the current startup. *I(Woman)* is an indicator equal to one if the founder is a woman. *I(Serial Founder)* is an indicator equal to one if the founder is already experienced, defined as founding another startup prior to the founding of the current startup. *I(CEO)* is an indicator equal to one if the founder is also listed as the current startup's CEO during any funding round. *Ln(Funding Current Startup)* is the natural log of the total amount of VC funding the startup has raised to date. *Ln(Startup Age)* is the natural log of the startup's age (in years) when it received its last round of funding. The number of observations is lower in Columns (4) and (5) because we only use startups with at least two founders to ensure variation within the startup. We estimate all coefficients via OLS regressions with standard errors clustered by startup. $^{***}p < 0.01$ denotes significance at the 1% level, $^{**}p < 0.05$ denotes significance at the 5% level, and $^{*}p < 0.10$ denotes significance at the 10% level.

	I(Invested); Mean = 6.34%				
	(1)	(2)	(3)	(4)	(5)
I(Woman)	-3.394***	-1.619***	-1.784***	-2.926***	-1.891***
	(0.157)	(0.155)	(0.158)	(0.243)	(0.239)
I(Serial Founder)		14.110***	13.953***		13.443***
		(0.349)	(0.347)		(0.423)
I(CEO)		-0.326**	-0.224*		0.050
		(0.131)	(0.131)		(0.148)
Ln(Funding Current Startup)		1.028***	0.902***		
		(0.039)	(0.040)		
Ln(Startup Age)		-0.783***	-0.699***		
		(0.110)	(0.112)		
Observations	122716	122716	122716	105749	105749
Adjusted R^2	0.018	0.065	0.068	0.189	0.215
Last Funding Year FE	YES	YES	YES	YES	YES
Industry FE	NO	NO	YES	NO	NO
State FE	NO	NO	YES	NO	NO
Startup FE	NO	NO	NO	YES	YES

Table 4: **Likelihood of VC funding for a new startup following success or failure**

This table shows results from regressions that estimate the relationship between a startup founder's gender and the likelihood that the founder raises a future round of funding for a new VC-backed startup following the current startup's failure (Panel A) or success (Panel B). The dependent variable is *I(Invested)*, an indicator equal to one if the founder receives VC funding for a new startup within 5 years after the failure or success event. The unit of observation is a startup-founder pair. *I(Woman)* is an indicator equal to one if the founder is a woman. *I(Serial Founder)* is an indicator equal to one if the founder is already experienced, defined as founding another startup prior to the founding of the current startup. *I(CEO)* is an indicator equal to one if the founder is also listed as the current startup's CEO during any funding round. *Ln(Age)* is the natural log of the startup's age (in years) when it failed or succeeded. *Ln(Pre-Exit Funding)* is the natural log of the amount of VC funding the startup raised before it failed or succeeded. We classify a VC-backed startup as a failure if Pitchbook flags that the startup has closed or gone bankrupt within five years of its last funding round. The company is also classified as a failure (without the Pitchbook designation) if, within five years of its last funding round, all of the following conditions hold: (i) the founder left the company; (ii) the company did not raise another round of financing following the founder's departure; (iii) the company did not provide an exit via an IPO or acquisition, and (iv) the startup's website is inactive. A startup is considered a success (*Success*) if it went public in an IPO or was acquired within five years of the last funding round. We estimate all coefficients via OLS regressions with standard errors clustered by startup. $^{***}p < 0.01$ denotes significance at the 1% level, $^{**}p < 0.05$ denotes significance at the 5% level, and $^{*}p < 0.10$ denotes significance at the 10% level.

Panel A: After failure	I(Invested); Mean = 7.66%				
	(1)	(2)	(3)	(4)	(5)
I(Woman)	-3.812***	-2.254***	-2.394***	-3.031***	-1.724***
	(0.416)	(0.410)	(0.417)	(0.653)	(0.634)
I(Serial Founder)		18.316***	18.078***		18.235***
		(1.047)	(1.043)		(1.303)
I(CEO)		1.630***	1.727***		2.135***
		(0.338)	(0.338)		(0.401)
Ln(Startup Age)		-2.383***	-2.326***		
		(0.415)	(0.416)		
Ln(Pre-Exit Funding)		1.038***	0.887***		
		(0.094)	(0.096)		
Observations	22386	22386	22386	18537	18537
Adjusted R^2	0.012	0.063	0.066	0.176	0.211
Year Failure FE	YES	YES	YES	YES	YES
Industry FE	NO	NO	YES	NO	NO
State FE	NO	NO	YES	NO	NO
Startup FE	NO	NO	NO	YES	YES

Panel B: After success	I(Invested); Mean = 14.13%				
	(1)	(2)	(3)	(4)	(5)
I(Woman)	-6.029***	-3.778***	-4.177***	-6.140***	-3.808***
	(0.600)	(0.591)	(0.601)	(0.879)	(0.849)
I(Serial Founder)		24.259***	24.023***		24.392***
		(0.938)	(0.932)		(1.149)
I(CEO)		3.747***	3.906***		4.312***
		(0.416)	(0.415)		(0.483)
Ln(Age)		-6.069***	-5.713***		
		(0.466)	(0.475)		
Ln(Pre-Exit Funding)		1.845***	1.631***		
		(0.121)	(0.122)		
Observations	25710	25710	25710	21920	21920
Adjusted R^2	0.024	0.101	0.105	0.201	0.254
Year Exit FE	YES	YES	YES	YES	YES
Industry FE	NO	NO	YES	NO	NO
State FE	NO	NO	YES	NO	NO
Startup FE	NO	NO	NO	YES	YES

Table 5: **Are the results driven by gender differences in cofounder roles? CEO analysis**

This table shows results from regressions that estimate the relationship between a startup founder's gender and the likelihood that the founder raises a future round of funding for a new VC-backed startup following the current startup's failure (Columns 1-2) or success (Column 3-4). The dependent variable is *I(Invested)*, an indicator equal to one if the founder receives VC funding for a new startup within 5 years after the failure or success event. The unit of observation is a startup-founder pair. *I(Woman)* is an indicator equal to one if the founder is a woman. *I(CEO)* is an indicator equal to one if the founder is also listed as the current startup's CEO during any funding round. We estimate all coefficients via OLS regressions with standard errors clustered by startup. $^{***}p < 0.01$ denotes significance at the 1% level, $^{**}p < 0.05$ denotes significance at the 5% level, and $^{*}p < 0.10$ denotes significance at the 10% level.

Dependent Variable:	I(Invested)			
Sample:	After Failure		After Success	
	(1)	(2)	(3)	(4)
I(Woman)	-2.466***	-1.598**	-4.157***	-4.214***
	(0.537)	(0.776)	(0.699)	(0.935)
I(CEO)	1.947***	2.641***	4.228***	4.847***
	(0.380)	(0.459)	(0.456)	(0.531)
I(Woman) X I(CEO)	0.006	-0.506	-0.079	0.208
	(0.858)	(1.134)	(1.271)	(1.604)
I(Serial Founder)	19.302***	19.299***	24.863***	24.549***
	(1.087)	(1.351)	(0.945)	(1.164)
Ln(Age)	-2.579***		-6.339***	
	(0.429)		(0.480)	
Ln(Pre-Exit Funding)	0.863***		1.766***	
	(0.099)		(0.125)	
Observations	22755	18886	26016	22261
Adjusted R^2	0.064	0.212	0.102	0.253
Year Founded FE	YES	YES	YES	YES
Industry FE	YES	NO	YES	NO
State FE	YES	NO	YES	NO
Startup FE	NO	YES	NO	YES

Table 6: **Starting the next firm: Likelihood of starting the next firm after failure or success according to LinkedIn**

This table examines the relationship between the founder's gender and the probability of starting a new startup within five years after the last funding round for the current startup. We identify new firms using founders' LinkedIn profiles. The unit of observation is a startup-founder pair. The sample includes founders of all startups that received their last funding between 2010 and 2022. This period allows all founders at least one year to start a new firm by the end of our sample in December 2023. In Panel A, the dependent variable is *I(New Firm)*, an indicator equal to one if the founder reports in their LinkedIn profile being the founder of new firm regardless of its funding status. In Panel B, the dependent variable is *I(Invested)*, an indicator equal to one if the founder receives VC funding for the new firm within five years after the last round of funding for the previous VC-backed startup. *I(Woman)* is an indicator equal to one if the founder is a woman. *I(Serial Founder LinkedIn)* is an indicator equal to one if the founder is already experienced, defined as founding another startup prior to the founding of the current startup according to information reported in LinkedIn Profiles. *I(CEO)* is an indicator equal to one if the founder is also listed as the current startup's CEO during any funding round. *Ln(Funding Current Startup)* is the natural log of the total amount of VC funding the startup has raised to date. *Ln(Age)* is the natural log of the startup's age (in years) when it received its last round of funding. In Columns 1 and 2, we focus on new firms after the failure of the current startup and in Columns 3 and 4, we focus on new firms after the exit through IPO or M&A of the current startup. We estimate all coefficients via OLS regressions with standard errors clustered by startup. $^{***}p < 0.01$ denotes significance at the 1% level, $^{**}p < 0.05$ denotes significance at the 5% level, and $^{*}p < 0.10$ denotes significance at the 10% level.

Panel A	I(Next Firm in LinkedIn)			
	After First Startup Failure Mean = 26.39%		After First Startup Success Mean = 35.11%	
	(1)	(2)	(3)	(4)
I(Woman)	-2.600***	-2.490**	-4.873***	-3.216***
	(0.944)	(1.136)	(1.060)	(1.199)
I(Serial Founder LinkedIn)	26.776***	21.363***	28.881***	23.394***
	(0.765)	(0.878)	(0.709)	(0.824)
I(CEO)	9.649***	7.131***	10.634***	8.465***
	(0.691)	(0.636)	(0.659)	(0.641)
Ln(Startup Age)	-8.446***		-10.891***	
	(0.791)		(0.745)	
Ln(Pre-Exit Funding)	1.411***		1.714***	
	(0.178)		(0.188)	
Observations	20107	20107	24855	24855
Adjusted R^2	0.194	0.379	0.244	0.431
Year Exit FE	YES	YES	YES	YES
Industry FE	YES	NO	YES	NO
State FE	YES	NO	YES	NO
Startup FE	NO	YES	NO	YES

Panel B	I(Next VC-backed Startup | Next Firm in LinkedIn)			
	After Current Startup Failure Mean = 37.01%		After Current Startup Success Mean = 53.46%	
	(1)	(2)	(3)	(4)
I(Woman)	-14.162***	-11.287**	-10.715***	-9.600**
	(3.420)	(5.275)	(3.500)	(4.421)
I(Serial Founder LinkedIn)	9.460***	4.061	15.702***	14.155***
	(2.546)	(3.551)	(1.912)	(2.681)
I(CEO)	0.825	2.073	2.863*	5.188***
	(2.210)	(2.376)	(1.734)	(1.886)
Ln(Startup Age)	-5.139*		-8.851***	
	(3.078)		(2.195)	
Ln(Pre-Exit Funding)	2.867***		4.257***	
	(0.628)		(0.540)	
Observations	3518	3518	6130	6130
Adjusted R^2	0.085	0.666	0.088	0.631
Year Exit FE	YES	YES	YES	YES
Industry FE	YES	NO	YES	NO
State FE	YES	NO	YES	NO
Startup FE	NO	YES	NO	YES

Table 7: **Amount raised following startup success or failure**

This table examines the relationship between a startup founder's gender and the amount of VC funding raised at the founder's next startup following the failure or success of the current startup. The unit of observation is a startup-founder pair. The dependent variable, *Ln(Funding Raised)*, is the natural log of the amount of VC funding raised by the new startup in the five years following the failure or success of the current startup. *I(Woman)* an indicator equal to one of the founders is a woman. *I(Serial)* is an indicator for founders who started another company before the current startup. *I(CEO)* is an indicator of whether the founder was also listed as the current startup's CEO during a funding round. *Ln(Age)* is the natural log of the startup's age when it failed or succeeded. *Ln(Pre-Exit Funding)* is the natural log amount of VC funding the startup raised before it failed or succeeded. We classify a VC-backed startup as a failure if Pitchbook flags that the startup has closed or gone bankrupt within five years of its last funding round. The company is also classified as a failure (without the Pitchbook designation) if, within five years of its last funding round, all of the following conditions hold: (i) the founder left the company; (ii) the company did not raise another round of financing following the founder's departure; (iii) the company did not provide an exit via an IPO or acquisition, and (iv) the startup's website is inactive. A startup is considered a success (*Success*) if it went public in an IPO or was acquired within five years of the last funding round. We estimate all coefficients via OLS regressions with standard errors clustered by startup. $^{***}p < 0.01$ denotes significance at the 1% level, $^{**}p < 0.05$ denotes significance at the 5% level, and $^{*}p < 0.10$ denotes significance at the 10% level.

Panel A: After Failure	Ln(Funding Raised)				
	(1)	(2)	(3)	(4)	(5)
I(Woman)	-0.729***	-0.471**	-0.526***	-0.840**	-0.759**
	(0.209)	(0.200)	(0.199)	(0.357)	(0.368)
I(Serial Founder)		0.358***	0.361***		0.637**
		(0.116)	(0.116)		(0.300)
I(CEO)		-0.166*	-0.134		0.064
		(0.096)	(0.097)		(0.147)
Ln(Startup Age)		-0.197*	-0.216*		
		(0.119)	(0.121)		
Ln(Pre-Exit Funding)		0.242***	0.210***		
		(0.028)	(0.028)		
Observations	1711	1711	1711	513	513
Adjusted R^2	0.014	0.090	0.117	0.534	0.542
Year Failure FE	YES	YES	YES	YES	YES
Industry FE	NO	NO	YES	NO	NO
State FE	NO	NO	YES	NO	NO
Startup FE	NO	NO	NO	YES	YES

Panel B: After Success	Ln(Funding Raised)				
	(1)	(2)	(3)	(4)	(5)
I(Woman)	-0.623***	-0.395***	-0.479***	-0.348***	-0.283**
	(0.151)	(0.139)	(0.140)	(0.131)	(0.129)
I(Serial Founder)		0.509***	0.470***		0.450***
		(0.075)	(0.073)		(0.135)
I(CEO)		-0.192***	-0.143**		0.118
		(0.058)	(0.057)		(0.073)
Ln(Startup Age)		-0.463***	-0.387***		
		(0.076)	(0.076)		
Ln(Pre-Exit Funding)		0.372***	0.311***		
		(0.021)	(0.021)		
Observations	3631	3631	3631	1382	1382
Adjusted R^2	0.024	0.169	0.199	0.562	0.571
Year Exit FE	YES	YES	YES	YES	YES
Industry FE	NO	NO	YES	NO	NO
State FE	NO	NO	YES	NO	NO
Startup FE	NO	NO	NO	YES	YES

Table 8: **VC-Backed Founder Characteristics Between and Within Startup**

The table shows the estimated relationship between various founder characteristics and the likelihood that a startup founder is a woman, *I(Woman)*, between and within startup. Each observation is a startup founder, with characteristics measured prior to their startup's last round of VC funding. We identify founder characteristics using LinkedIn profiles. The unit of observation is a startup-founder pair. The sample is the founders from Table 3 that we could match to their LinkedIn profile. Shrinkage is the difference between the within and between estimates, scaled by the between estimates. *I(Tech Experience)* indicates work at a top-50 funded startup or a computer science/engineering degree. *I(Past Startup Founder/Executive)* indicates prior founding or executive experience. *I(MBA/JD)* is an indicator for holding an MBA or a JD degree. *I(PhD/MD)* is an indicator for holding a Ph.D. or an MD degree. *Work Experience (Years)* measures cumulative years of work experience, accounting for overlapping job periods and gaps between jobs since graduation. *I(Elite School)* is an indicator for attending an elite university. We standardize all variables to ease comparison of relative effects across rows.

Dependent Variable	I(Tech Experience)		Work Experience (Years)		I(Past Startup Founder/Executive)		I(PhD/MD)		I(MBA/JD)		I(Elite School)	
	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women
Mean (all founders)	44.10%	26.04%	13.17	11.65	92.28%	91.61%	12.02%	11.20%	16.20%	19.70%	26.06%	32.07%
Mean (mixed gender teams)	41.64%	26.92%	13.19	11.71	91.84%	91.31%	13.73%	12.07%	16.76%	18.67%	27.75%	30.79%
	Between	Within	Between	Within	Between	Within	Between	Within	Between	Within	Between	Within
I(Woman)	-0.369***	-0.287***	-0.192***	-0.167***	-0.035***	-0.015	-0.032***	-0.045***	0.094***	0.040**	0.131***	0.059***
	(0.011)	(0.014)	(0.012)	(0.013)	(0.013)	(0.017)	(0.012)	(0.014)	(0.013)	(0.017)	(0.013)	(0.016)
Shrinkage	-22.2%		-13.0%		-57.1%		40.6%		-57.4%		-55.0%	
Observations	63034	63034	63034	63034	63034	63034	63034	63034	63034	63034	63034	63034
Adjusted R^2	0.015	0.247	0.010	0.346	0.007	0.154	0.004	0.339	0.001	0.125	0.004	0.224
Last Funding Year FE	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Startup FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

Table 9: **Differences in performance of the next startup**

This table examines the relationship between the founder's gender and the probability of a successful exit with the next VC-backed startup. The unit of observation is a founder-startup pair from Tables 3 and 4 sample. The sample includes founders who either succeeded or failed with the current startup between 2010 and 2022, and exited through success or failure with the next VC-backed startup by the end of our sample period, December 2023. In the first two columns, the dependent variable is *I(All IPOs & M&As)*, an indicator equal to one if the founder received VC funding for the next startup that exited via an IPO or an acquisition by the end of our sample period, and zero otherwise. In the last two columns, a startup is successful if the next startup exits via an IPO, and zero otherwise. *I(Woman)* is an indicator equal to one if the founder is a woman. *I(Serial Founder)* is an indicator equal to one if the founder is already experienced, defined as founding another startup prior to the founding of the current startup. *I(CEO)* is an indicator equal to one if the founder is also listed as the current startup's CEO during any funding round. *Ln(Pre-Exit Funding)* is the natural logarithm of all funding raised with the new startup before the exit. *Year Exit FE* is the exit year for the current startup. We estimate all coefficients via OLS regressions with standard errors clustered by startup. $^{***}p < 0.01$ denotes significance at the 1% level, $^{**}p < 0.05$ denotes significance at the 5% level, and $^{*}p < 0.10$ denotes significance at the 10% level.

Dependent Variable:	I(All IPOs & M&As)		I(IPOs Only)	
	(1)	(2)	(3)	(4)
I(Woman)	0.118	0.124*	0.152**	0.156**
	(0.082)	(0.069)	(0.076)	(0.072)
I(Serial Founder)	0.042	0.051	0.060	0.066
	(0.063)	(0.052)	(0.046)	(0.042)
I(CEO)	0.087**	0.065*	0.009	-0.004
	(0.035)	(0.033)	(0.019)	(0.017)
Ln(Pre-Exit Funding)		0.103***		0.064***
		(0.017)		(0.014)
Observations	588	588	588	588
Adjusted R^2	0.461	0.547	0.433	0.488
Year Exit FE	YES	YES	YES	YES
Previous Startup FE	YES	YES	YES	YES

Table 10: **Likelihood of VC funding for a new startup following abundant supply of capital**

This table examines the effects of abundant supply of capital conditions on the likelihood of raising VC funding for the next startup following the failure (Panel B) or the success of the current startup (Panel C). We measure the abundant supply of capital conditions, *Ln(Funding Supply)*, as is the natural log of the average pension fund assets in the state where the startup is headquartered in the four years preceding a deal. In Panel A the unit of observation is a startup year for startups that raised VC funding between 2010 and 2022. We cluster standard errors at the state level. *I(Follow-on)* is an indicator of whether the current startup raised a new round of funding in the five years following the current funding round. *I(Failure)* and *I(Success)* are indicators for startups that failed following the current round of funding. In Panel B, the unit of observation is a failed startup-founder pair, while Panel C is a successful startup-founder pair. *I(Woman)* is an indicator equal to one if the founder is a woman. *I(Serial)* is an indicator for founders who started another company before the current startup. *I(CEO)* is an indicator of whether the founder was also listed as the current startup's CEO during a funding round. *Ln(Startup Age)* is the natural log of the startup's age when it failed or succeeded. *Ln(Pre-Exit Funding)* is the natural log amount of VC funding the startup raised before it failed or succeeded. We calculate *Ln(Funding Supply)* in Panels B and C as of the year of the startup's last funding round before success or failure. $^{***}p < 0.01$ denotes significance at the 1% level, $^{**}p < 0.05$ denotes significance at the 5% level, and $^{*}p < 0.10$ denotes significance at the 10% level.

Panel A: Supply of Capital and Outcomes	I(Follow-on)	I(Failure)	I(IPO)	I(Acquired)	
	(1)	(2)	(3)	(4)	
Ln(Funding Supply)	0.837**	-1.263***	0.319***	1.350***	
	(0.369)	(0.375)	(0.089)	(0.339)	
Observations	92189	92189	92189	92189	
Adjusted R^2	0.029	0.057	0.021	0.074	
Last Funding Year FE	YES	YES	YES	YES	
Industry FE	YES	YES	YES	YES	

Panel B: Effects of Failure and Supply	I(Invested); Mean = 7.68%				
	(1)	(2)	(3)	(4)	(5)
I(Woman) X Ln(Funding Supply)	-0.519	-0.358	-0.318	-0.023	0.108
	(0.389)	(0.385)	(0.391)	(0.597)	(0.588)
I(Woman)	-3.870***	-2.283***	-2.372***	-3.087***	-1.795***
	(0.414)	(0.409)	(0.414)	(0.645)	(0.627)
Ln(Funding Supply)	1.443***	0.810***	1.809		
	(0.205)	(0.199)	(1.642)		
Observations	22119	22119	22119	18337	18337
Adjusted R^2	0.014	0.064	0.066	0.177	0.212
Year Exit FE	YES	YES	YES	YES	YES
Industry FE	NO	NO	YES	NO	NO
State FE	NO	NO	YES	NO	NO
Startup FE	NO	NO	NO	YES	YES
Other Controls	NO	YES	YES	NO	YES

Panel C: Effects of Success and Supply of Capital	I(Invested); Mean = 14.19%				
	(1)	(2)	(3)	(4)	(5)
I(Woman) X Ln(Funding Supply)	-0.346	0.008	0.013	-0.244	-0.045
	(0.510)	(0.516)	(0.514)	(0.777)	(0.742)
I(Woman)	-6.064***	-3.739***	-4.121***	-6.225***	-3.896***
	(0.604)	(0.597)	(0.608)	(0.879)	(0.849)
Ln(Funding Supply)	1.790***	0.563**	-1.069		
	(0.244)	(0.237)	(1.486)		
Observations	25196	25196	25196	21500	21500
Adjusted R^2	0.027	0.102	0.105	0.202	0.256
Year Exit FE	YES	YES	YES	YES	YES
Industry FE	NO	NO	YES	NO	NO
State FE	NO	NO	YES	NO	NO
Startup FE	NO	NO	NO	YES	YES
Other Controls	NO	YES	YES	NO	YES

Table 11: **Potential spillovers following startup failures**

This table examines the relationship between the gender of a failed startup founder and the sizes of deals for women-founded startups in the years following the failure event. The unit of observation is an investor-deal pair. *I(Women-Founded)* is an indicator equal to one if at least one member of the founding team is a woman. *I(Recent Failure)* is an indicator equal to one if the investor backed at least one startup over the previous five years that failed. *I(Failure Women)* is an indicator equal to one if the investor backed at least one startup that failed over the previous five years and that also had at least one woman founder. *Ln(Age Startup)* is the natural log of the age of the startup, and *Ln(Age VC)* is the natural log of the age of the VC firm (investor). *P(Investments Women)* is the size of deals in the VC firm's portfolio that fund startups with women founders over the previous five years, divided by the total size of all deals in which the investor participated. *P(Serial Founder)* represents the proportion of startup founders in the current deal who have launched at least one other startup prior to the current one, as recorded in Pitchbook. The dependent variable is *Ln(Deal Size)*, the natural log of deal size (in millions). We classify a startup as failed if it closes within five years of its last funding round or if a founder left the company, the company did not raise another round of funding following the founder's departure, the company did not successfully exit via an IPO or an acquisition, and the startup's website is inactive in the five years following their last funding round. A startup is successful if the startup exits via an IPO or an Acquisition within five years of its last funding round. The sample includes all investors in Pitchbook that experienced at least one failure between 2010 and 2022. We present coefficients from OLS regressions and cluster standard errors by investors. $^{***}p < 0.01$ denotes significance at the 1% level, $^{**}p < 0.05$ denotes significance at the 5% level, and $^{*}p < 0.10$ denotes significance at the 10% level.

Dependent Variable:	Ln(Deal Size)			
	(1)	(2)	(3)	(4)
I(Failure Women) x I(Women-Founded)	-0.163**	-0.179**	-0.074***	-0.091***
	(0.077)	(0.072)	(0.022)	(0.021)
I(Women-Founded)	-0.527***	-0.287***	-0.228***	-0.147***
	(0.018)	(0.015)	(0.011)	(0.010)
I(Failure Women)	-0.680***	-0.513***	0.027	0.011
	(0.211)	(0.176)	(0.020)	(0.019)
I(Recent Failure)	0.260***	-0.056	0.098***	0.049*
	(0.048)	(0.039)	(0.025)	(0.025)
P(Investments Women)		-0.180***		-0.019**
		(0.025)		(0.009)
Ln(Age Startup)		0.282***		0.116***
		(0.031)		(0.030)
Ln(Age VC)		1.083***		0.798***
		(0.052)		(0.017)
P(Serial Founder)		0.947***		0.513***
		(0.049)		(0.015)
Observations	182970	182970	182970	182970
Adjusted R^2	0.135	0.301	0.541	0.597
Year FE	YES	YES	YES	YES
Investor FE	NO	NO	YES	YES
State FE	YES	YES	NO	NO
Industry FE	YES	YES	NO	NO

Table 12: **Spillovers following startup success**

This table examines the relationship between the gender of a successful startup founder in the investor's portfolio and the size of deals for other women-founded startups in which the investor participates in the years following success. The unit of observation is an investor-deal pair. In Panel A, a startup is successful if the startup exits via an IPO or an Acquisition by December 2022. In Panel B, a startup is successful if the startup exits via an IPO or acquisition where the ratio of exit valuation to funding raised pre-exit (TVPI) is in the $90th$ percentile of all startup exits. We present coefficients from OLS regressions and cluster standard errors by investors. *I(Women-Founded)* is an indicator equal to one if at least one member of the founding team is a woman. *I(Recent Success)* is an indicator of whether the investor backed at least one startup over the previous five years that was successful (extremely successful in Panel B). *I(Success Women)* is an indicator of whether the investor backed at least one startup with a woman founder that was successful in the last five years. *Ln(Age Startup)* is the startup age and *Ln(Age VC)* is the age of the VC firm. *P(Investments Women)* is the proportion of investments in women over the previous five years. *P(Serial Founder)* represents the proportion of startup founders in the current deal who have launched at least one other startup prior to the current one, as recorded in Pitchbook. *Ln(Deal Size)* is the natural log of the deal size. Panel A only includes investors who have experienced at least one success, and Panel B only includes investors who have experienced at least one extreme success. $^{***}p < 0.01$ denotes significance at the 1% level, $^{**}p < 0.05$ denotes significance at the 5% level, and $^{*}p < 0.10$ denotes significance at the 10% level.

Panel A: All IPOs & M&As	Ln(Deal Size)			
	(1)	(2)	(3)	(4)
I(Success Women) X I(Women-Founded)	-0.107	-0.112*	-0.043**	-0.052***
	(0.068)	(0.064)	(0.020)	(0.019)
I(Women-Founded)	-0.483***	-0.287***	-0.214***	-0.146***
	(0.018)	(0.015)	(0.011)	(0.010)
I(Success Women)	-0.335*	-0.216	0.014	0.019
	(0.176)	(0.145)	(0.019)	(0.017)
I(Recent Success)	0.479***	0.201***	0.089***	0.026
	(0.042)	(0.039)	(0.022)	(0.020)
P(Investments Women)		-0.172***		-0.014
		(0.025)		(0.012)
Ln(Age Startup)		0.119***		0.090***
		(0.030)		(0.034)
Ln(Age VC)		1.124***		0.787***
		(0.057)		(0.016)
P(Serial Founder)		0.977***		0.526***
		(0.057)		(0.015)
Observations	177282	177282	177282	177282
Adjusted R^2	0.192	0.334	0.573	0.623
Year FE	YES	YES	YES	YES
Investor FE	NO	NO	YES	YES
State FE	YES	YES	NO	NO
Industry FE	YES	YES	NO	NO
Panel B: All IPOs & Select M&As:	Ln(Deal Size)			
	(1)	(2)	(3)	(4)
I(Success Women) X I(Women-Founded)	0.040	0.043	0.004	0.022
	(0.063)	(0.058)	(0.025)	(0.026)
I(Women-Founded)	-0.518***	-0.316***	-0.235***	-0.161***
	(0.045)	(0.030)	(0.012)	(0.011)
I(Success Women)	0.050	0.093	0.002	0.021
	(0.118)	(0.095)	(0.030)	(0.028)
I(Recent Success)	0.277*	0.107	0.050**	0.020
	(0.159)	(0.133)	(0.022)	(0.022)
P(Investments Women)		-0.142***		-0.013
		(0.032)		(0.011)
Ln(Age Startup)		0.114***		0.086**
		(0.030)		(0.037)
Ln(Age VC)		1.156***		0.801***
		(0.086)		(0.018)
P(Serial Founder)		0.920***		0.521***
		(0.083)		(0.017)
Observations	160350	160350	160350	160350
Adjusted R^2	0.149	0.307	0.538	0.595
Year FE	YES	YES	YES	YES
Investor FE	NO	NO	YES	YES
State FE	YES	YES	NO	NO
Industry FE	YES	YES	NO	NO

Financing The Next VC-Backed Startup: The Role of Gender

Internet Appendix

Table of Contents

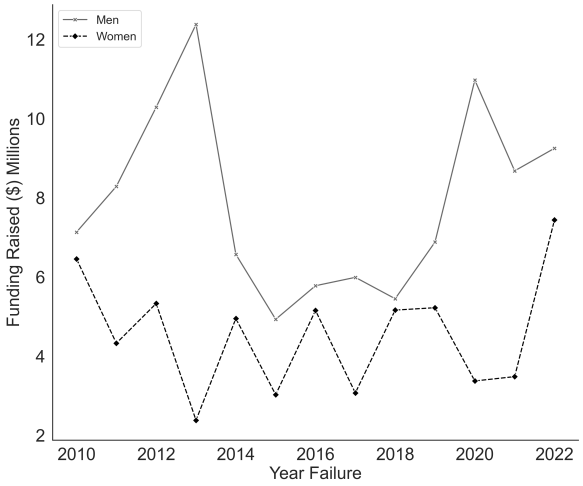
This Internet Appendix contains supplementary discussions and analyses organized as follows:

1. Figures:
    - Figure A.1: VC funding and time prior to failure and success
    - Figure A.2: Cumulative VC funding differences by gender after exit
    - Figure A.3: Spillover effects to women-founded startups
2. Tables:
    - Table A.1: Likelihood of VC funding for mixed-gender teams
    - Table A.2: Financing the next startup: Roles within the team
    - Table A.3: Likelihood of investment by the same investor after failure
    - Table A.4: Spillovers following startup failures (All Women Founders)
    - Table A.5: Potential spillovers following startup failures (Heterogeneity)
    - Table A.6: Potential spillovers following startup success (Heterogeneity)

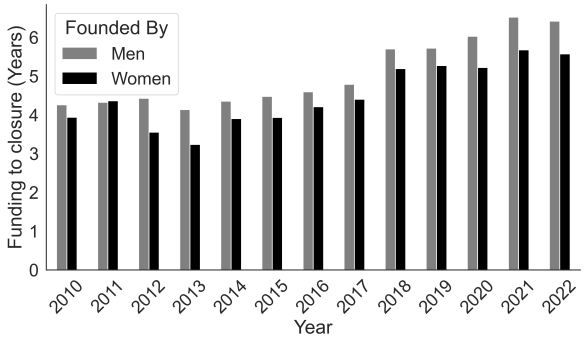
Appendix A. Supplementary Figures and Tables

Figure A.1: VC Funding and time prior to failure and success

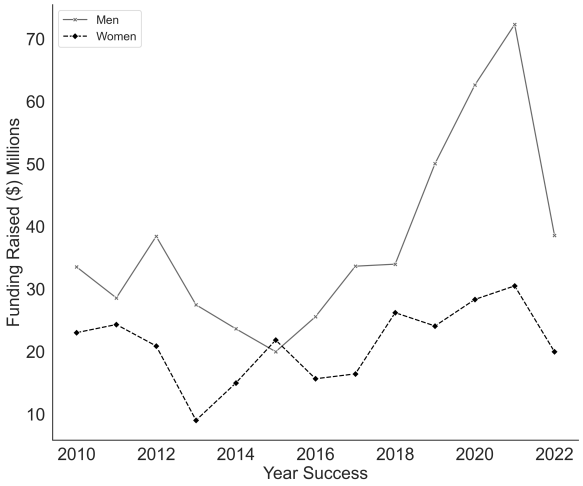
The figures show the amount of VC funding raised and the time from the first funding round to failure and success events for the sample of VC-backed startups, by founder gender. The unit of observation is a startup-founder. The sample includes founders of all VC-backed startups that failed (figures a and b) or all VC-backed startups that succeeded (figures c and d). Figures a and c show the amount of VC funding (in millions) raised prior to the failure and success events. Figures b and d show the time (in years) between the initial funding round and the event. We classify a VC-backed startup as a failure if Pitchbook flags the startup as closed or bankrupt by December 2023. The company is also classified as a failure (without the Pitchbook designation) if all of the following conditions hold: (i) the founder left the company; (ii) the company did not raise another round of financing following the founder's departure; (iii) the company did not provide an exit via an IPO or acquisition; and (iv) the startup's website is inactive. A startup is considered a success if it went public in an IPO or was acquired by December 2023.



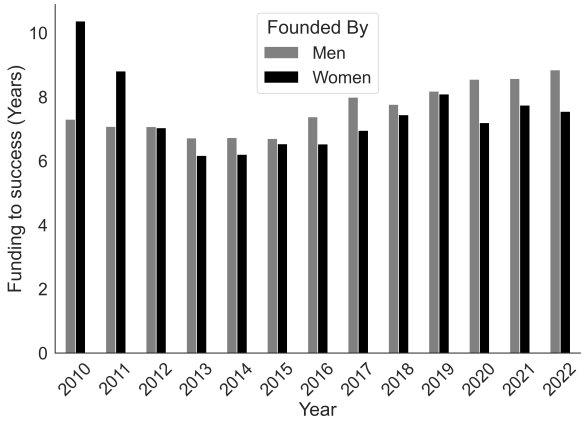
(a) VC Funding Raised before Failure



(b) Time between first VC funding round and failure



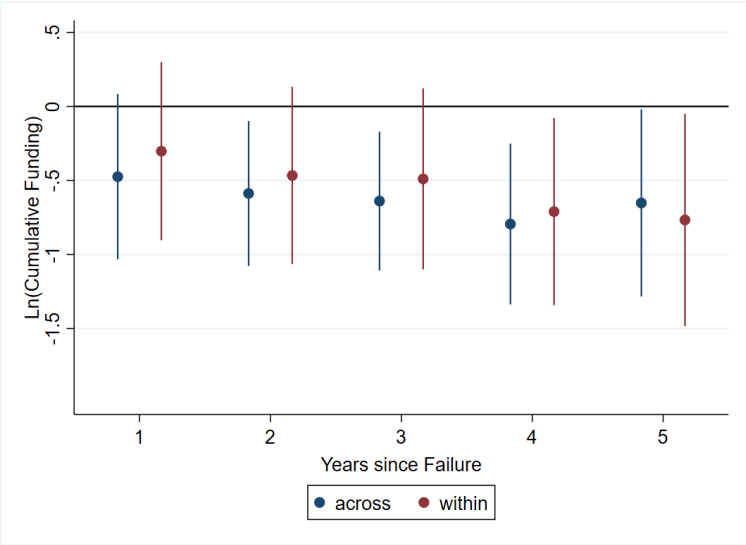
(c) VC Funding Raised before Success



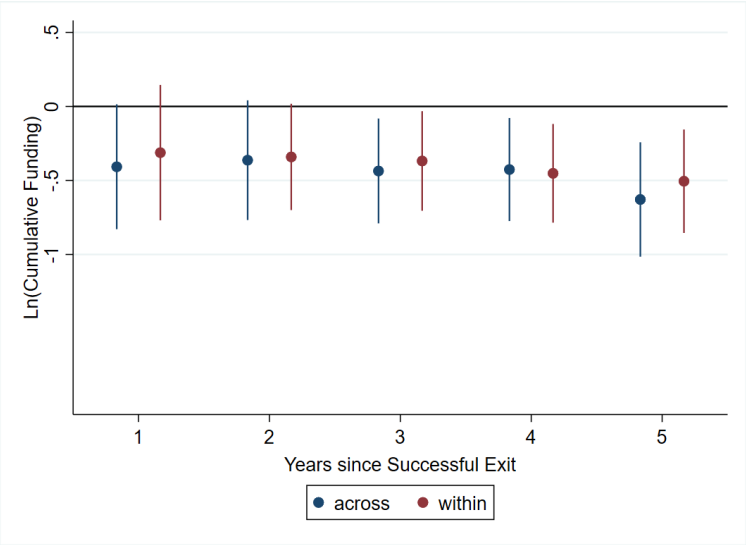
(d) Time between first VC funding round and success

Figure A.2: Cumulative VC funding differences by gender after the exit from the current Startup

This figure plots the regression coefficients and 95% confidence intervals from estimating the following equation: $\text{Ln(Cumulative Funding)}_{ijk} = \sum_{k=1}^{5} \beta_k \text{I(Woman)}_i + \beta' \text{Other Controls}_{ij} + \lambda_j + \lambda_{ind} + \lambda_k + \eta_{ijk}$. The "across" estimates use the sample of matched men and women founders who started the current startup in the same industry in the same state (λ_{ind}) and exited the current startup during the same year ($k = 0$). The "within" startup estimates compare the fundraising success of cofounders of the same current startup (λ_j). The outcome variable is the logarithm of the cumulative total amount of funding raised over the years after the exit of the current startup. In Panel A, the exit corresponds to the failure of the current startup, and in Panel B, it corresponds to the success of the current startup. Standard errors are clustered at the current startup level.



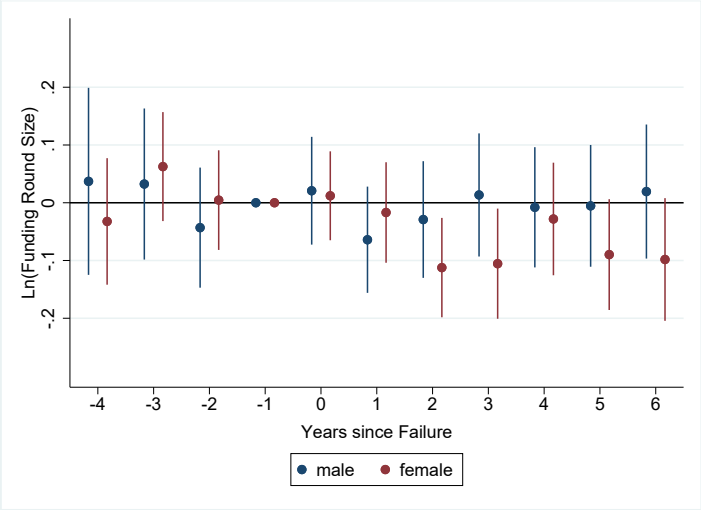
(a) Cumulative VC Funding differences after failure



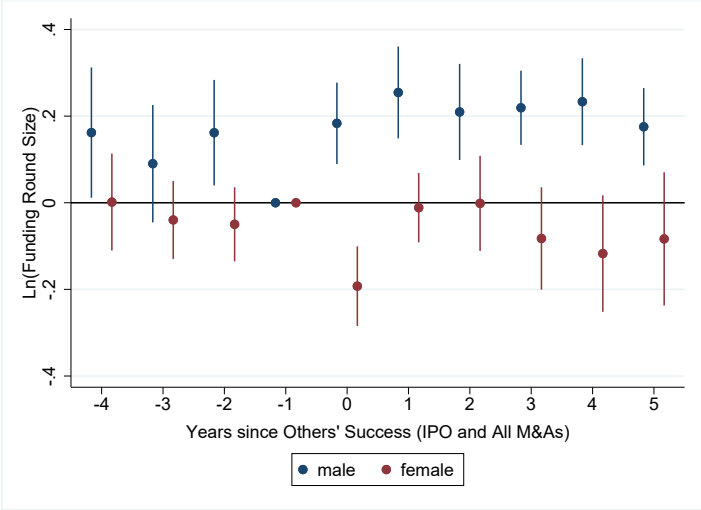
(b) Cumulative VC funding differences after success

Figure A.3: Spillover Effects to women-founded startup

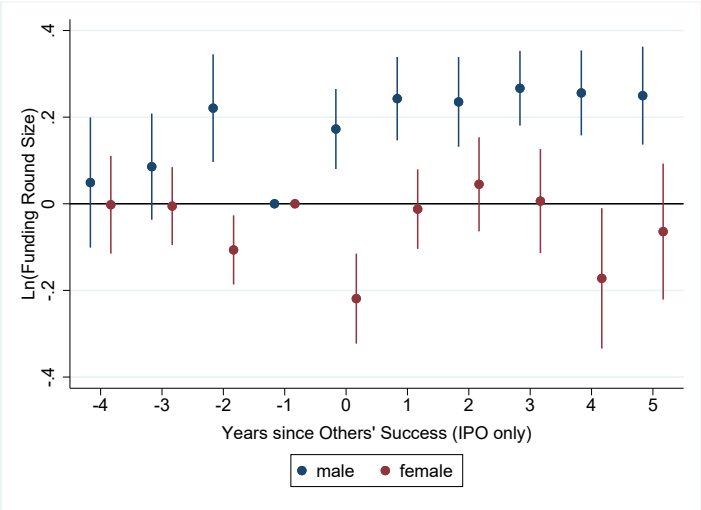
This figure shows how investors change their investments in women-founded startups following a failure (figure a) or a success (figures b, c, and d use alternative definitions of success) in their portfolios. The outcome variable is the natural logarithm of the funding amount raised by women- or men-founded startups. The blue circles are estimated from a regression using the funding amount going to men-founded startups after the failure or success of a startup founded by a man, and the red circles are estimated from a regression using the funding amount going to women-founded startups as the outcome. We estimate the following equation: $\text{Ln(Funding)}_{mnk} = \sum_{k=-4}^{6} \beta_k \text{I(Woman-founded startup)}_m * \text{I(Women-Exit)}_k + \beta' \text{Other Controls}_{mn} + \lambda_n + \delta_{WomanExit} + \delta_{ManExit} + \lambda_{ind} + \eta_{mnk}$. In figure (a), the coefficients are plotted relative to the first failure of a startup in the investor's portfolio and normalized in year $k = -1$. In figure (b), the coefficients are plotted relative to the first IPO in the investor's portfolio and normalized in year $k = -b$. We control for the success or the failure of founders of the other gender group and also include investors' fixed effects (λ_n) and year-relative to the first exit by gender group fixed effects ($\delta_{Woman-Exit}$ and $\delta_{Man-Exit}$). Standard errors are clustered at the investors level.



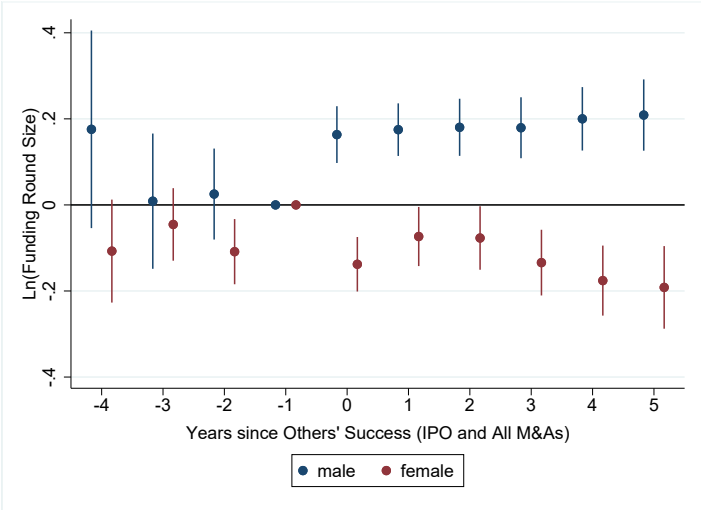
(a) After Failure



(b) After Success (IPO & Select M&As)



(c) After Success (IPO Only)



(d) After Success (IPO & All M&As)

Table A.1: **Likelihood of VC funding for a new startup following success or failure (Mixed teams only)**

This table shows results from regressions that estimate the relationship between a startup founder's gender and the likelihood that the founder raises a future round of funding for a new VC-backed startup following the current startup's failure (Panel A) or success (Panel B). The sample includes only teams that include a man and a woman cofounders. The dependent variable is *I(Invested)*, an indicator equal to one if the founder receives VC funding for a new startup within 5 years after the failure or success event. The unit of observation is a startup-founder pair. *I(Woman)* is an indicator equal to one if the founder is a woman. *I(Serial Founder)* is an indicator equal to one if the founder is already experienced, defined as founding another startup prior to the founding of the current startup. *I(CEO)* is an indicator equal to one if the founder is also listed as the current startup's CEO during any funding round. *Ln(Age)* is the natural log of the startup's age (in years) when it failed or succeeded. *Ln(Pre-Exit Funding)* is the natural log of the amount of VC funding the startup raised before it failed or succeeded. We classify a VC-backed startup as a failure if Pitchbook flags that the startup has closed or gone bankrupt within five years of its last funding round. The company is also classified as a failure (without the Pitchbook designation) if, within five years of its last funding round, all of the following conditions hold: (i) the founder left the company; (ii) the company did not raise another round of financing following the founder's departure; (iii) the company did not provide an exit via an IPO or acquisition, and (iv) the startup's website is inactive. A startup is considered a success (*Success*) if it went public in an IPO or was acquired within five years of the last funding round. We estimate all coefficients via OLS regressions with standard errors clustered by startup. $^{***}p < 0.01$ denotes significance at the 1% level, $^{**}p < 0.05$ denotes significance at the 5% level, and $^{*}p < 0.10$ denotes significance at the 10% level.

Panel A: After failure	I(Invested); Mean = 5.90%				
	(1)	(2)	(3)	(4)	(5)
I(Woman)	-2.984***	-1.720**	-1.692**	-3.003***	-1.762**
	(0.807)	(0.781)	(0.785)	(0.871)	(0.853)
I(CEO)		1.745**	1.883**		2.038**
		(0.828)	(0.831)		(1.000)
I(Serial Founder)		20.500***	20.502***		20.239***
		(3.194)	(3.201)		(3.636)
Ln(Age)		-1.249	-1.237		
		(0.974)	(0.940)		
Ln(Pre-Exit Funding)		0.530**	0.415**		
		(0.206)	(0.207)		
Observations	3748	3748	3745	2933	2933
Adjusted R^2	0.005	0.052	0.057	0.148	0.188
Year Failure FE	YES	YES	YES	YES	YES
Industry FE	NO	NO	YES	NO	NO
State FE	NO	NO	YES	NO	NO
Startup FE	NO	NO	NO	YES	YES

Panel B: After success	I(Invested); Mean = 11.58%				
	(1)	(2)	(3)	(4)	(5)
I(Woman)	-7.001***	-4.343***	-4.457***	-6.270***	-4.221***
	(1.090)	(1.040)	(1.049)	(1.195)	(1.170)
I(CEO)		5.793***	5.801***		6.056***
		(1.151)	(1.158)		(1.411)
I(Serial Founder)		26.158***	25.883***		24.844***
		(2.821)	(2.777)		(3.425)
Ln(Age)		-5.774***	-5.209***		
		(1.109)	(1.134)		
Ln(Pre-Exit Funding)		1.604***	1.357***		
		(0.295)	(0.294)		
Observations	3472	3472	3470	2803	2803
Adjusted R^2	0.025	0.111	0.116	0.156	0.216
Year Exit FE	YES	YES	YES	YES	YES
Industry FE	NO	NO	YES	NO	NO
State FE	NO	NO	YES	NO	NO
Startup FE	NO	NO	NO	YES	YES

Table A.2: **Financing the next startup: Roles Within the Team**

This table shows results from regressions that estimate the relationship between a startup founder's gender and the likelihood that the founder raises a future round of funding for a new VC-backed startup following the current startup's failure (Columns 1-2) or success (Column 3-4). The dependent variable is *I(Invested)*, an indicator equal to one if the founder receives VC funding for a new startup within 5 years after the failure or success event. The unit of observation is a startup-founder pair. *I(Woman)* is an indicator equal to one if the founder is a woman, and is interacted with several indicators for the founder's role within the team: *I(CEO)* is an indicator equal to one if the founder is also listed as the current startup's CEO during any funding round. *I(CTO)* is an indicator equal to one if the founder is the startup's Chief Technical Officer, chief scientist, or engineer, according to Pitchbook. *I(COO)* is an indicator equal to one if the founder is the startup's Chief Operating Officer or chief development officer. *I(CMO)* is an indicator equal to one if the founder is the startup's Chief Marketing Officer or product lead. *I(CFO)* is an indicator equal to one if the founder is the startup's Chief Financial Officer. We estimate all coefficients via OLS regressions with standard errors clustered by startup. $^{***}p < 0.01$ denotes significance at the 1% level, $^{**}p < 0.05$ denotes significance at the 5% level, and $^{*}p < 0.10$ denotes significance at the 10% level.

Dependent Variable:	I(Invested)			
Sample:	After Failure		After Success	
	(1)	(2)	(3)	(4)
I(Woman)	-2.300***	-1.707*	-5.091***	-5.361***
	(0.616)	(0.887)	(0.848)	(1.129)
I(CEO)	1.916***	2.466***	3.537***	4.078***
	(0.400)	(0.483)	(0.490)	(0.582)
I(Woman) X I(CEO)	-0.130	-0.397	0.684	1.023
	(0.877)	(1.169)	(1.329)	(1.669)
I(CTO)	0.018	-0.687	-2.329***	-2.587***
	(0.536)	(0.668)	(0.576)	(0.709)
I(Woman) X I(CTO)	1.050	-0.068	1.404	0.533
	(1.923)	(2.660)	(2.333)	(3.046)
I(COO)	-0.760	-0.825	-1.561*	-0.412
	(0.694)	(0.886)	(0.854)	(1.047)
I(Woman) X I(COO)	0.071	2.026	4.554**	2.273
	(1.378)	(1.886)	(2.185)	(2.708)
I(CMO)	0.767	0.669	-1.301	-1.005
	(1.037)	(1.191)	(1.032)	(1.224)
I(Woman) X I(CMO)	-2.340	-2.716	-0.563	3.619*
	(1.587)	(2.337)	(1.991)	(2.158)
I(CFO)	-3.436*	1.203	10.342**	7.061
	(2.034)	(2.058)	(5.057)	(6.099)
I(Woman) X I(CFO)	-1.031	5.634	-19.842***	-16.363
	(2.624)	(5.584)	(6.109)	(13.448)
I(Serial Founder)	19.273***	19.271***	24.714***	24.457***
	(1.088)	(1.352)	(0.944)	(1.163)
Ln(Age)	-2.585***		-6.449***	
	(0.429)		(0.482)	
Ln(Pre-Exit Funding)	0.864***		1.777***	
	(0.099)		(0.125)	
Observations	22755	18886	26016	22261
Adjusted R^2	0.064	0.212	0.103	0.254
Year Founded FE	YES	YES	YES	YES
Industry FE	YES	NO	YES	NO
State FE	YES	NO	YES	NO
Startup FE	NO	YES	NO	YES

Table A.3: **Likelihood of investment by the same investor following startup failure by founder gender**

This table examines the relationship between a startup founder's gender and the likelihood that the founder raises a future round of funding from the same investors following the startup's failure (Panel A) or success (Panel B). The unit of observation is a startup-founder pair. We present coefficients from OLS regressions and cluster standard errors by startup. The dependent variable, *I(Invested Same Investors)*, is an indicator that equals one if any investor in the current startup also backed the next startup involving the same founder in the five years following the failure or success of the current startup. *I(Woman)* is an indicator for a woman founder. *I(Serial)* is an indicator for founders who started another company before the current startup. *I(CEO)* is an indicator of whether the founder was also listed as the CEO during a funding round. *Ln(Age)* is the natural log startup's age when it failed or succeeded. *Ln(Pre-Exit Funding)* is the natural log amount of VC funding the startup raised before it failed or succeeded. We classify a startup as failed if it closes within five years of its last funding round or if a founder left the company, the company did not raise another round of funding following the founder's departure, the company did not successfully exit via an IPO or an acquisition, and the startup's website is inactive in the five years following their last funding round. A startup is successful if the startup exits via an IPO or an Acquisition within five years of their last funding round. $^{***}p < 0.01$ denotes significance at the 1% level, $^{**}p < 0.05$ denotes significance at the 5% level, and $^{*}p < 0.10$ denotes significance at the 10% level.

Panel A: After failure	I(Invested Same Investors); Mean = 1.13%				
	(1)	(2)	(3)	(4)	(5)
I(Woman)	-0.442***	-0.087	-0.152	-0.283	-0.146
	(0.167)	(0.165)	(0.168)	(0.207)	(0.207)
I(Serial Founder)		2.637***	2.604***		2.076***
		(0.476)	(0.475)		(0.508)
Ln(Age)		-1.169***	-1.224***		
		(0.199)	(0.198)		
Ln(Pre-Exit Funding)		0.478***	0.463***		
		(0.048)	(0.048)		
Observations	22386	22386	22386	18537	18537
Adjusted R^2	0.002	0.018	0.019	0.272	0.275
Year Failure FE	YES	YES	YES	YES	YES
Industry FE	NO	NO	YES	NO	NO
State FE	NO	NO	YES	NO	NO
Startup FE	NO	NO	NO	YES	YES

Panel B: After success	I(Invested Same Investors); Mean = 4.06%				
	(1)	(2)	(3)	(4)	(5)
I(Woman)	-1.996***	-1.323***	-1.428***	-1.358***	-1.012**
	(0.304)	(0.303)	(0.312)	(0.456)	(0.453)
I(Serial Founder)		4.892***	4.816***		4.171***
		(0.543)	(0.541)		(0.620)
Ln(Age)		-3.715***	-3.581***		
		(0.309)	(0.315)		
Ln(Pre-Exit Funding)		1.142***	1.049***		
		(0.079)	(0.078)		
Observations	25710	25710	25710	21920	21920
Adjusted R^2	0.013	0.038	0.040	0.265	0.269
Year Exit FE	YES	YES	YES	YES	YES
Industry FE	NO	NO	YES	NO	NO
State FE	NO	NO	YES	NO	NO
Startup FE	NO	NO	NO	YES	YES

Table A.4: **Spillovers following startup failures (All Women Founders)**

This table examines the relationship between the gender of a failed startup founder and the amount of funding the investor allocates to other women-founded startups in the years following failure. The unit of observation is an investor-deal pair. We present coefficients from OLS regressions and cluster standard errors by investors. *I(Women-Founded)* is an indicator equal to one if all founders are women. *I(Recent Failure)* is an indicator of whether the investor backed at least one startup over the previous five years that failed. *I(Failure Women)* is an indicator for whether the investor backed at least one woman-founded startup (startup with all women founders) over the previous five years that failed. *Ln(Age Startup)* is the startup's age and *Ln(Age VC)* is the age of the VC firm. *P(Investments Women)* is the proportion of investments in women over the previous five years. *P(Serial Founder)* represents the proportion of startup founders in the current deal who have launched at least one other startup prior to the current one, as recorded in Pitchbook. *Ln(Deal Size)*, the dependent variable, is the log of the deal size. $^{***}p < 0.01$ denotes significance at the 1% level, $^{**}p < 0.05$ denotes significance at the 5% level, and $^{*}p < 0.10$ denotes significance at the 10% level.

Dependent Variable:	Ln(Deal Size)			
	(1)	(2)	(3)	(4)
I(Failure Women) X I(All Women-Founded)	-0.020	-0.063	-0.113**	-0.151***
	(0.207)	(0.215)	(0.052)	(0.054)
I(All Women-Founded)	-0.865***	-0.589***	-0.436***	-0.358***
	(0.035)	(0.031)	(0.019)	(0.018)
I(Failure Women)	-0.884**	-0.710**	-0.053	-0.047
	(0.398)	(0.344)	(0.064)	(0.065)
I(Recent Failure)	-0.172**	-0.268***	0.097***	0.057***
	(0.081)	(0.063)	(0.023)	(0.022)
P(Investments Women)		-0.186***		-0.009
		(0.024)		(0.013)
Ln(Age Startup)		0.287***		0.118***
		(0.029)		(0.032)
Ln(Age VC)		1.091***		0.815***
		(0.047)		(0.017)
P(Serial Founder)		0.927***		0.507***
		(0.043)		(0.016)
Observations	179344	179344	179344	179344
Adjusted R^2	0.144	0.318	0.534	0.593
Year FE	YES	YES	YES	YES
Investor FE	NO	NO	YES	YES
State FE	YES	YES	NO	NO
Industry FE	YES	YES	YES	NO

Table A.5: **Potential spillovers following startup failures (Heterogeneity)**

This table examines the relationship between the gender of a failed startup founder and the sizes of deals for women-founded startups in the years following the failure event. The unit of observation is an investor-deal pair. The sample includes all investors in Pitchbook that experienced at least one failure between 2010 and 2022. We present coefficients from OLS regressions and cluster standard errors by investors. In Column (2), *I(Woman-founded)* equals 1 if all founders are women. In all other specifications, *I(Woman-founded)* equals 1 if at least one of the startup's founders is a woman. In Columns (3) and (4), we analyze follow-on and first-time investments separately. First-time investments are the initial funding rounds in which an investor provides capital to a startup. Follow-on investments refer to subsequent funding rounds in which the same investor continues to invest in the startup. *I(Failure Women)* is an indicator equal to one if the investor backed at least one startup that failed over the previous five years and that also had at least one woman founder. *I(Recent Failure)* is an indicator equal to one if the investor backed at least one startup over the previous five years that failed. *P(Investments Women)* is the size of deals in the VC firm's portfolio that fund startups with women founders over the previous five years, divided by the total size of all deals in which the investor participated. *Ln(Age Startup)* is the natural log of the age of the startup, and *Ln(Age VC)* is the natural log of the age of the VC firm (investor). *P(Serial Founder)* represents the proportion of startup founders in the current deal who have launched at least one other startup prior to the current one, as recorded in Pitchbook. The dependent variable is *Ln(Deal Size)*, the natural log of deal size (in millions). $^{***}p < 0.01$ denotes significance at the 1% level, $^{**}p < 0.05$ denotes significance at the 5% level, and $^{*}p < 0.10$ denotes significance at the 10% level.

Dependent Variable:	Ln(Deal Size)			
I(Women-Founded):	I(At least one)	I(All women)		
Deal:			I(Follow-on)	I(First time)
	(1)	(2)	(3)	(4)
I(Failure Women) x I(Women-Founded)	-0.091***	-0.137***	-0.022	-0.087***
	(0.021)	(0.035)	(0.036)	(0.026)
I(Women-Founded)	-0.147***	-0.326***	-0.125***	-0.147***
	(0.010)	(0.020)	(0.019)	(0.011)
I(Failure Women)	0.011	-0.005	0.008	-0.007
	(0.019)	(0.019)	(0.019)	(0.027)
I(Recent Failure)	0.049*	0.048*	0.009	0.075**
	(0.025)	(0.025)	(0.023)	(0.032)
P(Investments Women)	-0.019**	-0.016*	-0.009	-0.016*
	(0.009)	(0.009)	(0.017)	(0.009)
Ln(Age Startup)	0.116***	0.117***	0.135***	0.075**
	(0.030)	(0.030)	(0.050)	(0.033)
Ln(Age VC)	0.798***	0.801***	0.495***	0.696***
	(0.017)	(0.017)	(0.027)	(0.016)
P(Serial Founder)	0.513***	0.518***	0.314***	0.528***
	(0.015)	(0.015)	(0.025)	(0.016)
Observations	182,970	182,970	47,922	135,048
Adjusted R^2	0.597	0.597	0.489	0.611
Year FE	YES	YES	YES	YES
Investor FE	YES	YES	YES	YES

Table A.6: **Potential spillovers following startup success (Heterogeneity)**

This table examines the relationship between the gender of a successful startup founder and the amount of funding the investor allocates to other women-founded startups in the years following success. The unit of observation is an investor-deal pair. A startup is successful if the startup exits via an IPO or acquisition where the ratio of exit valuation to funding raised pre-exit is in the $90th$ percentile of all startup exits. The unit of observation is an investor-deal pair. The sample includes all investors in Pitchbook that experienced at least one success between 2010 and 2022. In Column (2), *I(Woman-founded)* equals 1 if all founders are women. In all other specifications, *I(Woman-founded)* equals 1 if at least one of the startup's founders is a woman. In Columns (3) and (4), we analyze follow-on and first-time investments separately. First-time investments are the initial funding rounds in which an investor provides capital to a startup. Follow-on investments refer to subsequent funding rounds in which the same investor continues to invest in the startup. *I(Failure Women)* is an indicator equal to one if the investor backed at least one startup that failed over the previous five years and that also had at least one woman founder. *I(Recent Failure)* is an indicator equal to one if the investor backed at least one startup over the previous five years that failed. *P(Investments Women)* is the size of deals in the VC firm's portfolio that fund startups with women founders over the previous five years, divided by the total size of all deals in which the investor participated. *Ln(Age Startup)* is the natural log of the age of the startup, and *Ln(Age VC)* is the natural log of the age of the VC firm (investor). *P(Serial Founder)* represents the proportion of startup founders in the current deal who have launched at least one other startup prior to the current one, as recorded in Pitchbook. The dependent variable is *Ln(Deal Size)*, the natural log of deal size (in millions). We present coefficients from OLS regressions and cluster standard errors by investors. $^{***}p < 0.01$ denotes significance at the 1% level, $^{**}p < 0.05$ denotes significance at the 5% level, and $^{*}p < 0.10$ denotes significance at the 10% level.

Dependent Variable:	Ln(Deal Size)			
I(Women-Founded):	I(At least one)	I(All women)		
Deal:			I(Follow-on)	I(First time)
	(1)	(2)	(3)	(4)
I(Success Women) x I(Women-Founded)	0.022	0.067	0.009	0.009
	(0.026)	(0.048)	(0.039)	(0.031)
I(Women-Founded)	-0.161***	-0.428***	-0.104***	-0.160***
	(0.011)	(0.020)	(0.018)	(0.012)
I(Success Women)	0.021	0.024	0.007	0.022
	(0.028)	(0.027)	(0.034)	(0.034)
I(Recent Success)	0.020	0.021	0.032	0.022
	(0.022)	(0.022)	(0.027)	(0.026)
P(Investments Women)	-0.013	-0.011	0.006	-0.014
	(0.011)	(0.011)	(0.016)	(0.011)
Ln(Age Startup)	0.086**	0.087**	0.124**	0.049
	(0.037)	(0.037)	(0.053)	(0.040)
Ln(Age VC)	0.801***	0.803***	0.498***	0.694***
	(0.018)	(0.018)	(0.027)	(0.018)
P(Serial Founder)	0.521***	0.524***	0.332***	0.530***
	(0.017)	(0.017)	(0.026)	(0.017)
Observations	160,350	160,350	42,090	118,260
Adjusted R^2	0.595	0.596	0.492	0.616
Year FE	YES	YES	YES	YES
Investor FE	YES	YES	YES	YES