

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

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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 only 13.3% of VC-backed founders, declining to just 4% among those who found three or more startups. We introduce a novel empirical design that exploits within-startup variation to study this gap, comparing future funding outcomes for men and women who co-founded the same startup. This approach, akin to twin studies, controls for unobservable differences in startup quality and founder ability. 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 and 24.6% less following success. Using founder LinkedIn data and pension fund supply shocks, we investigate potential demand- and supply-side drivers of these gaps. We rule out lack of interest by women in founding new firms and find no evidence of gender differences in founder quality. In fact, subsequent startups founded by women and men have higher success probabilities despite the large funding gap. The gender gaps appear driven by unequal treatment, particularly from new investors rather than existing ones. Our analysis reveals striking negative spillovers following investors' experiences with other women-founded startup failures but no positive spillovers following their successes, consistent with theories of stereotyping. These findings suggest potential efficiency gains from reducing frictions faced by experienced women founders in accessing venture capital.

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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 et al., 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, 2020](#); [Hebert, 2024](#)). These observations raise important questions about whether entrepreneurial experience shapes future venture outcomes differently for men and women.¹ Valuable experience from a previous startup should increase the likelihood of a positive outcome in subsequent ventures. At the same time, if investors interpret past failure as a negative signal about an entrepreneur’s ability, then the probability of receiving funding for a future startup might decrease with experience.

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. We introduce a new empirical design that compares future funding outcomes for men and women who are co-founders of the same startup, controlling for potential differences in the quality of businesses they found and their unobservable abilities as entrepreneurs. Our analysis reveals a large gender gap in VC-backed financing for the next startup. When we explore alternative mechanisms such as lower interest from women in launching a new startup, lower quality of women entrepreneurs, and investors’ lack of familiarity with women entrepreneurs, the evidence points to unequal treatment of women founders by investors.

Our empirical design directly addresses a fundamental challenge in understanding gender gaps in entrepreneurial financing: accounting for unobserved differences in the abilities of men and women as entrepreneurs and the resulting qualities of their startups.² By using startup fixed effects, we compare future funding outcomes between men and women co-founders of the same startup, ensuring that any identified gender gaps are not influenced by variations in the quality of the initial co-founded startup. This approach, akin to twin studies, goes beyond simply matching entrepreneurs on observable characteristics. It provides a unique opportunity to control for the inherent network differences between men and women entrepreneurs, as well as potential differences in unobserved abilities across co-founder teams. Our empirical design is, to our knowledge, new to the entrepreneurial finance literature and helps to ensure that any results are not

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

²For 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.

driven by unobservable differences in the businesses that men and women start.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 across serial entrepreneurship, failure, and success outcomes. Women founders comprise 16% of first-time VC-backed entrepreneurs. However, the representation of women declines to only 9% among those entrepreneurs who have founded two VC-backed startups and further down to 4% among those who have founded three or more VC-backed startups. Women are not only underrepresented among VC-backed entrepreneurs but also among serial entrepreneurs.

Our main empirical analysis reveals substantial gender gaps in VC-backed financing for the next startup, both generally and after a startup succeeds or fails.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 co-founders. This result is surprising, especially assuming that investors' future funding decisions are based on founders' abilities, skills, and the experience gained from launching a previous startup.

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 since recent exits (due to success or failure) are times when entrepreneurs are especially likely to attempt to raise more capital.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 co-founders who are men. Even following success, women are 26.9% less likely to found another VC-backed startup compared to their co-founders who are men (i.e., a gap that is similar to what we observe following failure).

We examine potential drivers of the funding gap results, both on the founder demand side and on the investor supply side: (1) differences in founder preferences (i.e., founder demand and desire to start another VC-backed firm), (2) differences in quality across men

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

⁴The 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 et al. \(2023\)](#) find that former VC-backed entrepreneurs re-entered the workforce without any penalty. However, [Botelho et al. \(2023\)](#) show that women get lower-ranked positions than men upon reentry.

⁵Following the literature (e.g., [Yimfor and Garfinkel \(2023\)](#); [Ewens and Farre-Mensa \(2020\)](#); [Bernstein et al. \(2016\)](#); [Hochberg et al. \(2007\)](#)), 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.

and women, and (3) potential unequal treatment of women. Unequal treatment could be due to incorrect initial priors about women entrepreneurs or due to investor preferences. We conduct tests to disentangle these potential drivers.

We begin with the founder demand channel. One possible explanation for the finding that women are less likely to receive VC in a subsequent startup is because they have less interest in pursuing entrepreneurship more generally (VC-backed or not). This could be due to risk tolerance, family, or other considerations.⁶ To test this hypothesis, we use founders' LinkedIn profiles to identify their newly launched firms that are not necessarily VC-backed. We proceed in two steps. First, we test for gender differences in the likelihood of founding a subsequent firm. Second, within the sample of entrepreneurs who launch a new firm, we test for a gender gap in obtaining VC funding. Following both failure and success of the current VC-backed startup, women are indeed less likely to start a new business compared to their male co-founders. However, conditional on founding another business (based on the LinkedIn data), they are still 30% less likely to raise VC for the next firm following failure of the current startup and 18% less likely following success. Thus, the VC funding gap cannot be explained by men's and women's propensities to start new businesses.

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 a similar amount of capital.⁷ Conditional on raising VC funding for a new startup, we find economically significant disparities between men and women co-founders, particularly following startup failure. Women founders of VC-backed startups raise 53.3% less capital than men following failure. Following success, that gap is smaller but still meaningful, at 24.6 percent. The evidence from both of the demand-side tests is inconsistent with a founder-demand side explanation for the gender gaps.

Given that our findings are not driven by the founder-demand channel, we turn to potential supply-side explanations for the funding gap in subsequent startups. Even within the stringent within-startup design, gender differences in ability could reflect investors' correct beliefs that women are worse entrepreneurs than men. If there are quality differences between men and women, we would expect suppliers of capital to respond

⁶The perception of failure and access to finance are important considerations in the choice to enter or reenter entrepreneurship (e.g., [Puri and Robinson, 2013](#); [Hvide and Panos, 2014](#)).

⁷As opposed to the average women who 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](#)).

accordingly.

We begin with an outcomes test that compares the exit outcomes of the subsequent startups that men and women launch (Becker, 1993; Hebert, 2024; Cook et al., 2022). We do not find any differences in the probability of a successful exit for the next startup, despite the fact that women raise less money for the next startup compared to men. We view the outcomes test as the ideal test for potential differences in quality. However, the test requires that founders have raised venture capital for at least two startups, exited the first one, and then raised financing and exited the second one during the sample period. This filter limits the sample size to 588, which is sufficient to conduct basic tests, but limits our ability to conduct cross-sectional tests or to make statements about whether the results extend to the overall sample. We therefore take a second, complementary approach to understanding whether quality differences between men and women explain our findings.

Our second approach to analyzing potential quality differences begins with the idea that, if the gender variable is capturing unobservable differences in quality, then the gender gap in future VC financing following failure will be particularly severe when failure is more likely to indicate low founder quality. We exploit a plausibly exogenous driver of startup 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. Moreover, they exhibit local biases in their venture capital portfolios (Hochberg and Rauh, 2013; González-Urbe, 2020), which arguably can influence the success or failure of local startups that benefit from more available capital.⁸ We use favorable supply of capital conditions to help identify failures of firms that are likely to be of particularly low quality (Ljungqvist and Wilhelm Jr, 2003; Janeway et al., 2021). In our tests, we assume that the average quality of founders whose startups fail following abundant capital supply conditions are of lower quality than those that fail following tighter capital market conditions. If startups founded by women are systematically of worse quality than those founded by men, then failed startups when capital supply conditions are favorable are more likely to be woman-founded and we would observe a larger gender gap among founders who fail following periods of robust capital supply. Conversely, we can examine successes. If the (assumed) lower-quality startups founded by women succeed because of abundant capital, we would expect the market to correct this when successful women founders raise VC for the next startup. We fail to find empirical support for either of these hypotheses. The evidence is inconsistent with the idea that women founders who fail or succeed following periods of strong capital supply are of worse quality compared to the men exposed to the same

⁸We confirm that the local supply of capital proxied by the natural log of the four-year average pension fund assets in the state in which the startup is located is positively related to follow-on rounds, successful exits, and negatively related to failures.

favorable conditions. Since quality differences are not driving the gender gaps, we turn to investor bias or stereotyping as potential mechanisms.

Current investors are a useful starting point for investigating potential supply-side drivers that are not due to founder quality. However, the data reveal that these investors are not the primary source of funding for subsequent ventures, with only 1% of investors backing the same founders following failure and only 4% following success.⁹ Moreover, for investors who continue to back the same founders after failure events, we do not find evidence of a gender gap in new startup funding. Thus, serial entrepreneurs rely mainly on new VC investors for their subsequent startups and the gender gaps that we observe following failure are driven primarily by new outside investors.

Because new investors are the main source of capital for subsequent startups, we turn to the possibility that unequal funding from this group stems from bias or stereotyping. To do so, we exploit our dynamic setting. The fact that we observe VC investors' investment portfolios over time provides a useful lens for evaluating the source of the funding gaps. [Bohren et al. \(2019\)](#) demonstrate that dynamics can help researchers identify sources of systematic differences between groups. In their framework, when initial gaps are due to incorrect beliefs, they will decrease over time. Preference-based gaps, by contrast, are predicted to persist over time. In our setting, VC-backed startups produce observable outcomes that future investors can use to evaluate founders. If initial disparities decline with similar outcomes across groups, then disparities are likely due to incorrect beliefs. Instead, if they persist with similar performance, preferences are a more likely driver of gaps. We use this intuition to motivate a set of spillover tests. Specifically, we examine the relationship between the plausibly exogenous recent experience with founders in their portfolios and the funding outcomes for unrelated founders of the same gender ([Sarsons, 2017a](#)). Without directly observing investors' decision-making processes, looking into their portfolios and analyzing their history of failures and successes is useful for isolating potential supply-side channels of the gender gap. Our analysis reveals striking negative spillovers following investors' experiences with failures by *other* unrelated women-founded startups.¹⁰ Within investors' portfolios, we find a funding gap of 14% for all startups with women founders and an additional gap of 7.8% when the investor has experienced a failure of at least one startup with a different woman founder in the last five years.

If startups led by women founders are penalized following the failure of another

⁹This is consistent with [Bengtsson \(2005\)](#) and [Gompers et al. \(2010\)](#).

¹⁰In a very different setting, [Sarsons \(2017a\)](#) presents evidence that physicians penalize women surgeons by offering fewer referrals after experiencing a negative patient outcome associated with another woman surgeon. There is no evidence of these negative spillovers to other men after a poor patient outcome of a surgery performed by a man.

woman-founded startup, do the negative spillovers turn positive following success? On the contrary, we find that women founders still receive less funding following a successful exit in an investor's portfolio of another startup with women founders. In our initial tests, we define success as an IPO or acquisition, as is common in the literature. When we narrow the definition of success to include only IPOs and any acquisitions where the ratio of exit valuation to all funding raised prior to the exit price (TVPI) exceeds the 90th percentile value.¹¹ Under this narrow definition of success, we find that investors still allocate lower amounts to their women-founded startups, this is unrelated to their previous experience with successful women founders. In other words, investors who experienced success with women-founded startups do not allocate more capital to new women-founded startups, whereas they do allocate larger amounts to men-founded startups after experiencing the success of other men's teams in the past. Taken together, our results show negative spillovers following failure of other women-founded firms but no positive spillovers following success of other firms founded by women. The asymmetric results of the spillover analysis are inconsistent with a pure Bayesian updating explanation in which investors attempt to learn about the success probabilities of women-founded startups based on the outcomes of other startups founded by women. The results are not symmetric and imply that anything less than the significant success of a startup founded by women results 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 preferences and stereotyping play meaningful roles in the gaps that we observe in the data.

This paper contributes to the literature in two 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 found are less common in the literature. Our empirical approach, in which we compare funding outcomes for men and women co-founders of the same firm, allows us to make substantial progress toward identifying true differences in outcomes for men and women. Our paper builds 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 on observable characteristics (e.g., Brush et al., 2003; Gompers and Wang, 2017; Ewens and Townsend, 2020; Raina, 2020; Hebert, 2024). Second, our paper uncovers potential mechanisms related to the supply of capital that drive the gap. Existing studies have primarily focused on factors such as investor homophily and

¹¹This approach ensures that the right tail of acquisition does not include not fire sales (e.g., Yimfor and Garfinkel, 2023).

network effects to explain disparities in VC funding (Ewens and Townsend, 2020; Howell and Nanda, 2022; Gornall and Strebulaev, 2022).¹²

Our focus on serial entrepreneurship, which is linked to startup success (e.g., Hsu, 2007; Gompers et al., 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.¹³ Overall, the results suggest that the observed gender gaps are not driven by the quality of businesses women entrepreneurs launch or their interest in serial entrepreneurship. The evidence of unequal treatment in serial entrepreneurship 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. 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 6 concludes.

2. Data and Methodology

PitchBook is the main source of data for the analysis. The sample period begins in January 2010 and extends through December 2022. We end one year prior to the end of the data (December 2023) to capture at least one year of post-event funding outcomes.¹⁴ VC deals are those deals classified in PitchBook as “Early Stage VC,” “Later Stage VC,” “Seed Round,” “Angel (individual),” and “Accelerator/Incubator.” We maintain information on the amount of funding raised for each deal, as well as the identities of the VC investors participating in each deal. Throughout the paper, we refer to a startup as a VC-backed company (i.e., a company in PitchBook).

The startup and founder-level data are also from PitchBook. For each startup, PitchBook provides information on the identities and gender of cofounders. PitchBook also provides flags to indicate startup outcomes, including whether a given company is out of business, bankrupt, acquired, or went public. We use this information to construct

¹²Ewens and Townsend (2020) find that investors who are men are less likely to target women-led firms, whereas women investors are not. Even if the presence of homophily seems to help women, Ewens and Townsend (2020) conclude on the existence of investors’ biases. Hebert (2024) is able to rule out motivations and selection into entrepreneurial strategies as explanations of the gender gap in sectors dominated by men, suggesting the existence of context-dependent stereotypes (Bordalo et al., 2016).

¹³Among the very 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. Using French administrative data, Hebert (2024) shows that serial entrepreneurs are more likely to be VC-backed. However, women who are serial founders have the same probability of being VC-backed as men who are first-timers.

¹⁴PitchBook has been recognized as the most comprehensive database for private deals, particularly in the period following 2010 (Cook et al., 2022).

the failure and success datasets. Following the literature (e.g., [Yimfor and Garfinkel \(2023\)](#); [Ewens and Farre-Mensa \(2020\)](#); [Bernstein et al. \(2016\)](#); [Hochberg et al. \(2007\)](#)), 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 additional information from PitchBook, LinkedIn, and internet searches of company websites to help identify failed startups. We classify a startup as a failure if PitchBook flags the startup as closed or bankrupt by December 2023. If there is no flag in PitchBook, 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.

2.1. 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 2 shows gender differences in serial entrepreneurship and startup success. We begin by sorting founders according to the number of VC-backed companies they have founded. We then calculate the proportion of women founders within each bin. Figure 2, Panel A shows that women account for 16% of all single VC-backed company founders, but they represent only 4% of founders of 3 or more companies. Figure 2, 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.¹⁵ 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.

¹⁵IPOs 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 et al. \(2010\)](#) 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 Figure 2, 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 treat women differently and impose a higher bar for women entrepreneurs (due to stereotypes or to discrimination).

The following analysis aims to uncover some of the mechanisms underlying this result. 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 1 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, see also Figures 1b and 1c).

[INSERT FIGURE 1 ABOUT HERE.]

In addition to analysis at the extensive margin (i.e., whether founders receive VC funding for a new startup), we examine potential gender gaps at the intensive margin, especially following failure. Figure A.1a shows that men raise substantially more funding than women, suggesting shorter runways for women-founded firms.

It is well-known that failure is ubiquitous among VC-backed startups. This observation is important, given that lack of funding and running out of cash are common reasons startups fail. Consistent with shorter runways, 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, 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 Figure A.1c) to work quickly to generate faster exits.

2.2. Summary Statistics

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.¹⁶ VC-backed startups are approximately two years old before they receive their first round of funding. In our data, they are 7.1 years old at failure and only 4 to 6 years from receiving their first round of VC funding to failure (Figure 1b).

[INSERT TABLE 1 ABOUT HERE.]

Table 1 also 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 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.

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, 6.4 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 important gender differences. Among founders who are men, 6.9 percent receive financing for a new startup within five years, compared to 3.2 percent of women founders. This difference is statistically significant.

[INSERT TABLE 2 ABOUT HERE.]

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 also shows that men and women are equally likely to serve as founder-CEOs. Still, women in the sample are considerably less likely to be serial founders than men, consistent with Figure 2.

Table 2 Panel B shows data for the subsample of failed startups.¹⁷ 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

¹⁶The 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, which 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.

¹⁷Note 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.

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. Not surprisingly, the likelihood of receiving VC funding for a new startup following success is 14.1 percent, nearly twice that following failure. However, the probability that women founders of successful startups receive VC funding for a new startup is just 7.8%, which is lower than it is for men following failure.

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.¹⁸

The data in Panel D of Table 2 are used in the spillover tests, where we examine the role of investors' experiences with the gender of founders of firms they previously funded. These data are at the venture capital investor-startup level and are further disaggregated according to the gender of the startup team. 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 deals where founder teams are all men have approximately 17% of deals in their portfolios allocated to firms founded by at least a woman ($P(\text{Investments in Women})$). Investors in 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.

¹⁸Average deal sizes are driven by very large deals in the right tail of the distribution and uncover substantial variations. 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. Also note that 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 et al., 2007).

2.3. 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:

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

The dependent variable, $I(\text{Invested})$, 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 $I(\text{Woman})$, an indicator equal to one if the founder is a woman. We include controls for founder experience in a previous startup (*Serial Founder*), the founder’s role as CEO in the current startup ($I(\text{CEO})$), total funding the current startup has raised to date ($\ln(\text{Funding Current Startup})$), and the current startup age ($\ln(\text{Age})$). We also include year, state (where the start 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 by addressing unobserved differences in the abilities of men and women as entrepreneurs and the resulting quality of their startups. This approach is akin to twin studies and goes beyond simply matching entrepreneurs on observable characteristics and 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 et al., 2020; Cullen and Perez-Truglia, 2023). Hence, as opposed to cross-sectional studies, we rely on founders’ endogenous matching to define the control group for women founders.¹⁹ 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.

¹⁹Prior research shows that teams do not form randomly (Bloom et al., 2020). In academia, men and women coauthors tend to sort on quality (Sarsons et al., 2021). Homophily seems to explain the team formation process (e.g., Boisjoly et al., 2006; Ductor et al., 2023; Gompers et al., 2022; Cullen and Perez-Truglia, 2023).

Moreover, our empirical setting allows us to control for complementarities of skills within teams, by controlling for the founders role and previous startup experience. Specifically, we add a dummy capturing the CEO role, that typically involves fundraising responsibilities within entrepreneurial teams.²⁰ We also control for serial founders in a former VC-backed company to account for pre-existing differences in access to VCs and startup experience. Note that we aim to remain parsimonious in the number of control variables we use in our analysis and only address the most obvious alternative explanations.

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. The baseline percentage of founders who do so is 6.34%. In other words, 6.34% of VC-backed startup founders will raise funding for a new startup in the next five years from the last recorded funding round of their current startup.

The results are in Table 3 and imply large differences between men and women. 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% 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.]

It is also useful to note that the estimated coefficients on the control variables shown in Columns 2 and 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.

²⁰In Appendix Tables A.2 and A.3 we add other important roles in the founding team, including CTO, COO, CMO and CFO.

The specifications in Columns 1 through 3 provide results from cross-sectional tests, in which 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. In these specifications, $I(Woman)$ is identified based on differences between men and women co-founders 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. The startup fixed effects also ensure that any results are distinct from potential investor effects (e.g., [Snellman and Solal \(2023\)](#)). 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 co-founders).

Moreover, we observe significant differences in R-squared values between the cross-sectional (columns 1–3) and within-startup specifications (columns 4–5). The R-squared values increase more than threefold, from 1–7% in the between-startup analysis to 19–21% in the within-startup analysis. This underscores the importance of controlling for startup quality through co-founder matching.²¹ These results further validate our empirical approach of comparing co-founders within the same startup.

With regard to the control variables included in these models, we observe a strong positive correlation between serving as the CEO in the current startup and the likelihood of raising VC funding for the next startup. In entrepreneurial teams, where complementary skills among co-founders often exist, CEOs are typically responsible for fundraising activities. As a result, controlling for the founder’s role in the current startup likely captures differences in access to investors within co-founder teams. In Appendix Table [A.2](#), we interact the CEO role, along with other roles, with the founder’s gender. Notably, we do not find evidence that women serving as CEOs in their current startup have a significantly higher likelihood of raising VC for their next VC-backed startup.

²¹VC financing typically exhibits low explained variation in funding decisions, as noted in prior studies (e.g., ??). For example, [Hu and Ma \(2024\)](#), who quantify positivity and personality traits using videos of entrepreneurs pitching to angel investors, report R-squared values of around 20%, which they argue represents an empirical upper bound for studies of this nature.

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.

3.2. *Financing the next startup following failure and success*

Given the strong relationship between serial entrepreneurship and future success (e.g., Gompers et al., 2010; Lafontaine and Shaw, 2016), 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.

[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 14.13% 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 84% higher following success compared to failure is expected since one would expect success to be correlated with founders' ability. This increases our confidence that we are capturing true successes, given the empirical challenge associated with observing both success and failure outcomes (Yimfor and Garfinkel, 2023).

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 between-firm results in Columns 1 through 3, the estimated coefficients imply a gender gap in the likelihood of securing funding for another startup between 29.4% and 49.8% relative to the mean. The within-firm specifications with the full set of controls in (Column 5), 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.²²

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. The between-firm estimates imply a gap between 26.7 and 42.7 percent. Within startup, the estimate in Column 5 implies a gap of 26.9 percent. 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.

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, it is possible that women founders experience entrepreneurship differently from men and have weaker desires to start another VC-backed firm. 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 the propensity to launch another startup

It is possible that women have less interest in pursuing subsequent ventures (VC-backed or not) following both failure and success. If so, the VC funding gap could reflect the lower propensity of women to launch new businesses more generally. This difference in demand could stem from risk tolerance, family, or other considerations. To examine this hypothesis that the gender gaps in subsequent VC-backed businesses that we observe are driven by differences in the propensity of women to launch new firms, 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 5, 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 5, 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. Panel A of Table 5 reveals that, following both the failure and success of the current

²²As 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.

VC-backed startup, women are indeed less likely to start a new business compared to their male co-founders. 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 co-founders. These gaps are both significant statistically but much smaller in magnitude than what we find for VC-backed businesses.

[INSERT TABLE 5 ABOUT HERE.]

To test formally whether the VC funding gap is due to women starting fewer businesses, we repeat the Table 5 Panel A analysis using only the subsample of founders who actually start new firms. Results are in Panel B of Table 5. 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 womens’ propensities to start new businesses.

Moreover, it is noteworthy that the R-squared values increase significantly from 8—9% in the cross-sectional regressions to 63—66% in the within-startup specifications. This suggests that our empirical design effectively captures and explains the majority of the variation in VC funding (see [Hu and Ma, 2024](#)).

4.1.2. *Understanding 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, it is unlikely that women would systematically demand less (or more) capital compared to men.

In Table 6, the dependent variable is the natural log of total funding raised in a new startup in the 5 years following an exit event ($\ln(\text{Funding Amount})$). 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 co-founder of the same startup to raise VC funding for the next startup).

[INSERT TABLE 6 ABOUT HERE.]

Panel A shows the analysis of VC funding for a new startup post-failure. The estimated coefficients on *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. 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. It is, therefore, useful to note that this test results in the largest estimated gender gap.

Following success, the magnitude of the gap is still significant statistically, but it is smaller. The estimated coefficient of -0.283 on $I(\text{Woman})$ 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).²³

We interpret the evidence as inconsistent with a founder-demand side explanation for the gender gap that we observe at the extensive margin. The results in Column 5 of Table 6 bolster this interpretation since one might expect co-founders to have similar aspirations and entrepreneurial interests.

Taken together, the results in Table 6 show that the demand channel is unlikely to drive our results. 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. Supply from Investors

4.2.1. Lower Quality Entrepreneurs? Comparing Observable Characteristics

To examine potential gender differences in founder and startup quality, we begin with a descriptive analysis of gender differences in observables. If founders are more similar to their co-founders in terms of observable characteristics than to other startup founders within the same industry, they are also likely to be more similar to their co-founders in terms of unobservable characteristics (Altonji et al., 2005; Oster, 2019). In Table 7, we investigate the estimated relationship between various work experience and educational background characteristics on the likelihood that a founder is a woman. We compare co-founders of the same startups and founders within the same industry. All variables are standardized so that comparisons across variables are straightforward.

²³In Appendix Figure A.2, we show results of regressions that capture the cumulative funding differences between men and women founders during each year following success and failure events. The funding gap begins immediately at Year 1, and it becomes statistically significant during the following years.

[INSERT TABLE 7 ABOUT HERE.]

The combination of coefficient shrinkage and the increase in Adjusted R^2 as one moves from the between-startup to the within-startup specifications provides further validation for our empirical design of comparing co-founders 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%. This suggests homophily among co-founders and reveals that gender differences are smaller when comparing co-founders of the same company. Similar patterns emerge across most other characteristics we consider. For instance, work experience shows a 34-fold increase in Adjusted R^2 with a 13% coefficient decline on the gender dummy. Doctoral level education (*PhD/MD*) is the only exception. Overall, our results help rule out founder quality differences as an explanation for the gender gaps we observe in serial entrepreneurship.

4.2.2. Lower Quality Startups? Comparing Startup Outcomes

Although Table 7 suggests that men and women co-founders 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 co-founders launch following success or failure of the current startup (Becker, 1993; Hebert, 2024; Cook et al., 2022). 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 outcomes are in Table 8. 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 VC-backed startup that failed. In Columns 3 and 4, we focus on IPOs only.

[INSERT TABLE 8 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 successfully exit, consistent with the idea that they have better outcomes while having access to less 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.

Finally, it is noteworthy that the R-squared values in these tests range from 43% to 55%, which is remarkable considering that success in entrepreneurial finance is notoriously difficult to predict (Gompers et al., 2010; Yimfor and Garfinkel, 2023). This result further underscores the value of our approach of comparing co-founders within the same startup.

4.2.3. Lower Quality Startups? Exogenous Contributors to Startup Outcomes

Given the 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.²⁴ Moreover, pension funds exhibit local biases in their venture capital portfolios (Hochberg and Rauh, 2013; González-Uribe, 2020).²⁵ Thus, the availability of 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 et al., 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 during favorable capital supply conditions.

We measure local capital supply conditions as $\ln(\text{Capital Supply})$, the natural log of the four-year average pension fund assets in the state in which the startup is located, and the year of the last VC deal. Before adding $\ln(\text{Capital Supply})$ as an exogenous supply shift variable, we first confirm the hypothesized relationship between local capital supply and startup outcomes. Table 9 Panel A shows that increases in local funding supply from state

²⁴According 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.

²⁵For 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.

pension funds ($\ln(\text{Capital Supply})$) 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 9 ABOUT HERE.]

In Table 9 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 $I(\text{Woman})$ 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 $I(\text{Woman})$ and $\ln(\text{Capital Supply})$. 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 ($I(\text{Woman})$) across all specifications shows that all women founders, regardless of capital supply conditions, face a funding gap.

In Table 9 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 $I(\text{Woman})$ 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 $I(\text{Woman})$ and $\ln(\text{Capital Supply})$). We fail to find any significance. The evidence suggests that women are not of worse quality than 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 differential demand from women or to differences in the quality of women founders. In the analysis that follows, we turn our attention to the investor level. We use the dynamic setting of portfolio investments over time to help us determine whether the gap is due to initial bias due to lack of familiarity with women founders - or to unequal treatment of women.

4.3. Supply-side and Potential Role of Investors

In this section, we distinguish between current investors and outside investors (i.e., those not invested in the current startup). Given the importance of networks and relationships in venture capital (Gompers et al., 2020; Howell and Nanda, 2022), 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. Outside investors, by contrast, might be more likely to rely on heuristics to evaluate unfamiliar startups and their founders.

4.3.1. Investment in New Startups by Current Investors

In Table 10, we repeat the Table 4 regressions, but we focus only on investments by current investors after a failure (Panel A) or successful exit event (Panel B).

[INSERT TABLE 10 ABOUT HERE.]

One important observation from Table 10 is that while there is some evidence of repeat investing in multiple startups with the same founder, the practice is not common (Bengtsson, 2005; Gompers et al., 2010). On average, 1.13% of founders who fail to receive future funding in new startups from the same VC investors. This value is much higher following success, but it is still relatively modest, with 4.06% of successful founders receiving funding from repeat investors for their new VC-backed startups. Following failure (Panel A), we fail to find evidence of a gender gap in new startup funding from current investors. Thus, nearly all of the gender gap that we observe following failure appears to come from outside investors. This finding suggests that the initial disparity in VC funding for experienced women-founded startups decreases over time within the subset of current investors, as they learn from their experience with individuals (Bohren et al., 2019; Cook et al., 2022). However, this is not enough to close the gender gap because current investors are not the primary sources of funding for subsequent ventures. Interestingly, Panel B of Table 10 shows a gender gap following success that is quite similar in magnitude (relative to the mean) to what we observe in Table 4. Taken together, the results suggest that women founders receive less credit for success from both current investors and outsiders (consistent with Sarsons (2017b)). However, failure penalties are more likely to come from outside. The latter can pose a particular challenge since outside investors account for a larger percentage of investors in new startups following failure relative to success. Moreover, failure is a ubiquitous feature of the entrepreneurial journey.

4.3.2. Investment in new Startups by Outside Investors

New investors are the main source of capital for subsequent VC-backed businesses. We therefore turn to the question of whether unequal funding from this group stems from stereotyping (based on investors' preferences or incorrect beliefs about women founders). These are natural questions to ask in light of the findings in the prior tables that the gaps exist between same-startup founders and that neither differences in quality nor founder demand appear to be driving them.

Without observing the decision-making processes of investors directly, bias and stereotyping are difficult to identify empirically. However, spillovers in a dynamic

investment setting can help distinguish effects due to potentially incorrect initial beliefs (bias and stereotyping) from gender gaps due to investor preferences. [Bohren et al. \(2019\)](#) demonstrate that dynamics can help researchers identify sources of systematic differences between groups. In their framework, when initial gaps are due to incorrect beliefs, they will decrease over time. Preference-based gaps, by contrast, are predicted to persist over time.

VC-backed startups produce observable outcomes that future investors can use to evaluate founders. If initial disparities (i.e., the direct $I(Women)$ effect) decline with similar outcomes across groups, then disparities are likely due to incorrect beliefs. If, instead, they persist with similar performance, then preferences are a more likely driver of gaps. The startup fixed effects in Column 5 of the main regressions, where we compare men and women co-founders of the same firm, help control for unobservable differences in the types of startups that women found; however, we can use funding outcomes over time to learn more about the underlying mechanisms. Our empirical strategy is simple: We examine the relationship between the plausibly exogenous recent experience with unrelated founders and the funding outcomes for unrelated founders of the same gender.²⁶

4.3.2.1 *Portfolio Spillovers Following Failure*

In this section, we conduct analyses at the investor-deal level to examine a potentially important channel through which a gap in funding from outside investors could occur: spillovers. Specifically, we test whether the failure of a portfolio company founded by a woman spills over into the funding outcomes for other, unrelated women founders. We interpret spillovers due to the (arguably exogenous) investor experiences of this type as evidence of bias due to stereotyping, rather than investor preferences, which would be insensitive to new information or experiences, [Bohren et al. \(2019\)](#).

Analogous to the tests in Table 6, the dependent variable in the spillover regressions 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. Because we do not observe all women-founded teams that *could* have received funding but did not, any tests at the extensive margin would be difficult to interpret.

²⁶The results in Tables 8 and 9 help to rule out quality differences as a primary driver of our findings, but even if quality were one driver of the results, bias or stereotyping can result in further unequal treatment [Bordalo et al. \(2016\)](#).

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 $\ln(\text{Deal Size})$, the natural log of the deal size (in millions).²⁷ Given that the regressions are at the investor-deal (rather than founder-deal level, as in Tables 3 through 10), the gender variables are modified to capture the gender of a given startup's founding team. $I(\text{Women-Founded})$ is an indicator equal to one if at least one member of the founding team of the current investment is a woman. $I(\text{Recent Failure})$ is an indicator equal to one if the investor backed at least one startup over the previous five years that failed. $I(\text{Failure Women})$ 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 $I(\text{Women-Founded}) \times I(\text{Failure Women})$, 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. 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. $P(\text{Investments Women})$ 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. $P(\text{Serial Investments})$ is the number of serial founders in the investor's portfolio, divided by the total number of founders in the portfolio. Other controls include startup age, VC firm age, and the proportion of serial founders in the investor's portfolio. We also include time, industry, and state-fixed effects.²⁸

[INSERT TABLE 11 ABOUT HERE.]

²⁷We do not observe an individual investor's allocations in a given deal. Thus, an underlying assumption of 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.

²⁸In Appendix Tables A.7 and A.8, we conduct spillover tests using difference-in-differences estimators, where the post-period corresponds to the first failure an investor experiences within their portfolio. However, a limitation of this specification is that investors may encounter multiple failures successively, potentially confounding the post-treatment period.

Across all specifications, the results in Table 11 imply that, following the experience of a failure of a startup with a woman founder, the investor participates in smaller subsequent deals with women founders are smaller. The estimated coefficients on the $I(\text{Women-Founded}) \times I(\text{Failure Women})$ 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, which we consider to be the most powerful test, the estimated coefficients of -0.147 on *Women-Founded* and -0.091 on the interaction of $I(\text{Women-Founded})$ with $I(\text{Failure Women})$ imply a funding gap of 14.0 percent $((1-\exp(-0.147)) \times 100)$ for all startups with women founders and an additional gap of 8.7 percent $((1-\exp(-0.091)) \times 100)$ 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 stereotyping, 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 Appendix Table ??, we repeat the Table 11 analysis, but we change the definition of a *Women Founded* startup to include only those firms with all-women founders. The results in Table ?? are striking in that the estimated magnitudes on the $I(\text{Women-Founded}) \times I(\text{Failure Women})$ interaction in Columns 3 and 4 are twice those in the Table 11 regressions, implying much greater spillovers for startups with all-women founders.²⁹ 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.

²⁹Focusing on the Column 4 specification in Appendix Table ??, the estimated coefficients of -0.358 on *Women-Founded* and -0.151 on the interaction of $I(\text{Women-Founded})$ with $I(\text{Failure Women})$ imply a funding gap of 29.6 percent for all startups with all-women founders, and an additional gap of 14.0 percent when the investor has experienced a failure of at least one startup with all-women founders in the last five years. The estimated coefficients on the interactions are insignificant in the specifications in Columns 1 through 3 of Tables 11 and ??, but these specifications capture cross-sectional differences across investors (they do not include investor fixed effects, which we consider to be our most stringent test). The evidence suggests that spillover effects are driven by the experience of failure associated with women-founded firms in which a given investor actually invested rather than by failures experienced by other investors.

4.3.2.2 Potential Portfolio Spillovers Following Success

If startups led by women founders are penalized following the failure of another woman-founded startup, do the negative spillovers turn positive 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 analysis, but we replace the failure variables with success indicators. As before, $I(\text{Women-Founded})$ is an indicator equal to one if at least one member of the founder team is a woman. $I(\text{Recent Success})$ 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. $I(\text{Success Women})$ 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 $I(\text{Women-Founded}) \times I(\text{Success Women})$, 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. Somewhat surprisingly, we still find evidence of negative spillovers across all specifications. 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. 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 90th 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 results of the spillover analyses are inconsistent with a rational belief-based explanation in which investors attempt to learn about the success probabilities of

women-founded startups based on the outcomes of other startups founded by women. Instead, anything less than the significant success of a startup 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 preferences and stereotyping play a role in the gaps that we observe in the data.³⁰

5. Rationalizing our finding

5.1. 1. Model Setup

5.1.1. Agent's Objective Function

Individuals maximize utility when deciding whether to enter or reenter entrepreneurship. The objective functions for entry and reentry are as follows:

Entry:

$$U_i^{\text{entry}} = zx_i - (\eta_i u_g^{\text{entry}} + C_g), \quad (2)$$

where:

- z : Productivity multiplier (common across genders at entry).
- $x_i \sim \text{LogN}(\mu_g, \sigma^2)$: Entrepreneurial ability drawn from a gender-specific distribution.
- μ_g : Mean entrepreneurial ability perceived by investors.
- u_g^{entry} : Gender-specific disutility of participation in entrepreneurship (e.g., lack of affordable childcare, investor funding discrimination, societal skepticism, and isolation in male-dominated ecosystems).
- C_g : Fixed costs of entry and reentry (assumed constant across stages).
- $\eta_i \sim U[0, 1]$: Idiosyncratic personal costs.

³⁰Appendix 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 funding to 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. Appendix Tables A.7 and A.8 formalize the dynamics in the figures using a difference-in-differences specification where the dependent variable is the natural log of funding raised and the key explanatory variable is the interaction of founder gender with same-gender success or failure. Results are consistent with the spillover tests in the main tables.

Reentry:

$$U_i^{\text{reentry}} = z_{\text{reentry}}x_i - (\eta_i u_g^{\text{reentry}} + C_g), \quad (3)$$

where:

- z_{reentry} : Productivity multiplier at reentry, common across genders.
- u_g^{reentry} : Gender-specific disutility of participation in reentry.
- C_g : Fixed costs of entry and reentry (same as in entry).

5.1.2. Proposition 1: Entry Decision Rule

An individual enters entrepreneurship if the utility derived from entrepreneurial activity exceeds their costs.

Decision Rule: Entry occurs if:

$$zx_i > \eta_i u_g^{\text{entry}} + C_g. \quad (4)$$

The probability of entry for gender g is given by:

$$P(\text{entry} \mid g) = \int \int_{zx_i > \eta_i u_g^{\text{entry}} + C_g} f(x_i \mid \mu_g, \sigma^2) f(\eta_i) dx_i d\eta_i. \quad (5)$$

5.1.3. Proposition 2: Reentry Decision Rule

After an initial venture, individuals reenter if their expected utility exceeds the costs of reentry:

Decision Rule: Reentry occurs if:

$$z_{\text{reentry}}x_i > \eta_i u_g^{\text{reentry}} + C_g. \quad (6)$$

The probability of reentry for gender g is:

$$P(\text{reentry} \mid g) = \int \int_{z_{\text{reentry}}x_i > \eta_i u_g^{\text{reentry}} + C_g} f(x_i \mid \mu_g, \sigma^2) f(\eta_i) dx_i d\eta_i. \quad (7)$$

5.1.4. Proposition 3: Feedback Loop Through Reentry Gap

Investor spillovers link reentry outcomes to perceived ability. Let:

$$\mu_f = \bar{\mu}_f - \psi \cdot \Delta_{\text{reentry}}, \quad (8)$$

where:

- $\bar{\mu}_f$: Baseline perceived ability for women.
- ψ : Sensitivity of perceived ability to the reentry gap.

- $\Delta_{\text{reentry}} = P_m^{\text{reentry}} - P_f^{\text{reentry}}$: Reentry gap.

This feedback loop reduces μ_f , lowering women's reentry rates and amplifying spillovers, which perpetuates reentry gaps.

5.2. 2. Calibration and Counterfactuals

5.2.1. Step 1: Entry Calibration

Entry calibration estimates parameters μ_g (mean entrepreneurial ability), C_g (fixed costs), and u_g^{entry} (disutility) by minimizing the difference between observed and model-predicted entry rates.

Calibration Procedure:

1. ** Parameters for Calibration:**

- $\theta = \{\mu_g, C_g, u_g^{\text{entry}}\}$: Parameters to be estimated.
- z (productivity multiplier) and σ^2 (variance of ability) are assumed known.

2. **Distance Function:** The distance function measures the difference between observed entry rates ($P_{\text{obs}}^{\text{entry},g}$) and model-predicted entry rates ($P(\text{entry} | g; \theta)$):

$$\text{Distance}(\theta) = \sum_g \left[P_{\text{obs}}^{\text{entry},g} - P(\text{entry} | g; \theta) \right]^2. \quad (9)$$

3. **Optimization:** Solve for $\hat{\theta}$ by minimizing the distance function:

$$\hat{\theta} = \arg \min_{\theta} \text{Distance}(\theta), \quad (10)$$

where:

$$P(\text{entry} | g; \theta) = \int \int_{zx_i > \eta_i u_g^{\text{entry}} + C_g} f(x_i | \mu_g, \sigma^2) f(\eta_i) dx_i d\eta_i. \quad (11)$$

4. **Numerical Integration:** Use numerical methods (e.g., Monte Carlo simulation or quadrature) to evaluate the double integral for $P(\text{entry} | g)$.

5. **Iterate Until Convergence:** Adjust θ iteratively using optimization algorithms (e.g., Nelder-Mead or gradient descent) until the distance function is minimized.

5.2.2. Step 2: Reentry Calibration

Use observed reentry rates ($P_m^{\text{reentry}}, P_f^{\text{reentry}}$) and z_{reentry} to solve for u_g^{reentry} :

$$\text{Error} = \sum_g (P(\text{reentry} | g) - \text{Observed reentry rate for } g)^2. \quad (12)$$

5.2.3. Step 3: Feedback Estimation

Estimate ψ by linking Δ_{reentry} to μ_f and calibrating reentry rates:

$$P(\text{reentry} | f) \propto \mu_f = \bar{\mu}_f - \psi \cdot \Delta_{\text{reentry}}. \quad (13)$$

5.2.4. Counterfactuals

Scenario 1: Equalize Reentry Costs

$$C_f = C_m. \quad (14)$$

Simulate increased reentry rates for women and the impact on aggregate welfare.

Scenario 2: Mitigate Spillovers

$$\psi \rightarrow 0. \quad (15)$$

Simulate reduced spillover effects, improving μ_f and closing reentry gaps.

Scenario 3: Equalize Perceived Ability

$$\mu_f = \mu_m. \quad (16)$$

Simulate equalized reentry rates and evaluate welfare gains.

5.3. 3. Welfare Analysis

Define aggregate welfare as the total productivity from entry and reentry:

$$W = \int \int_{zx_i > \eta_i u_g + C_g} zx_i f(x_i) f(\eta_i) dx_i d\eta_i + \int \int_{z_{\text{reentry}} x_i > \eta_i u_g^{\text{reentry}} + C_g} z_{\text{reentry}} x_i f(x_i) f(\eta_i) dx_i d\eta_i. \quad (17)$$

Simulate welfare gains under counterfactual scenarios to assess the impact of reduced spillovers, equalized costs, and improved perceived ability.

6. Conclusion

Repeat chances are an important ingredient for entrepreneurial success (e.g., [Lafontaine and Shaw \(2016\)](#), [Gompers et al. \(2010\)](#)). Founders gain valuable experience from their prior startups (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 founder preferences or quality differences between men and women. 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.

Figure 1: Single and Mixed Gender Teams

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

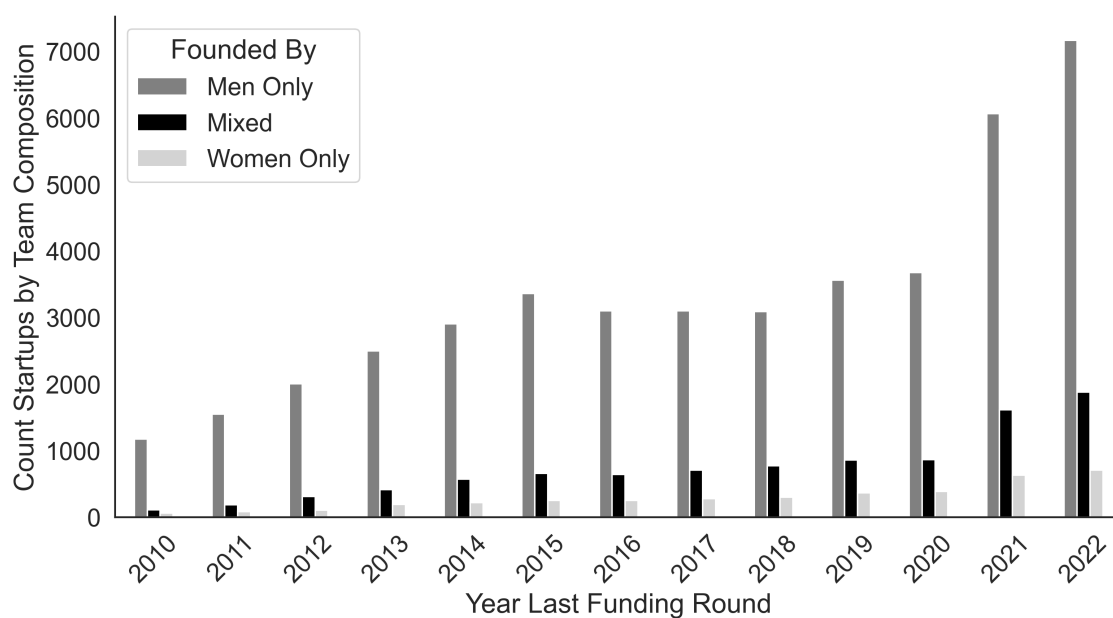
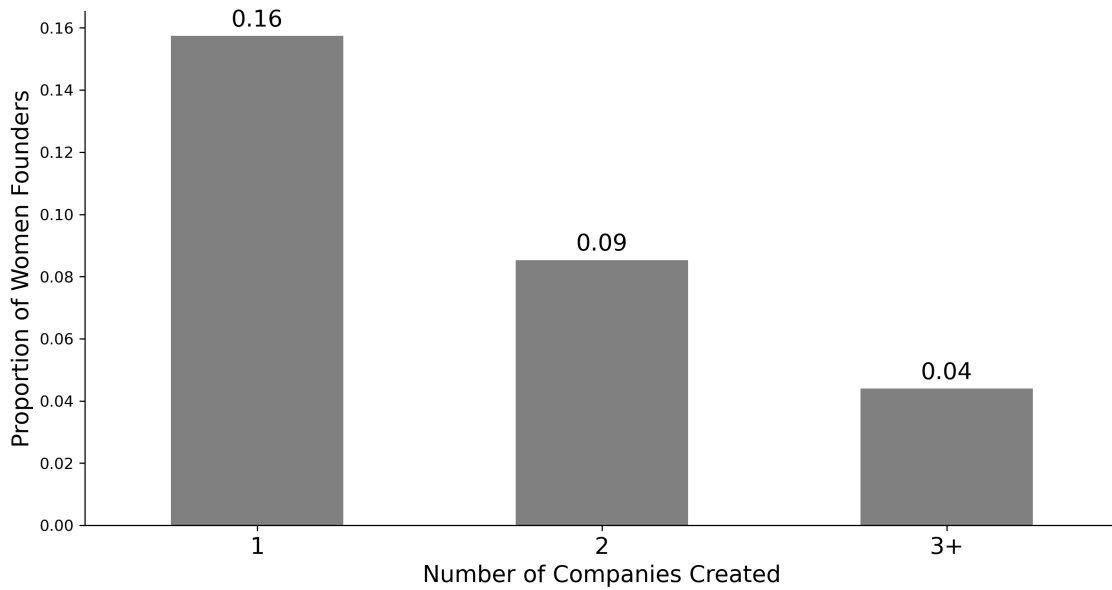
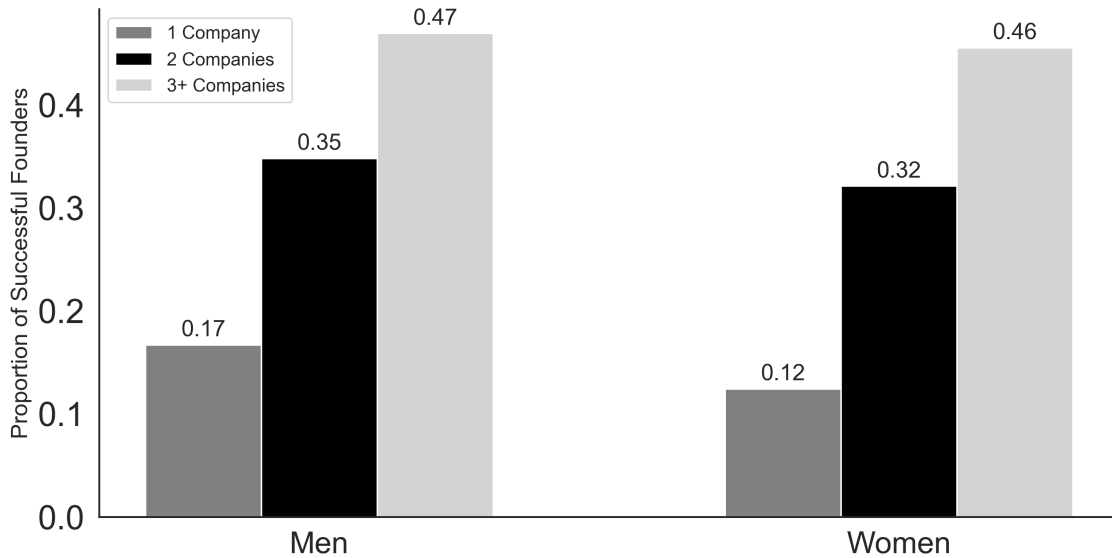


Figure 2: Serial Entrepreneurship by Gender

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

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 the investor-startup 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)* is the size of deals in the VC firm's portfolio over the previous five years that fund startups with women founders. 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	122716	106330			16386			122716
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	22386	19470			2916			22386
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	25710	23340			2370			25710

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	183042	139320			34562			9160			183042

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 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*** (0.157)	-1.619*** (0.155)	-1.784*** (0.158)	-2.926*** (0.243)	-1.891*** (0.239)
I(Serial Founder)		14.110*** (0.349)	13.953*** (0.347)		13.443*** (0.423)
I(CEO)		-0.326** (0.131)	-0.224* (0.131)		0.050 (0.148)
Ln(Funding Current Startup)		1.028*** (0.039)	0.902*** (0.040)		
Ln(Startup Age)		-0.783*** (0.110)	-0.699*** (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*** (0.416)	-2.254*** (0.410)	-2.394*** (0.417)	-3.031*** (0.653)	-1.724*** (0.634)
I(Serial Founder)		18.316*** (1.047)	18.078*** (1.043)		18.235*** (1.303)
I(CEO)		1.630*** (0.338)	1.727*** (0.338)		2.135*** (0.401)
Ln(Startup Age)		-2.383*** (0.415)	-2.326*** (0.416)		
Ln(Pre-Exit Funding)		1.038*** (0.094)	0.887*** (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*** (0.600)	-3.778*** (0.591)	-4.177*** (0.601)	-6.140*** (0.879)	-3.808*** (0.849)
I(Serial Founder)		24.259*** (0.938)	24.023*** (0.932)		24.392*** (1.149)
I(CEO)		3.747*** (0.416)	3.906*** (0.415)		4.312*** (0.483)
Ln(Age)		-6.069*** (0.466)	-5.713*** (0.475)		
Ln(Pre-Exit Funding)		1.845*** (0.121)	1.631*** (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: 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 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*** (0.944)	-2.490** (1.136)	-4.873*** (1.060)	-3.216*** (1.199)
I(Serial Founder LinkedIn)	26.776*** (0.765)	21.363*** (0.878)	28.881*** (0.709)	23.394*** (0.824)
I(CEO)	9.649*** (0.691)	7.131*** (0.636)	10.634*** (0.659)	8.465*** (0.641)
Ln(Startup Age)	-8.446*** (0.791)		-10.891*** (0.745)	
Ln(Pre-Exit Funding)	1.411*** (0.178)		1.714*** (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*** (3.420)	-11.287** (5.275)	-10.715*** (3.500)	-9.600** (4.421)
I(Serial Founder LinkedIn)	9.460*** (2.546)	4.061 (3.551)	15.702*** (1.912)	14.155*** (2.681)
I(CEO)	0.825 (2.210)	2.073 (2.376)	2.863* (1.734)	5.188*** (1.886)
Ln(Startup Age)	-5.139* (3.078)		-8.851*** (2.195)	
Ln(Pre-Exit Funding)	2.867*** (0.628)		4.257*** (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 6: 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 next startup following the failure or success of the current startup. The unit of observation is a startup-founder pair. The dependent variable, $\ln(\text{Funding Raised})$, 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. $I(\text{Woman})$ an indicator equal to one if the founder is a woman. $I(\text{Serial})$ is an indicator for founders who started another company before the current startup. $I(\text{CEO})$ is an indicator of whether the founder was also listed as the CEO during a funding round. $\ln(\text{Age})$ is the startup's age when it failed or succeeded. $\ln(\text{Pre-Exit Funding})$ is the 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*** (0.209)	-0.471** (0.200)	-0.526*** (0.199)	-0.840** (0.357)	-0.759** (0.368)
I(Serial Founder)		0.358*** (0.116)	0.361*** (0.116)		0.637** (0.300)
I(CEO)		-0.166* (0.096)	-0.134 (0.097)		0.064 (0.147)
Ln(Startup Age)		-0.197* (0.119)	-0.216* (0.121)		
Ln(Pre-Exit Funding)		0.242*** (0.028)	0.210*** (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*** (0.151)	-0.395*** (0.139)	-0.479*** (0.140)	-0.348*** (0.131)	-0.283** (0.129)
I(Serial Founder)		0.509*** (0.075)	0.470*** (0.073)		0.450*** (0.135)
I(CEO)		-0.192*** (0.058)	-0.143** (0.057)		0.118 (0.073)
Ln(Startup Age)		-0.463*** (0.076)	-0.387*** (0.076)		
Ln(Pre-Exit Funding)		0.372*** (0.021)	0.311*** (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 7: 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)		Years Work Experience		I(Past Startup Founder/Executive)		I(PhD/MD)		I(MBA/JD)		I(Elite School)	
Mean	40.62%		13.11		92.13%		12.64%		17.08%		27.46%	
	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 8: 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 $I(\text{All IPOs \& M\&As})$, 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. $I(\text{Woman})$ is an indicator equal to one if the founder is a woman. $I(\text{Serial Founder})$ 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. $I(\text{CEO})$ is an indicator equal to one if the founder is also listed as the current startup's CEO during any funding round. $\ln(\text{Pre-Exit Funding})$ is the 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 (0.082)	0.124* (0.069)	0.152** (0.076)	0.156** (0.072)
I(CEO)	0.087** (0.035)	0.065* (0.033)	0.009 (0.019)	-0.004 (0.017)
I(Serial Founder)	0.042 (0.063)	0.051 (0.052)	0.060 (0.046)	0.066 (0.042)
Ln(Pre-Exit Funding)		0.103*** (0.017)		0.064*** (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 9: Likelihood of VC funding for a new startup following abundant supply of capital

This table examines the effects of the 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, $\ln(\text{Funding Supply})$, as is the 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. $I(\text{Follow-on})$ is an indicator of whether the current startup raised a new round of funding in the five years following the current funding round. $I(\text{Failure})$ and $I(\text{Success})$ 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. $I(\text{Woman})$ is an indicator equal to one if the founder is a woman. $I(\text{Serial})$ is an indicator for founders who started another company before the current startup. $I(\text{CEO})$ is an indicator of whether the founder was also listed as the CEO during a funding round. $\ln(\text{Startup Age})$ is the startup's age when it failed or succeeded. $\ln(\text{Pre-Exit Funding})$ is the log amount of VC funding the startup raised before it failed or succeeded. We calculate $\ln(\text{Funding Supply})$ 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)
$\ln(\text{Funding Supply})$		0.837** (0.369)	-1.263*** (0.375)	0.319*** (0.089)	1.350*** (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 $\ln(\text{Funding Supply})$		-0.519 (0.389)	-0.358 (0.385)	-0.318 (0.391)	-0.023 (0.597)	0.108 (0.588)
I(Woman)		-3.870*** (0.414)	-2.283*** (0.409)	-2.372*** (0.414)	-3.087*** (0.645)	-1.795*** (0.627)
$\ln(\text{Funding Supply})$		1.443*** (0.205)	0.810*** (0.199)	1.809 (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 $\ln(\text{Funding Supply})$		-0.346 (0.510)	0.008 (0.516)	0.013 (0.514)	-0.244 (0.777)	-0.045 (0.742)
I(Woman)		-6.064*** (0.604)	-3.739*** (0.597)	-4.121*** (0.608)	-6.225*** (0.879)	-3.896*** (0.849)
$\ln(\text{Funding Supply})$		1.790*** (0.244)	0.563** (0.237)	-1.069 (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 10: 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, $I(\text{Invested Same Investors})$, 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. $I(\text{Woman})$ is an indicator for a woman founder. $I(\text{Serial})$ is an indicator for founders who started another company before the current startup. $I(\text{CEO})$ is an indicator of whether the founder was also listed as the CEO during a funding round. $\ln(\text{Age})$ is the startup's age when it failed or succeeded. $\ln(\text{Pre-Exit Funding})$ is the 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*** (0.167)	-0.087 (0.165)	-0.152 (0.168)	-0.283 (0.207)	-0.146 (0.207)
I(Serial Founder)		2.637*** (0.476)	2.604*** (0.475)		2.076*** (0.508)
Ln(Age)		-1.169*** (0.199)	-1.224*** (0.198)		
Ln(Pre-Exit Funding)		0.478*** (0.048)	0.463*** (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*** (0.304)	-1.323*** (0.303)	-1.428*** (0.312)	-1.358*** (0.456)	-1.012** (0.453)
I(Serial Founder)		4.892*** (0.543)	4.816*** (0.541)		4.171*** (0.620)
Ln(Age)		-3.715*** (0.309)	-3.581*** (0.315)		
Ln(Pre-Exit Funding)		1.142*** (0.079)	1.049*** (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 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. $I(\text{Women-Founded})$ is an indicator equal to one if at least one member of the founding team is a woman. $I(\text{Recent Failure})$ is an indicator equal to one if the investor backed at least one startup over the previous five years that failed. $I(\text{Failure Women})$ 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. $\ln(\text{Age Startup})$ is the natural log of the age of the startup, and $\ln(\text{Age VC})$ is the natural log of the age of the VC firm (investor). $P(\text{Investments Women})$ 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. $P(\text{Serial Investments})$ is the number of serial founders in the investor's portfolio divided by the total number of founders in the portfolio. The dependent variable is $\ln(\text{Deal Size})$, 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)
$I(\text{Failure Women}) \times I(\text{Women-Founded})$	-0.163** (0.077)	-0.179** (0.072)	-0.074*** (0.022)	-0.091*** (0.021)
$I(\text{Women-Founded})$	-0.527*** (0.018)	-0.287*** (0.015)	-0.228*** (0.011)	-0.147*** (0.010)
$I(\text{Failure Women})$	-0.680*** (0.211)	-0.513*** (0.176)	0.027 (0.020)	0.011 (0.019)
$I(\text{Recent Failure})$	0.260*** (0.048)	-0.056 (0.039)	0.098*** (0.025)	0.049* (0.025)
$P(\text{Investments Women})$		-0.180*** (0.025)		-0.019** (0.009)
$\ln(\text{Age Startup})$		0.282*** (0.031)		0.116*** (0.030)
$\ln(\text{Age VC})$		1.083*** (0.052)		0.798*** (0.017)
[1em] $P(\text{Serial Founder})$		0.947*** (0.049)		0.513*** (0.015)
Observations	182,970	182,970	182,970	182,970
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 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. 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. $I(\text{Women-Founded})$ is an indicator equal to one if at least one member of the founding team is a woman. $I(\text{Recent Success})$ 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). $I(\text{Success Women})$ is an indicator of whether the investor backed at least one startup with a at least woman founder that was successful in the last five years. $\ln(\text{Age Startup})$ is the startup and $\ln(\text{Age VC})$ is the age of the VC firm. $P(\text{Investments Women})$ is the proportion of investments in women over the previous five years. $P(\text{Serial Investments})$ is the number of serial founders in the investor's portfolio, divided by the total number of founders in the portfolio. $\ln(\text{Deal Size})$ is the 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)
$I(\text{Success Women}) \times I(\text{Women-Founded})$	-0.107 (0.068)	-0.112* (0.064)	-0.043** (0.020)	-0.052*** (0.019)
$I(\text{Women-Founded})$	-0.483*** (0.018)	-0.287*** (0.015)	-0.214*** (0.011)	-0.146*** (0.010)
$I(\text{Success Women})$	-0.335* (0.176)	-0.216 (0.145)	0.014 (0.019)	0.019 (0.017)
$I(\text{Recent Success})$	0.479*** (0.042)	0.201*** (0.039)	0.089*** (0.022)	0.026 (0.020)
$P(\text{Investments Women})$		-0.172*** (0.025)		-0.014 (0.012)
$\ln(\text{Age Startup})$		0.119*** (0.030)		0.090*** (0.034)
$\ln(\text{Age VC})$		1.124*** (0.057)		0.787*** (0.016)
$P(\text{Serial Founder})$		0.977*** (0.057)		0.526*** (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)
$I(\text{Success Women}) \times I(\text{Women-Founded})$	0.040 (0.063)	0.043 (0.058)	0.004 (0.025)	0.022 (0.026)
$I(\text{Women-Founded})$	-0.518*** (0.045)	-0.316*** (0.030)	-0.235*** (0.012)	-0.161*** (0.011)
$I(\text{Success Women})$	0.050 (0.118)	0.093 (0.095)	0.002 (0.030)	0.021 (0.028)
$I(\text{Recent Success})$	0.277* (0.159)	0.107 (0.133)	0.050** (0.022)	0.020 (0.022)
$P(\text{Investments Women})$		-0.142*** (0.032)		-0.013 (0.011)
$\ln(\text{Age Startup})$		0.114*** (0.030)		0.086** (0.037)
$\ln(\text{Age VC})$		1.156*** (0.086)		0.801*** (0.018)
$P(\text{Serial Founder})$		0.920*** (0.083)		0.521*** (0.017)
Observations	160,350	160,350	160,350	160,350
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

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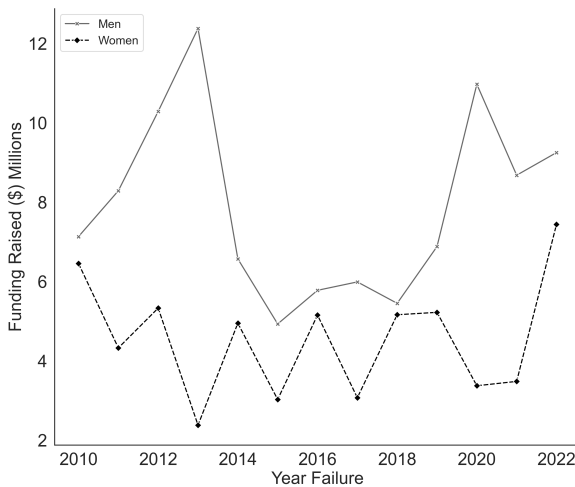
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Supplementary Material

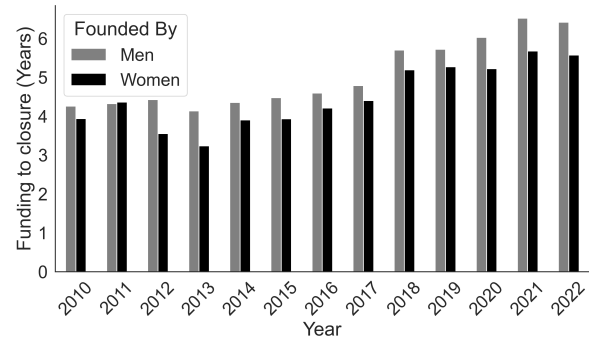
Appendix A. Supplementary Figures and Tables

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

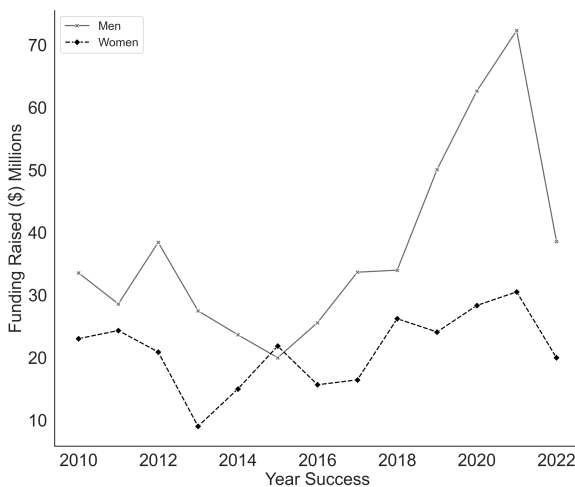
The figures show the amount of VC funding raised and the time from the first funding round to failure and success events for the sample of VC-backed startups, by founder gender. The unit of observation is a startup-founder. The sample includes founders of all VC-backed startups that failed (figures a 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.



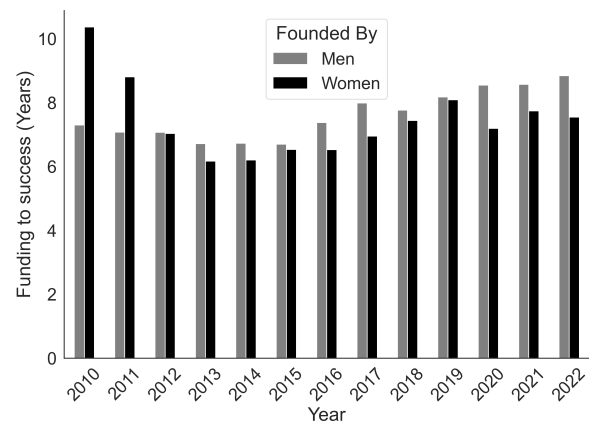
(a) VC Funding Raised before Failure



(b) Time between first VC funding round and failure



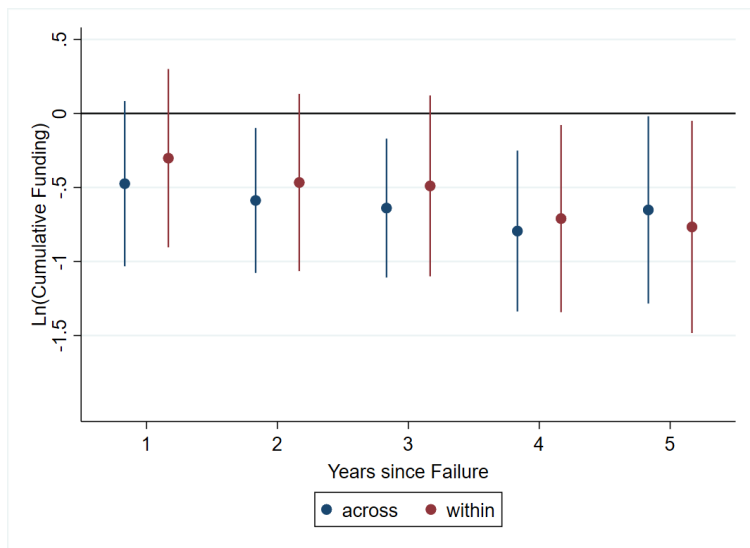
(c) VC Funding Raised before Success



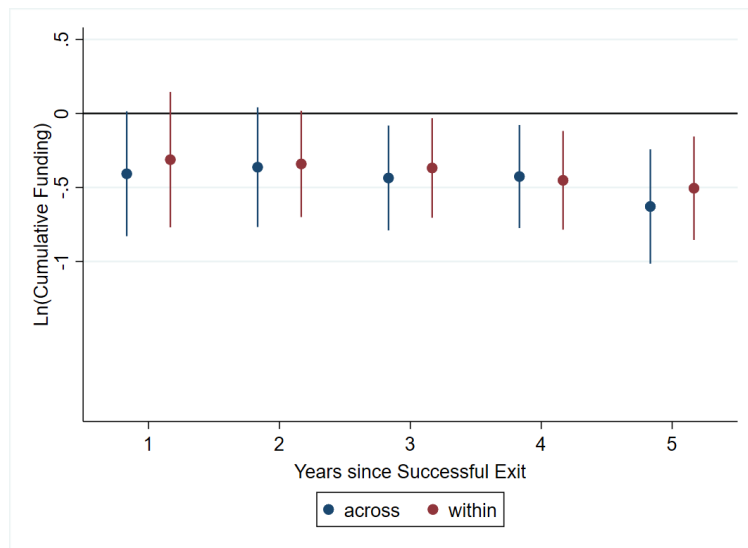
(d) Time between first VC funding round and success

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: $\text{Ln}(\text{Cumulative Funding})_{ijk} = \sum_{k=1}^5 \beta_k I(\text{Woman})_i + \beta' \text{Other Controls}_{ij} + \lambda_j + \lambda_{ind} + \lambda_k + \eta_{ijk}$. 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.



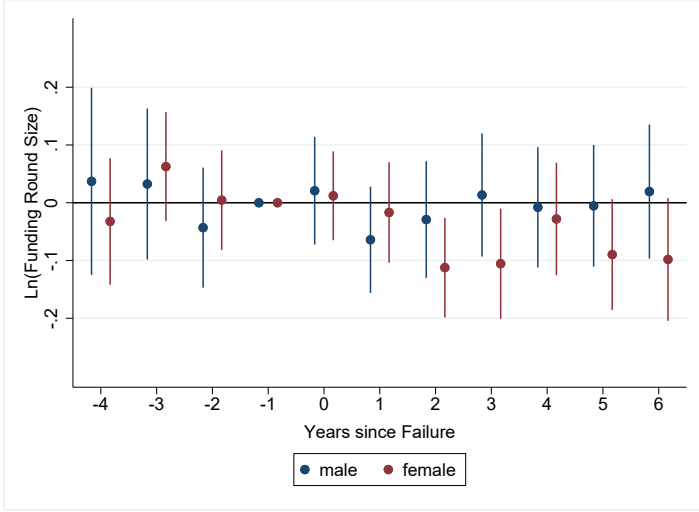
(a) Cumulative VC Funding differences after failure



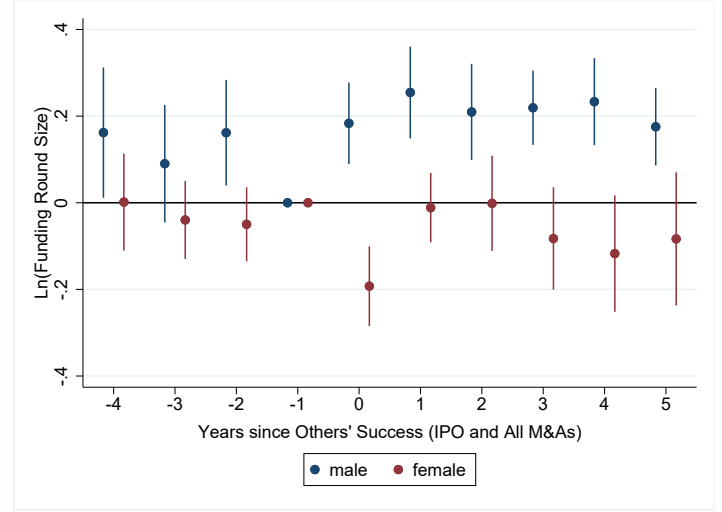
(b) Cumulative VC funding differences after success

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

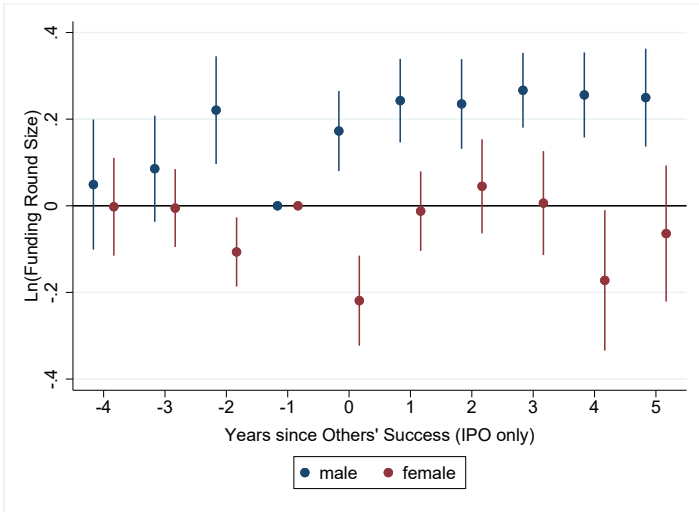
This figure shows how investors change their investments in women-founded startups following a failure (figure a) or a success (figures b, c, and d use alternative definitions of success) in their portfolios. The outcome variable is the natural logarithm of the funding amount raised by women- or men-founded 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: $\text{Ln}(\text{Funding})_{mnk} = \sum_{k=-4}^6 \beta_k \text{I}(\text{Woman-founded startup})_m * \text{I}(\text{Women-Exit})_k + \beta' \text{Other Controls}_{mn} + \lambda_n + \delta_{\text{WomanExit}} + \delta_{\text{ManExit}} + \lambda_{ind} + \eta_{mnk}$. 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 ($\delta_{\text{Woman-Exit}}$ and $\delta_{\text{Man-Exit}}$). Standard errors are clustered at the investors level.



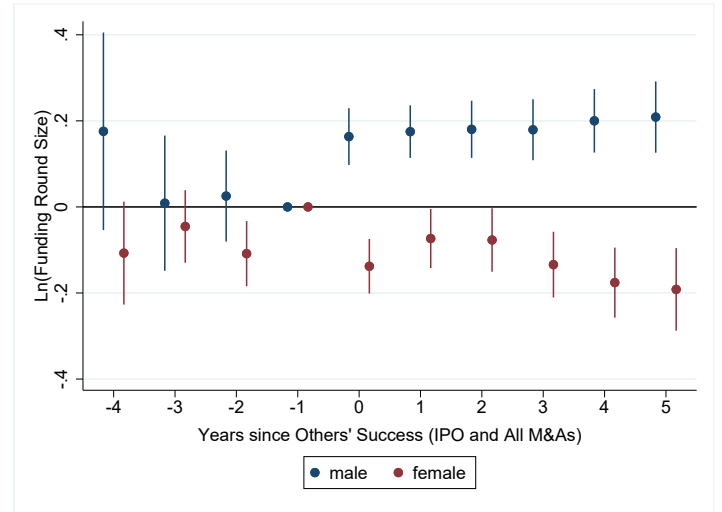
(a) After Failure



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



(c) After Success (IPO Only)



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

Table A.1: Amount of VC funding for a new startup

This table examines the relationship between a startup founder's gender and the amount of VC funding raised at the next startup. The sample corresponds to startups of Table 3 that raised VC funding for the next startup. The unit of observation is a startup-founder pair. The dependent variable, $\ln(\text{Funding Raised})$, 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. $I(\text{Woman})$ an indicator equal to one of the founders is a woman. $I(\text{Serial})$ is an indicator for founders who started another company before the current startup. $I(\text{CEO})$ is an indicator of whether the founder was also listed as the CEO during a funding round. $\ln(\text{Age})$ is the startup's age when it failed or succeeded. $\ln(\text{Pre-Exit Funding})$ is the log amount of VC funding the startup raised 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.

	Ln(Funding Raised)				
	(1)	(2)	(3)	(4)	(5)
I(Woman)	-0.500*** (0.095)	-0.223** (0.087)	-0.278*** (0.087)	-0.347*** (0.096)	-0.254*** (0.097)
I(Serial Founder)		0.815*** (0.052)	0.782*** (0.052)		0.505*** (0.099)
I(CEO)		-0.169*** (0.043)	-0.127*** (0.043)		0.110* (0.057)
Ln(Funding Current Startup)		0.353*** (0.013)	0.312*** (0.013)		
Ln(Age)		-0.244*** (0.041)	-0.195*** (0.041)		
Observations	7772	7772	7772	2610	2610
Adjusted R^2	0.057	0.213	0.231	0.681	0.691
Year Founded 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)	-2.138*** (0.616)	-1.722* (0.886)	-4.829*** (0.849)	-4.769*** (1.123)
I(CEO)	1.651*** (0.398)	1.967*** (0.479)	3.139*** (0.481)	3.466*** (0.569)
I(Woman) X I(CEO)	0.221 (0.863)	0.258 (1.147)	0.107 (1.295)	0.537 (1.653)
I(CTO)	-0.066 (0.523)	-0.767 (0.653)	-2.607*** (0.564)	-2.658*** (0.690)
I(Woman) X I(CTO)	-0.809 (1.581)	-1.408 (2.405)	1.237 (2.161)	0.077 (2.983)
I(COO)	-0.566 (0.687)	-0.691 (0.855)	-1.881** (0.828)	-0.246 (1.015)
I(Woman) X I(COO)	-0.909 (1.210)	1.110 (1.723)	3.842* (2.082)	1.893 (2.622)
I(CMO)	0.984 (1.028)	0.368 (1.205)	-1.168 (1.010)	-1.215 (1.170)
I(Woman) X I(CMO)	-3.018** (1.468)	-2.316 (2.141)	-0.715 (1.903)	3.769* (2.127)
I(CFO)	-2.898 (2.096)	0.910 (2.201)	11.593** (5.057)	6.575 (6.214)
I(Woman) X I(CFO)	-0.500 (2.559)	6.167 (5.320)	-19.791*** (6.097)	-19.196 (12.766)
I(Serial Founder)	17.972*** (1.042)	18.262*** (1.302)	23.896*** (0.930)	24.290*** (1.148)
Ln(Age)	-2.341*** (0.415)		-5.798*** (0.477)	
Ln(Pre-Exit Funding)	0.869*** (0.096)		1.653*** (0.122)	
Observations	22334	18488	25711	21921
Adjusted R ²	0.065	0.209	0.106	0.255
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: Who is More Likely to be the CEO?

This table asks what is the role of women co-founders within VC-backed startups. The sample includes all startup founders of Table ???. The dependent variables are indicators for the founder's role: $I(CEO)$ 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. The main independent variable, $I(Woman)$, is an indicator equal to one if the founder is a woman. 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:	CEO (1)	CTO (2)	COO (3)	CMO (4)	CFO (5)
$I(Woman)$	-0.026*** (0.007)	-0.145*** (0.004)	0.046*** (0.004)	0.042*** (0.003)	-0.001 (0.001)
$I(Serial\ Founder)$	0.183*** (0.007)	-0.089*** (0.005)	-0.034*** (0.003)	-0.020*** (0.003)	-0.002*** (0.001)
Adjusted R^2	0.155	0.330	0.345	0.346	0.372
Observations	105,749	105,749	105,749	105,749	105,749
Mean dep. var.	0.3781	0.1718	0.0822	0.0496	0.0033
Year Founded FE	YES	YES	YES	YES	YES
Startup FE	YES	YES	YES	YES	YES

Table A.4: **Spillovers following startup failures (Theranos case study)**

This table examines the relationship between the startup founder's gender and the amount of funding investors allocate to their startup after experiencing the failure of Theranos. The unit of observation is an investor deal during the 2013 to 2019 sample period (three years before through three years following the Wall Street Journal's article highlighting fraud at Theranos). All investors in this analysis directly invested in Theranos prior to its failure. The test excludes Theranos from the sample. *Healthcare* is an indicator equal to one if the startup is in the same sector as Theranos (Healthcare sector). *Post* is an indicator for the years following the Wall Street Journal investigative articles about Theranos. *I(Women)* is an indicator of whether any of the founders of the startup in the deal are women. *** $p < 0.01$ 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)
I(Women)	0.408** (0.190)	-0.119 (0.223)	0.306 (0.221)
I(Women) X I(Post)	-0.923** (0.342)		-0.922* (0.489)
I(Healthcare)		-0.022 (0.341)	-0.134 (0.374)
I(Healthcare) X I(Post)		0.058 (0.318)	0.152 (0.348)
I(Healthcare) X I(Women)			0.404 (0.396)
I(Healthcare) X I(Post) X I(Women)			-0.169 (0.582)
Observations	580	580	580
Adjusted R^2	0.314	0.302	0.311
Year FE?	YES	YES	YES
Investor FE?	YES	YES	YES

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. $I(W. Founder)$ is an indicator equal to one if at least one member of the founder 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. $I(FW. Founder)$ 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. $P(Serial Investments)$ is the number of serial founders in the investor's portfolio, divided by the total number of founders in the portfolio. 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 investor. *** $p < 0.01$ 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*** (0.021)	-0.137*** (0.035)	-0.022 (0.036)	-0.087*** (0.026)
I(Women-Founded)	-0.147*** (0.010)	-0.326*** (0.020)	-0.125*** (0.019)	-0.147*** (0.011)
I(Failure Women)	0.011 (0.019)	-0.005 (0.019)	0.008 (0.019)	-0.007 (0.027)
I(Recent Failure)	0.049* (0.025)	0.048* (0.025)	0.009 (0.023)	0.075** (0.032)
P(Investments Women)	-0.019** (0.009)	-0.016* (0.009)	-0.009 (0.017)	-0.016* (0.009)
Ln(Age Startup)	0.116*** (0.030)	0.117*** (0.030)	0.135*** (0.050)	0.075** (0.033)
Ln(Age VC)	0.798*** (0.017)	0.801*** (0.017)	0.495*** (0.027)	0.696*** (0.016)
[1em] P(Serial Founder)	0.513*** (0.015)	0.518*** (0.015)	0.314*** (0.025)	0.528*** (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. We present coefficients from OLS regressions and cluster standard errors by investors. *I(W. Founder)* is an indicator for a Woman founder at the startup receiving VC funding. *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(SW. Founder)* is an indicator of whether the investor backed at least one startup with a woman over the previous five years that was successful. *Ln(Age Startup)* is the startup 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 Investments)* is the number of serial founders in the investor's portfolio, divided by the total number of founders in the portfolio. *Ln(Deal Size)* is the 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.

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 (0.026)	0.067 (0.048)	0.009 (0.039)	0.009 (0.031)
I(Women-Founded)	-0.161*** (0.011)	-0.428*** (0.020)	-0.104*** (0.018)	-0.160*** (0.012)
I(Success Women)	0.021 (0.028)	0.024 (0.027)	0.007 (0.034)	0.022 (0.034)
I(Recent Success)	0.020 (0.022)	0.021 (0.022)	0.032 (0.027)	0.022 (0.026)
P(Investments Women)	-0.013 (0.011)	-0.011 (0.011)	0.006 (0.016)	-0.014 (0.011)
Ln(Age Startup)	0.086** (0.037)	0.087** (0.037)	0.124** (0.053)	0.049 (0.040)
Ln(Age VC)	0.801*** (0.018)	0.803*** (0.018)	0.498*** (0.027)	0.694*** (0.018)
[1em] P(Serial Founder)	0.521*** (0.017)	0.524*** (0.017)	0.332*** (0.026)	0.530*** (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

Table A.7: Potential spillovers following startup failures (Diff-in-Diff specification)

This table shows how investors change their investments in women-founded startups following a failure in their portfolio. It 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. $I(\text{Woman-Founded})$ is an indicator equal to one if at least one member of the founder team is a woman. $I(\text{Post Woman Failure})$ is an indicator equal to one for years after the first failure of a woman-founded startup experienced by an investor. $I(\text{Post Man Failure})$ is an indicator equal to one for years after the first failure of a man-founded startup experienced by an investor. $\ln(\text{Age Startup})$ is the natural log of the age of the startup, and $\ln(\text{Age VC})$ is the natural log of the age of the VC firm (investor). $P(\text{Investments Women})$ 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. The dependent variable is $\ln(\text{Deal Size})$, 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.

	Ln(Deal Size)			
	(1)	(2)	(3)	(4)
I(Woman-Founded)	-0.538*** (0.026)	-0.331*** (0.027)	-0.232*** (0.014)	-0.179*** (0.014)
I(Post Woman Failure)	-0.411*** (0.145)	-0.364*** (0.122)	0.085*** (0.022)	0.054*** (0.021)
I(Woman-Founded) X I(Post Woman Failure)	-0.105** (0.053)	-0.132*** (0.049)	-0.054** (0.022)	-0.073*** (0.021)
I(Post Man Failure)	0.156* (0.085)	-0.207*** (0.080)	0.080** (0.034)	0.036 (0.034)
I(Man-Founded) X I(Post Man Failure)	0.019 (0.037)	0.053 (0.039)	0.021 (0.020)	0.015 (0.019)
Ln(Age VC)		0.323*** (0.033)		0.111*** (0.030)
Ln(Age Startup)		1.027*** (0.056)		0.773*** (0.017)
P(Investments Women)		-0.185*** (0.026)		-0.017 (0.013)
Observations	183256	183210	183256	183210
Adjusted R^2	0.135	0.289	0.544	0.596
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 A.8: **Potential spillovers following startup success (Diff-in-Diff specifications)**

This table shows how investors change their investments in women-founded startups following success in their portfolio. We examine the relationship between the gender of a successful startup founder and the sizes of deals for women-founded startups in the years following the successful event. 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. $I(\text{Woman-Founded})$ is an indicator equal to one if at least one member of the founder team is a woman. $I(\text{Post Woman Failure})$ is an indicator equal to one for years after the first failure of a woman-founded startup experienced by an investor. $I(\text{Post Man Failure})$ is an indicator equal to one for years after the first failure of a man-founded startup experienced by an investor. $\text{Ln}(\text{Age Startup})$ is the natural log of the age of the startup, and $\text{Ln}(\text{Age VC})$ is the natural log of the age of the VC firm (investor). $P(\text{Investments Women})$ 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. The dependent variable is $\text{Ln}(\text{Deal Size})$, 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.

	Ln(Deal Size)			
	(1)	(2)	(3)	(4)
I(Women-Founded)	-0.436*** (0.030)	-0.315*** (0.026)	-0.195*** (0.015)	-0.164*** (0.014)
I(Post Woman Success)	0.146 (0.124)	0.147 (0.113)	-0.005 (0.034)	0.027 (0.031)
I(Women-Founded) X I(Post Woman Success)	0.089** (0.045)	0.080* (0.043)	0.018 (0.024)	0.032 (0.024)
I(Post Man Success)	0.206 (0.214)	0.052 (0.190)	-0.003 (0.038)	-0.026 (0.038)
I(Men-Founded) X I(Post Man Success)	0.170** (0.079)	0.143* (0.076)	0.091*** (0.020)	0.077*** (0.019)
Ln(Age VC)		0.088*** (0.032)		0.087** (0.038)
Ln(Age Startup)		1.098*** (0.086)		0.764*** (0.018)
P(Investments Women)		-0.147*** (0.033)		-0.015 (0.015)
Observations	160730	160691	160730	160691
Adjusted R ²	0.158	0.301	0.548	0.600
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 A.9: **Financing the next Black-founded startup**

This table examines the relationship between the founder's race 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. In panel A, the dependent variable is $I(Invested)$, 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. $I(Woman)$ is an indicator equal to one if the founder is a woman. $I(Black)$ is an indicator equal to one if the founder is Black. $I(Serial\ Founder)$ 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 total amount of VC funding the current 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. 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.

	(1)	I(Invested); Mean = 7.02%		(4)	(5)
		(2)	(3)		
I(Black)	-1.114*** (0.431)	0.948** (0.428)	1.098** (0.430)	0.394 (0.849)	0.618 (0.836)
I(Woman)	-3.600*** (0.192)	-1.742*** (0.190)	-1.946*** (0.194)	-3.113*** (0.307)	-2.086*** (0.302)
I(Serial Founder)		13.875*** (0.381)	13.716*** (0.378)		13.120*** (0.509)
I(CEO)		-0.458*** (0.157)	-0.330** (0.157)		0.078 (0.187)
Ln(Funding Current Startup)		1.109*** (0.048)	0.983*** (0.049)		
Ln(Age)		-0.658*** (0.149)	-0.584*** (0.151)		
Observations	94027	94027	94027	74324	74324
Adjusted R^2	0.017	0.061	0.065	0.197	0.221
Year Founded 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.10: **Financing the next Black-founded startup following success or failure**

This table shows results from regressions that estimate the relationship between a startup founder's race and 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 five 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. $I(Black)$ is an indicator equal to one if the founder is Black. $I(Serial Founder)$ 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 = 8.18%			
	(1)	(2)	(3)	(4)	(5)
I(Black)	0.254 (1.104)	1.487 (1.064)	1.782* (1.065)	1.080 (2.059)	0.352 (1.977)
I(Woman)	-4.242*** (0.469)	-2.607*** (0.463)	-2.738*** (0.473)	-3.428*** (0.787)	-2.160*** (0.760)
I(Serial Founder)		17.537*** (1.102)	17.286*** (1.096)		17.496*** (1.474)
Ln(Age)		-2.257*** (0.523)	-2.218*** (0.524)		
Ln(Pre-Exit Funding)		1.131*** (0.107)	0.979*** (0.109)		
I(CEO)		1.391*** (0.384)	1.512*** (0.384)		2.369*** (0.467)
Observations	18303	18303	18303	14175	14175
Adjusted R ²	0.014	0.061	0.065	0.176	0.208
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 = 14.60%			
	(1)	(2)	(3)	(4)	(5)
I(Black)	0.302 (2.185)	2.109 (2.168)	2.541 (2.178)	1.092 (3.131)	1.524 (3.072)
I(Woman)	-5.954*** (0.662)	-3.622*** (0.653)	-3.976*** (0.664)	-5.666*** (0.982)	-3.471*** (0.945)
I(Serial Founder)		24.156*** (1.007)	23.887*** (1.002)		23.774*** (1.306)
Ln(Age)		-4.791*** (0.574)	-4.450*** (0.587)		
Ln(Pre-Exit Funding)		1.879*** (0.130)	1.666*** (0.134)		
I(CEO)		3.507*** (0.462)	3.689*** (0.462)		4.530*** (0.551)
Observations	21376	21376	21376	17285	17285
Adjusted R ²	0.028	0.100	0.104	0.199	0.251
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.11: Potential spillovers following startup failures of Black founders

This table examines the relationship between the race of a failed startup founder and the sizes of deals for Black-founded startups in the years following the failure event. The unit of observation is an investor-deal pair. $I(\text{Black Founder})$ is an indicator equal to one if at least one member of the founder team is Black. $I(\text{Recent Failure})$ is an indicator equal to one if the investor backed at least one startup over the previous five years that failed. $I(\text{FB, Founder})$ 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 Black founder. $\text{Ln}(\text{Age Startup})$ is the natural log of the age of the startup, and $\text{Ln}(\text{Age VC})$ is the natural log of the age of the VC firm (investor). $P(\text{Investments Women})$ 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. The dependent variable is $\text{Ln}(\text{Deal Size})$, 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(Black Founder) X I(Failure Black Founder)	-0.332 (0.262)	-0.425* (0.245)	-0.233*** (0.056)	-0.295*** (0.056)
I(Black Founder)	-0.694*** (0.035)	-0.423*** (0.030)	-0.276*** (0.024)	-0.209*** (0.024)
I(Failure Black Founder)	-2.276*** (0.424)	-1.921*** (0.384)	-0.219 (0.157)	-0.271* (0.163)
I(Recent Failure)	0.128** (0.063)	-0.127** (0.053)	0.101*** (0.022)	0.041** (0.020)
P(Black Investments)		-0.138*** (0.019)		-0.005 (0.008)
Ln(Age Startup)		0.293*** (0.028)		0.117*** (0.031)
Ln(Age VC)		1.064*** (0.029)		0.826*** (0.017)
[1em] P(Women)		-0.796*** (0.027)		-0.429*** (0.017)
P(Serial Founder)		0.846*** (0.031)		0.482*** (0.015)
Observations	167137	167137	167138	167138
Adjusted R ²	0.177	0.347	0.530	0.592
Year FE?	YES	YES	YES	YES
Investor FE?	NO	NO	YES	YES
State FE?	YES	YES	YES	NO
Industry FE?	YES	YES	YES	NO