Uncertain Science, Certain Bias?
Drivers of Same-Gender Investment in Biomedicine

Michael Nguyen-Mason

The Dartmouth Institute for Health Policy and Clinical Practice

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Abstract

Does gender bias distort venture capital allocation in biomedicine? This paper examines whether gender bias leads venture capital (VC) funds to systematically forgo profit in early-stage biomedical investment. I study gender homophily, the tendency of general partners (GPs) to invest in founders who share their gender, and deconstruct its underlying drivers to distinguish profit-maximizing selection from bias. Using comprehensive data on U.S. biomedical VC investments from 2005 to 2024, I proceed in three steps. First, exploiting within-city, over-time variation in the gender composition of GPs and controlling for geographic distance, technological specialization, and shifts in potential founder supply, I show that a one standard deviation increase in the share of GPs who are women is associated with a 22 percent increase in the share of funded founders who are women in first-round investments. Second, I test whether gender-concordant investments are more successful and find the opposite. Gender-discordant investments are significantly more likely to exit via IPO, with no corresponding difference in M&A rates, implying that both men and women GPs leave money on the table. Third, I show that homophily disappears in funding rounds where information about start-up quality is more readily available, consistent with biased beliefs rather than taste-based discrimination. Finally, I document that women-founded start-ups are substantially more likely to develop technologies addressing women's health-care needs, raising concerns that gender bias may distort not only who is funded but also which biomedical problems are prioritized. Together, the results indicate that gender bias under uncertainty distorts capital allocation in biomedical entrepreneurship and may contribute to underinvestment in women's health technologies.

Venture capital (VC) plays a central role in medical innovation, funding more than half of successful biomedical start-ups (Lerner and Nanda, 2020).[1] Compared to other VC-backed sectors, biomedical start-ups face scientific and regulatory hurdles that make project viability uniquely uncertain (Kerr et al., 2014). This uncertainty has the potential to magnify the role of bias in investor decisions, leading investors to rely on unreliable heuristics such as "gut feeling," shared identity, or attractiveness (Huang, 2018; Brooks et al., 2014; Bahlmann, 2023; Huang et al., 2023).

A growing literature documents that gender shapes VC investment (Calder-Wang and Gompers, 2021; Ewens and Townsend, 2020; Einiö et al., 2026; Koning et al., 2021; Gupta et al., 2022; Hébert, 2025; Ewens, 2023; Guzman and Kacperczyk, 2019; Gompers et al., 2022; Kanze et al., 2018; Howell and Nanda, 2024). Gender gaps in funding may reflect rational differences in expected return on investment (ROI), but they may also reflect profit-forgoing gender bias. In biomedicine, such distortions may carry downstream costs by limiting investment in technologies that address the health needs of specific populations, such as women's health.

This paper investigates whether gender bias affects VC investment decisions in biomedical start-ups and assesses the extent to which gender differences in VC investment reflect systematic, profit-forgoing gender bias. To test for bias-driven gender differences, I examine gender homophily, the tendency for VC decision makers, known as general partners (GPs), to invest disproportionately in founders who share their gender. If gender homophily affects investment decisions in ways not explained by differences in expected profitability, then homophily, in part, reflects gender bias. I find three things. First, investments where GPs share founder gender are less successful on average than mixed-gender investments, consistent with profit-forgoing bias. Second, these investment decisions are consistent with gender bias driven by mistaken beliefs rather than preference. Finally, gender bias likely skews investment away from women's healthcare technologies.

The primary methodological challenge in quantifying gender bias in investment decisions is that lower rates of investment in women-led start-ups could reflect differences in expected productivity rather than bias. To address this challenge, I present a simple model in which GPs evaluate investments based on expected return and any preference for gender concordance with a start-up founder. The model illustrates that homophily can arise from four channels: (i) lower search and due-diligence costs for same-gender matches; (ii) true ROI differences (statistical discrimination) (Phelps, 1972; Arrow, 1973); (iii) mistaken beliefs about gender differences in ROI (stereotyping) (Bordalo et al., 2016); or (iv) taste-based preference

[1] Between 2005 and 2020, 47% of biomedical initial public offerings (IPOs) were VC-backed, a share that has grown to 59% post-2020 (Russo, 2003; PitchBook Data, 2025).

(taste-based discrimination) (Becker, 1957). Only the latter two imply that VC funds systematically forgo profit, making it crucial that I isolate each channel (Knowles et al., 2001; Ayres, 2002; Argyle et al., 2025). My empirical approach investigates the gender disparity in funded biomedical entrepreneurs by deconstructing gender homophily into these underlying components.

I begin by documenting disparities among GPs and funded founders in VC biomedical investment. Using a comprehensive dataset of VC investments from PitchBook, I find that between 2005 and 2024, women accounted for an average of 13.8% of GPs and 12.2% of funded founders. These shares are markedly lower than in the upstream education pipeline, where more than 50% of life-science PhD graduates are women (National Science Foundation, NCSES, 2017). Moreover, from the beginning to the end of the sample, the shares of women GPs and women founders each rose by less than two percentage points. In comparison, the share of full professors in the life sciences who are women is estimated to have increased by nearly 10 percentage points between 2008 and 2022 (Baker and Koedel, 2024).

Given the low rate of women's participation both as GPs and as founders, I next investigate gender homophily as a channel that may contribute to the persistent gender gap among biomedical founders. To verify the presence of gender homophily in my sample, I estimate a regression of the share of women founders on the share of women GPs. At both the deal and city levels, a higher proportion of women GPs is associated with a higher proportion of women founders, evidence of gender homophily in VC investment. Because multiple mechanisms could generate this pattern, I next undertake a three-step empirical deconstruction of the drivers of gender concordance.

First, I test whether gender homophily can be explained by pre-investment costs, exploiting the steep rise in search, due-diligence, and monitoring costs that VCs face when investing outside their local market (Chen et al., 2010; Sorenson and Stuart, 2001; Hochberg et al., 2007). Consistent with this friction, nearly 40% of investments in my sample occur between GPs and start-ups headquartered in the same city. This segmentation means that the gender composition of a city's GPs determines the set of potential GP–founder pairings in that market. If investment decisions were invariant to founder gender, the gender composition of a city's funded founders would track the supply of potential founders but not the gender composition of its GPs. I therefore estimate the within-city, over-time relationship between the share of GPs who are women and the deal share of funded founders who are women, controlling for a proxy for the supply of potential founders and start-up technology type. I find that for first-round VC investments, a one-standard-deviation (23.2-percentage-point) increase in a city's share of GPs who are women is associated with a 22% increase in the deal share of founders who are women. To address the concern that unobserved factors could

drive both where women GPs and potential founders locate, I perform several robustness checks. First, I show that 83% of within-city changes in the share of GPs who are women are due to local promotions rather than movement to a city. Second, following Oster (2019), I test the sensitivity of my estimate to selection on unobservables. I find I would need seleciton on unobservables to be more than six times stronger than selection on observables to drive the homophily coefficient to zero.

Second, to test whether the remaining gender homophily is driven by productive synergies that lead to true differences in ROI, I examine whether gender-concordant investments are, on average, more profitable. To test for productive synergies I use an outcomes test in the tradition of Becker (1957) and Knowles et al. (2001) (Anwar and Fang, 2006; Arnold et al., 2018, 2022; Bartlett et al., 2022; Canay et al., 2024; Bohren et al., 2025) where I compare the likelihood of participating in an initial public offering (IPO) or merger and acquisition (M&A) between investments made by same-gender versus opposite-gender GP–founder pairs. I find that gender-discordant investments are 44% more likely to exit in an IPO than gender-concordant investments. Additionally, there is no statistically significant difference in the rates of M&A. Since the gender concordance estimated in the first step cannot be explained by either gender differences in pre-investment costs or productive synergies, disproportionate same-gender investment likely reflects, in part, profit-forgoing gender bias (Hull, 2021). I further find that this bias is proportionally symmetric for men and women GPs.

Third, to understand the behavioral foundations of this bias, I examine whether gender homophily reflects mistaken beliefs (inaccurate statistical discrimination) or a preference for gender concordance (taste-based discrimination). Profit-forgoing bias due to mistaken beliefs should attenuate in response to new information (Bordalo et al., 2016, 2019; Coffman et al., 2021; Altonji and Pierret, 2001). To test this prediction, I run three complementary tests leveraging variation in the information about start-up quality available to investing GPs. I re-estimate gender homophily comparing the following groups, across which information on start-up quality differs: (i) first-round investments to follow-on round investments, (ii) repeat founders' first start-ups to their follow-up start-ups, and (iii) founders not validated by previous grants to those who had been validated. Running the same within-city, over-time regression with technology controls from the first step across these three comparisons, I find that the gender-homophily effect disappears in follow-on rounds, in repeat founders' follow-up start-ups, and among founders with prior grant awards compared to positive homophily effects for low information funding rounds. All three tests are consistent with the idea that the availability of better information on start-up quality leads to decreased reliance on gender homophily, in line with bias driven by mistaken beliefs rather than a taste for gender concordance.

Finally, to understand whether gender-biased homophily shapes the types of technologies that receive funding, I explore heterogeneity in the gender distribution of patent inventors, GPs, and founders. I find that funded women founders are around 2.5 times more likely to found start-ups that develop technologies or therapies targeting women's healthcare needs. In addition, using a back-of-the-envelope calculation, I find that increasing women GPs to parity with men GPs would lead to a 12% increase in women's-health-targeted start-ups. This suggests that, given the low representation of women among general partners, venture capital is likely misallocating resources away from women's healthcare technologies.

This paper adds to a sparse literature on how gender bias in financing affects the direction of innovation and extends it to the biomedical setting. Existing work shows that who innovates shapes what gets invented, where women inventors and founders are disproportionately likely to develop products that serve women in consumer markets (Einiö et al., 2026). Upstream, existing work also shows that representation in medical research can lead to skewed research agendas (Nielsen et al., 2017; Truffa and Wong, 2025; Kozlowski et al., 2022) and that women inventors are more likely to patent biomedical technologies focused on women's health (Koning et al., 2021). Here, I find this same pattern extends to the funding of medical technologies, where funded women founders are roughly 2.5 times as likely to develop women's-health technologies such as treatments for ovarian cancer or therapies related to maternal health. Further, I show that because women remain a small share of GPs, even symmetric bias can skew capital away from women's healthcare needs and affect what healthcare technologies are prioritized.

This paper also contributes to a growing literature on how gender shapes investment decisions. Prior work documents a persistent gender gap in venture funding and finds evidence that, in addition to gender differences in founder supply, investor-side bias contributes to it (Greenberg and Mollick, 2017; Raina, 2019; Ewens and Townsend, 2020; Calder-Wang and Gompers, 2021; Snellman and Solal, 2023; Hébert, 2025; Calder-Wang et al., 2022; Guzman and Kacperczyk, 2019; Gompers et al., 2022; Kanze et al., 2018; Howell and Nanda, 2024; Ewens, 2023). This paper adds two findings. First, in biomedical VC the profit-forgoing component of homophily is proportionally symmetric: relative to baseline exit rates within each GP-gender subsample, both men and women investors leave money on the table by not investing in gender-discordant founders. This symmetry indicates that the origin of the funding disparity lies upstream of the investment decision and is transmitted through the low share of GPs who are women. Second, I begin to isolate the behavioral mechanism driving gender homophily: homophily declines in more informative follow-on rounds, consistent with a model in which mistaken beliefs, rather than a stable taste for concordance, drive biased investing.

1 Background

1.A VC investment in early stage start-ups

Venture capital (VC) is a form of private equity financing that start-ups often seek in early stages of development and supports a large share of successful, high growth start-ups. VC investments are made by specialized investment firms through VC funds that raise capital from outside investors (limited partners) with the promise of high returns, then search for and vet start-ups to build a portfolio of investments. A VC deal typically involves a long-term contract where a general partner (GP) from the fund often takes a board seat and gains leverage over the start-up's strategic decisions (e.g., hiring executives, securing follow-on funding, and planning exit strategies), In addition, GPs connect the start-up to their network of possible investors for follow on financing. VC financing is often grouped into 'rounds' of investment.

The ultimate goal for most VC funds is to *exit* their investment with a high return. A highly sought outcome is an initial public offering (IPO) of the start-up, which can yield substantial returns if the company's stock gains value. Another common successful exit is acquisition of the start-up by a larger company, also potentially generating high returns for the VC.

Before making an investment, VC funds conduct due diligence on prospective investments – for example, verifying the founders' backgrounds and the soundness of the science behind a product. The search and due diligence process is costly where, for the average VC fund, just the time cost takes 83 days from start to close with 118 hours being dedicated to due diligence (Gompers et al., 2020). Beyond time cost VC funds hire legal counsel and hire scientific experts to advise on their decision. In addition to due diligence, VC funds will spend time to assess several criteria.

Classic research finds that VCs focus on factors such as the target market's attractiveness (size and growth), the product's differentiation or proprietary technology, the management team's capabilities, the business's risk resilience (e.g., barriers to competition, economic cycle insensitivity), and the potential for a lucrative exit (cash-out) via IPO or acquisition (Tyebjee and Bruno, 1984). Empirical surveys confirm the importance of the founding team's quality, but also the business model, product/technology, market, and industry fit as important considerations (Gompers et al., 2020). In a large survey, most VCs (95%) rated the management team as an important factor, with 47% calling it the single most important factor (Gompers et al., 2020). Given the importance of management "fit", gender may play an especially important role in determining on whether a start-up founder is funded.

1.B Medical innovation pipeline

The medical innovation pipeline in the U.S. faces unique scientific and regulatory hurdles, which may affect how any gender biases play out in biomedical start-up funding. Developing a biomedical product often requires lab facilities, specialized equipment, and scientific expertise, as well as navigating strict clinical trial standards and FDA regulations. As a result, both the qualities that VCs prioritize in health startups and the qualifications needed to found a health venture tend to differ from other tech sectors.

For example, the characteristics of start-ups that attract VC interest have been shown to differ between biomedical and information technology (IT) sectors. In a representative survey of VCs by Gompers et al. (2020), health-focused investors placed relatively less emphasis on the founding team and far more emphasis on the product compared to IT investors. In fact, the healthcare VC subgroup was the only one in which the management team was not ranked the top factor, as product/technology considerations took on greater importance. If gender bias manifests primarily through investor preferences for certain founding teams, one might expect weaker gender disparities in health venture funding, where investors focus more on the underlying science and product.

Another difference is that biotech entrepreneurs, a large subset of health entrepreneurs, are more likely to hold doctoral degrees than founders in other industries. One study of biotech start-ups that went public in 2020-2021 found that about 32% of biotech CEOs had a PhD, while roughly 60-65% of biotech start-up founders had PhDs (Huayamares et al., 2022). The rate of PhD-founded firms in biotechnology is on the order of 3-4 times higher than the cross-industry average (Lassébie et al., 2019), reflecting the specialized training often required to innovate in life sciences.

Women have attained near parity with men in life-science educational pipelines, in contrast to the persistent gender gaps in fields like computer science or engineering. In 2018, women earned only about 19% of computer science degrees and 22% of engineering degrees at the bachelor's level, but about 49% of degrees in life sciences fields (National Science Foundation, NCSES, 2019). At the doctorate level, women comprised roughly 21% of new PhDs in computer science and 24-25% in engineering, versus about 50-51% of PhDs in biological and life sciences (National Science Foundation, NCSES, 2019). In other words, the pool of PhD-trained talent in biotech and related fields is much more gender-balanced than in other high-growth sectors. This higher representation of women in the advanced degrees relevant to health entrepreneurship could help mitigate gender disparities: women are simply more present in the founder pipeline for biotech. Therefore, to the extent that venture funding in health is more contingent on technical credentials and product milestones (and women are equally likely to possess those credentials), one might expect smaller gender gaps in VC

outcomes for health startups compared to tech startups.

2 Model of gender homophily in VC investment

2.A Model setup

To formalize the drivers of gender homophily this paper explores, I model the investment decision of a VC fund's GP in a potential biomedical start-up. GP i makes an investment decision in a start-up j to maximize their own utility, which is aligned with the VC fund's goal of maximizing financial returns as well as an additional preference about founder gender.

Assume GP i evaluates a potential investment in start-up j independently of other investments, where each start-up has a founder of a given gender. The pairing of a GP's gender and a founder's gender is denoted by q. A pairing is concordant ($q = C$) if the GP and founder share the same gender, and discordant ($q = N$) otherwise.

The GP's expected utility U_{ijq} from investing in start-up j is a function of the predicted financial return and a preference for gender concordance with the start-up founder. The GP invests iff expected utility exceeds the reservation utility of zero:

$$U_{ijq} = \mathbb{E}_i[\pi_{ijq}] + D_{iq} > 0$$

where $\mathbb{E}_i[\pi_{ijq}]$ is GP i's *subjective* expected financial return on investment (ROI)—which may diverge from the true expectation through a gender stereotype, specified below—and D_{iq} is the utility or disutility GP i derives from the gender pairing itself. Following the classic model of taste-based discrimination (Becker, 1957), D_{iq} can be interpreted as a psychic cost or benefit.

The expected ROI, $\mathbb{E}_i[\pi_{ijq}]$, is the expected revenue from a successful exit, r_{ijq}, minus the minimum investment outlay for any start-up, I, and the pre-investment costs C_{ijq} (e.g., search and due diligence). The GP therefore invests if:

$$U_{ijq} = \mathbb{E}_i[r_{ijq}] - I - C_{ijq} + D_{iq} > 0$$

Pre-investment costs decompose into a geographic and a pairing-specific component:

$$C_{ijq} = \kappa(d_{ij}) + c_{iq}$$

where $\kappa(\cdot)$ is increasing in the geographic distance d_{ij} between GP i and start-up j, and c_{iq} captures gender-pairing-specific costs of search and start-up quality verification. I find that

a steep, implied κ segments VC matching markets geographically where investing outside the local market is costly for most pairings. Thus, the primary set of potential pairings a founder faces is determined by the local composition of GPs.

Let $\rho_{jq} \equiv \mathbb{E}[r_{ijq} \mid j]$ denote start-up j's true expected exit revenue, where $\mathbb{E}[\,\cdot\,]$ is the empirical expectation over exit outcomes; ρ_{jq} is distributed across potential type-q start-ups with mean $\bar{r}_q$. The GP does not observe ρ_{jq}. Instead, GP i forms a subjective expectation by combining a prior about pairing type q with objective information about start-up j (pitch materials and founder credentials in a first round or operating milestones, clinical progress, and prior-investor validation in follow-on rounds). The prior may be distorted by a stereotype with mean of $\bar{r}_q + \nu_{iq}$, where ν_{iq} is the wedge between GP i's belief about type q and the true type mean. Because the wedge is a property of the GP's beliefs about gender concordance pairing q rather than of any particular start-up, it does not average away across start-ups. GP i's subjective expected return for start-up j is therefore

$$\mathbb{E}_i[r_{ijq}] = (1-\lambda)\,(\bar{r}_q + \nu_{iq}) + \lambda\,\rho_{jq},$$

where $\lambda \in (0,1)$ is the weight the GP places on objective information about the specific start-up and $1-\lambda$ the weight on the prior.[2] Averaging across potential start-ups of type q, the GP's subjective mean return is $\bar{r}_q + (1-\lambda)\nu_{iq}$. The stereotype distorts assessments in proportion to $1-\lambda$ where it is strongest when the GP has little to go on beyond the founder's type and disappears as information about the start-up itself becomes complete. By contrast, the taste term D_{iq} enters utility directly and is unaffected by information. This asymmetry is what separates the two profit-forgoing channels below.

2.B Investment conditions for gender homophily

Gender homophily is observed if a GP is more likely to invest in a gender-concordant start-up than a gender-discordant one. This occurs when expected utility from a concordant investment exceeds that from a discordant investment, on average, across the potential start-ups available to GP i:

$$\mathbb{E}\left[U_{ijq} \mid q = C\right] \;>\; \mathbb{E}\left[U_{ijq} \mid q = N\right]$$

where the expectation is taken across potential start-ups j within each pairing type. Let $\bar{C}_{iq} \equiv \mathbb{E}[C_{ijq} \mid q]$ denote the mean pre-investment cost GP i faces for pairing type

[2] With a normal prior and a normal noisy signal of ρ_{jq}, Bayesian updating delivers exactly this form with $\lambda = \sigma_\rho^2/(\sigma_\rho^2 + \sigma_\varepsilon^2)$, rising as signal noise σ_ε^2 falls. Nothing below depends on the normality; only on λ increasing in the information available.

q. Substituting the components of the utility function and averaging within pairing type, the gender concordance investing advantage ΔU_i is defined as the average net utility gain from concordant over discordant investments. Homophily arises when there exists a gender concordance investing advantage where $\Delta U_i > 0$:

$$\Delta U_i = [(\bar{r}_C + (1-\lambda)\nu_{iC}) - (\bar{r}_N + (1-\lambda)\nu_{iN})] - (\bar{C}_{iC} - \bar{C}_{iN}) + (D_{iC} - D_{iN}) > 0$$

where $\bar{r}_q + (1-\lambda)\nu_{iq}$ is GP i's subjective mean return for pairing type q. Grouping terms, I decompose this advantage into four distinct components:

$$\Delta U_i = \underbrace{(\bar{r}_C - \bar{r}_N)}_{\text{Case 2: True Return}} + \underbrace{(1-\lambda)(\nu_{iC} - \nu_{iN})}_{\text{Case 3: Belief Error}} - \underbrace{(\bar{C}_{iC} - \bar{C}_{iN})}_{\text{Case 1: Cost Difference}} + \underbrace{(D_{iC} - D_{iN})}_{\text{Case 4: Taste}} > 0$$

The belief-error component depends on the information environment where it is largest when signals are least informative (λ low) and vanishes as information becomes complete ($\lambda \to 1$).

This decomposition yields four predictions for when gender homophily arises, two of which are consistent with efficient (profit-maximizing) investment and two of which imply profit-forgoing behavior.

Case 1: Differences in Pre-Investment Costs

Homophily can arise if pre-investment costs are lower for same-gender pairings ($\bar{C}_{iC} < \bar{C}_{iN}$). Social networks have been shown to reduce information asymmetry and transaction costs (McPherson et al., 2001; Gompers et al., 2016), and gender-based sorting into geographies or technological specializations could generate such cost differences. In terms of the cost decomposition, such differences can operate through the pairing-specific component ($c_{iC} < c_{iN}$) or through geographic sorting that makes concordant pairs closer on average ($\mathbb{E}[\kappa(d_{ij}) \mid C] < \mathbb{E}[\kappa(d_{ij}) \mid N]$). Homophily from this channel is observed if, holding all else equal:

$$\bar{C}_{iN} > \bar{C}_{iC}$$

Case 2: True Differences in Expected Return (Statistical Discrimination)

Homophily may be driven by genuine productive synergies in concordant teams, leading to higher average returns. This is a form of statistical discrimination in which gender concor-

dance is a productivity-relevant signal. Homophily is observed if:

$$\bar{r}_C > \bar{r}_N$$

Like cost differences, this form of homophily is profit-maximizing for the GP and the fund.

Case 3: Perceived Differences in Expected Return (Stereotyping)
Homophily can result from a GP's biased beliefs, where they incorrectly overestimate the performance of concordant pairings or underestimate discordant ones, even if no true performance difference exists ($\bar{r}_C = \bar{r}_N$). This is driven by the belief error term ν_{iq}, with force proportional to the weight $(1 - \lambda)$ that beliefs place on the prior. Homophily arises if GPs are systematically more optimistic about same-gender founders:

$$\nu_{iC} > \nu_{iN}$$

This leads to investment decisions that forgo profit on average, as capital is allocated based on biased projections rather than true expected value.

Case 4: Preference for Gender Concordance (Taste-Based Discrimination)
Finally, homophily can stem from a preference for working with one's own gender, where a GP derives additional utility from a concordant pairing ($D_{iC} > 0$) or incurs a psychic cost from a discordant one ($D_{iN} < 0$). This preference exists independently of costs or returns. Homophily is observed if:

$$D_{iC} - D_{iN} > 0$$

Like stereotyping, taste-based discrimination leads to profit-forgoing investments, as the GP may sacrifice financial returns to satisfy a personal preference.

3 Data and variable construction

To identify the role gender bias plays in driving GP investments in same-gender founders, I construct a panel dataset of biomedical start-ups and investing GPs from 2005 to 2024. My primary data source is PitchBook, a leading venture financing database that provides granular information on start-ups and their founders, GPs and their associated VC funds, and rounds of investment that link start-ups and GPs. For my primary analysis I further restrict my sample to first round VC investments as to avoid investment selection driven by previously invested GPs. Importantly, PitchBook identifies the gender of both founders and

GPs.

3.A Founder and GP Gender

To measure gender homophily between investing GPs and start-up founders I, first, must be able to identify the gender of the set of investing GPs and founders participating in the biomedical related start-ups. I begin by identifying start-ups that fall under biomedical, pharmaceutical, or medical technology industry classifications as defined by Pitchbook. I restrict the sample to U.S.-headquartered start-ups with an observed first round of VC funding and drop start-ups whose first round occurs before the sample start date. I also record the city and state of the start-up headquarters provided by Pitchbook.

For each start-up's first deal, I identify employees with active tenure at the time of deal. PitchBook reports the start and end date of an individual's employment. Using PitchBook's occupational titles, I identify first-round employees labeled as founders and link them to PitchBook's gender classification. I can identify founder gender for 98.7% of founders.

A limitation of the PitchBook data is that it only contains start-ups that receive at least one round of funding at some point in time. Without data on unfunded founders, I cannot directly measure the gender distribution in the underlying potential founder supply. To approximate this, I supplement PitchBook with USPTO patent inventor data, which includes the gender and location of patent inventors. Using all inventors listed on patents related to pharmaceuticals, biologics, and medical devices, I construct a city-by-year gender composition measure to proxy for the local pool of potential founders.

To identify the gender distribution in investing GPs I start by identifying all the individuals that Pitchbook lists as participating in the investing side of a deal. These individuals can range from the GPs themselves to investment consultants. To capture the full relevant GP population, I include in my sample all GPs associated with the investing fund during the investment period in addition to those listed on the deal itself. I identify GPs using PitchBook's occupational titles and assign gender using PitchBook's gender information. I can identify GP gender for 99.8% of GPs.

3.B Accounting for Pre-Investment Costs and Outcomes

A key methodological challenge in isolating gender-homophily driven by bias, rather than rational profit expectations, is accounting for differences in expected profitability between potential gender-concordant and gender-discordant investments. To address this, I incorporate three categories of pre-investment cost variation: costs due to geographic distance,

technological specialization mismatch, and gender composition shifts in the supply of potential founders.

To measure geographic distance, I start by using the recorded locations of start-ups and GPs. For 76% of GPs, PitchBook reports an individual city–state–country identifier distinct from the VC fund's address. For the remaining GPs, I fill in missing locations using the fund's location. GP location may differ from the deal location and from the start-up's headquarters. I then identify the distance between GP and start-up locations using National Bureau of Economic Research (NBER) provided city distances. These city distances are great-circle distances calculated using the Haversine formula based on internal points in the geographic area. Figure 1 shows the distribution of these distances.

To account for technological differences between start-ups, I use two PitchBook variables. First, I include the PitchBook sub-industry classifications (e.g., "Drug Discovery," "Monitoring Equipment," "Discovery Tools"), which span 12 categories. Second, I use PitchBook's text descriptions of each start-up to construct flexible therapeutic categories by textually identifying key pathologies, drugs, and body systems associated with a therapeutic class as described in the U.S. Food and Drug Administration's (FDA) "Spectrum of Diseases by Therapeutic Area" documentation (See more on variable construction in appendix A).

Finally, PitchBook reports start-up exit outcomes, including whether a start-up undergoes an IPO or acquisition at some point in the life of the start-up. The final dataset comprises deal-level observations, where each observation corresponds to a single financing round/deal involving a life sciences start-up.

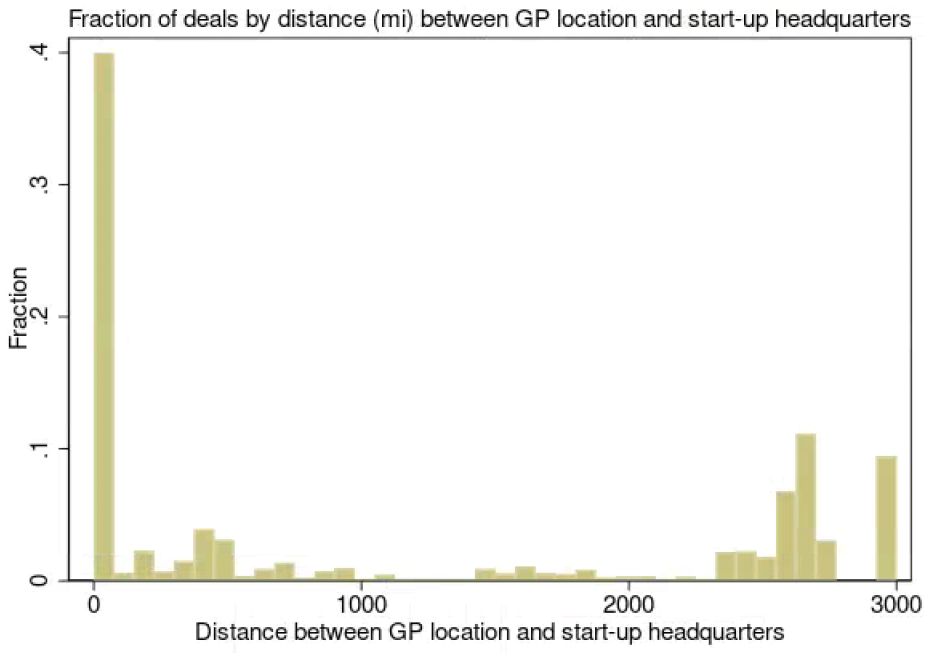


Figure 1: Distribution of distances between start-up headquarters and investing GPs

4 Summary statistics

Table 1 presents summary statistics for my sample of first-round VC investment deals. My analysis sample includes 2121 first-round deals (number of deals found in panel C), where first-round deals make up 35% of all VC investments in life sciences start-ups. I find that women represent 10-16.8% of founders, GPs and patented biomedical inventors.

Panel A presents deal-level statistics, my unit of observation. The average deal share of founders who are women is 12.2%, my preferred metric of analysis. This share is 50% lower than the share of start-ups with at least one woman founder which averages at 18.5%. There are 6,967 GPs represented in first-round deals and 20,088 represented in follow-on rounds. Note, however, that GPs are aggregated at the city-year level and not differentiated by round type in the primary analysis.

Panel B presents summary statistics at the city-year level of treatment. My analysis includes the 155 cities where there is variation in both the share of GPs who are women and variation in deal share of founders who are women. Across all city-years, women make up an average of 13.8% of GPs associated with funds investing in biomedical start-ups and 10.5% of inventors on patents. Finally panel C presents the number of observations in each deal type as well as the number of fixed effects for city, year, and technology area.

Women are underrepresented as founders, GPs, and patent inventors compared to the

Table 1: Summary statistics for first round of funding

Panel A: Deal-Level Statistics	Mean	SD
Share of founders women	0.122	0.259
Has a woman founder	0.185	
Number of founders	1.693	1.472
Has a woman leader	0.335	
Number of GPs	3.209	5.968
Panel B: City-Year Statistics		
Number of deals	3.366	4.346
Share of GPs women	0.138	0.231
Number of inventors	103.16	162.27
Share of inventors women	0.168	0.068
Panel C: Unique Counts		
Number of deals	2121	
City	155	
Year	19	
Technology area	15	

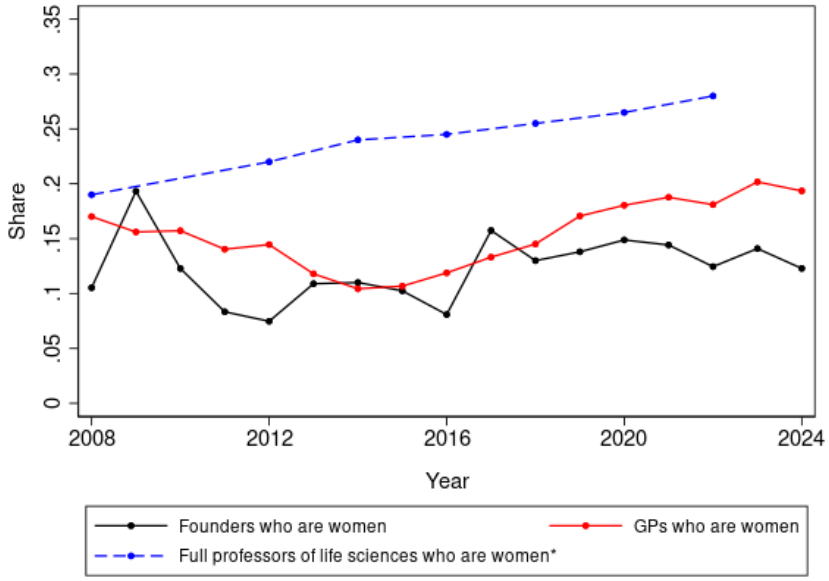
Note: Table 1A presents summary statistics on the gender composition of health start-up founders and GPs at the deal level for deals in all US city-years with at least one health start-up for first round investments. Table 1B presents the city-year level gender composition of GPs and inventors, aggregating by GP and inventor location. Table 1c presents total unique values of deals, cities, years, and technology areas in my analysis sample.

upstream educational market where more than 50% of graduating PhDs in the life sciences are women. The share of founders who are women, however, is not representative of women's total participation in biomedical start-ups. 33.5% of founding team members are women, often taking leadership roles such as Chief Medical Officer (CMO) or Chief of Operations (COO).

Figure 2 compares trends in the share of founders who are women with the share of life science GPs who are women for the first-round of VC funding over 17-years of my 19-year study period. The share of founders who are women does not trend upwards or downwards consistently over this period, oscillating around the average of 12.2% share. The share of GPs who are women does trend upwards starting from 2014 from a low of 10.4% to a high

of 20.2% in 2024.

Figure 2: Share of funded life science founders and investing GPs who are women as share of US total each year.



*Baker and Koedel, 2024

While some of this disparity may be explained by women leaving the labor force to have children (Goldin, 2014), the gender disparity in both biomedical founders and biomedical GPs are considerably larger and subject to less change than for jobs earlier in the biomedical labor supply pipeline as well as comparable positions laterally. For instance, the National Science Foundation calculated that in 2019, 48% of all working life scientists with a bachelors degree or higher were women. Furthermore, the share of life sciences faculty that are women was estimated to have increased from 25% in 2015 to 37% in 2022 representing both a higher level and larger change in women's representation (Baker and Koedel, 2024).

4.A Gender homophily in VC health investment

Given the tight link between gender disparities in funded health entrepreneurs and investing health GPs, this paper investigates one likely source of the founder gender disparity: gender homophily. Gender homophily in VC investment is the observation that VC investors are more likely to invest in founders of their own gender. Before investigating drivers of gender homophily, I begin by verifying that I observe gender homophily in my data by running a regression to test for the presence of gender homophily without any controls for the underlying

drivers.

Table 2 presents a descriptive regression results estimating the relationship between deal and city level share of GPs who are women on deal share of founders who are women without controls for VC investments in health start-ups. I find that, like VC investment more broadly, VC investments in biomedical start-ups exhibit gender homophily where both deals and cities with a higher share of GPs who are women are associated with a larger share of funded founders who are women. In particular, a GP gender composition shift in having all men GPs at the deal level to all women GPs at the deal level predicts a 5.7 percentage point increase in the share of women who are founders. When estimating gender homophily at the city-year level I find that a shift in having all men to all women GPs in a city predicts an increase in the share of founders who are women by 3.4 percentage points.

Isolating homophily estimates to the first round I find a more pronounced effect for first-round investments. I estimate that a shift from all men to all women GPs in a city-year predicts a 7.9 percentage point increase in the share of funded founders who are women in first-round deals.

Table 2: Estimating average homophily effect without controls for cost at the deal and city level

Dependent var:	Deal share of founders who are women		
	All rounds	All rounds	First-round
Deal share of GPs	0.057		
who are women	(0.018)		
City share of GPs		0.034	0.079
who are women		(0.017)	(0.031)
Observations	6022	6022	2121

Note: Table 2 compares deal level and city level gender homophily when there are no controls for costs. These regressions estimate the relationship between the share of GPs who are women, either at the deal level or city level, on the deal share of founders who are women. Regression 1 presents results for deal level analysis on first and follow-on round VC investments, regression 2 presents results for city level analysis on first and follow-on VC investments, and regression 3 presents results for city-level gender homophily in first round deals.

The descriptive trends in gender homophily in VC biomedical investment reveal two insights. First, there is consistency between the homophily correlation estimated at the deal level, the treatment level that is most often used in analysis of gender homophily in VC investment, and at the city level which is the treatment level for analysis in this paper.

Second, gender homophily is strongest in first round-investments. The difference between homophily estimated for first and follow-on round investments is, for example, consistent with a world where GPs face larger investing frictions caused by asymmetric information in first rounds. Larger asymmetries of information can then lead them to GPs relying on gender stereotypes to compensate for additional uncertainty.

Given that gender homophily is present in my setting, I move on to investigate the possible drivers and whether those drivers may contribute to investment decisions that forgo profit. Gender homophily can happen for many reasons, some of which are ROI maximizing and some which cut away from the market optimal investment. For example, women may disproportionately invest in other women because it is less costly to ascertain signals of profitability - an ROI maximizing reason for gender homophily. Alternatively, women may invest disproportionately in other women due to a preference to advance gender representation - a reason for gender homophily that is not necessarily ROI maximizing.

5 Deconstructing gender homophily in investment

To estimate the extent to which gender bias leads VC funds to forgo profit, this paper deconstructs the observed gender homophily correlation. I do so by either controlling or testing for gender-concordance–related differences in expected ROI that may contribute to the correlation. If a gender homophily effect remains after accounting for these economically rational, profit-maximizing mechanisms, I infer that the residual effect reflects gender bias that results in forgone profit. The deconstruction proceeds in three steps.

First, this paper uses a fixed-effects regression design to control for gender homophily driven by VC selection on pre-investment costs. Pre-investment costs arise during the search process or while assessing the quality and viability of a start-up. Selection on cost may generate gender homophily if investments in gender-concordant founders differ in the average cost of search or due diligence. Once I sufficiently control for cost selection, the remaining estimated homophily effect can be attributed to some combination of three mechanisms: true gender differences in expected return, mistaken beliefs about such differences, and a preference for investing in one's own gender.

Second, this paper tests whether the homophily effect, unexplained by gender-concordance differences in pre-investment costs, may be caused by true gender differences in expected return. I apply an adapted outcomes test to assess whether gender-concordant investments are more likely to IPO or undergo M&A, which could imply productive synergies in gender-concordant deals. The key identifying assumption is that GPs invest in gender-concordant founders only when they expect higher returns . Otherwise, GPs are either making a mistake

or hold a preference for gender concordance. Under this assumption, the average difference in outcomes provides a lower bound on the marginal difference in exit likelihood between concordant and discordant investments (Hull, 2021).

Finally, if a gender homophily effect persists after controlling for pre-investment costs and, further, cannot be explained by true gender differences in start-up success, I investigate the possible mechanisms that lead to the remaining profit-forgoing gender homophily. Step 3 compares the strength of homophily in first-round investments compared with follow-on rounds. This comparison helps disentangle homophily driven by mistaken beliefs about productive synergies from homophily driven by GP preference for gender concordance. Because these investments are made under different levels of asymmetric information, attenuation of the homophily effect in follow-on rounds would be consistent with models of mistaken beliefs. In models of mistaken beliefs initial GP held stereotypes about the productivity of a particular gender of founder diminish as better information becomes available compared with a preference-based explanation.

5.A Control for gender differences in pre-investment cost

The first step in quantifying the effect of gender bias on the biomedical founder gender gap is to estimate gender homophily while controlling for gender-concordance related pre-investment costs. The ideal experiment would randomize founder gender composition across start-ups for the same set of investing GPs, both men and women. Under such randomization, start-ups gender share would be orthogonal to start-up expected profitability. Any gender differences in the rate of investment could, then, be attributed to profit-forgoing gender bias. In the absence of a natural experiment, my first empirical step instead estimates gender homophily within GP–start-up clusters that share underlying average pre-investment costs. Gender differences in the rate of gender-concordant investment, then, can be attributed to (i) gender concordance differences in expected sell price or to (ii) profit-forgoing gender bias.

Regression Specification

To compare investment decisions with equal, average ex-ante investing costs, I estimate the following regression. Let d index deals, s index start-ups, c index cities, and t index years:

$$SWF_{sdct} = \beta_1 \times SWGP_{ct} + \beta_2 \times SWI_{ct} + TA_s + X_{ct} + \lambda_t + \delta_c + \epsilon_{sdct} \tag{1}$$

My outcome variable of interest is SWF, which measures the deal share of founders that are women at the time of deal, starting with the first-round of VC fundraising. $SWGP$ is the city-year share of GPs who are women, where β_1 serves as my homophily coefficient.

$\beta_1 \times 100$ should be interpreted as the average effect that a complete shift of a city's GP population from all men to all women would have on the percentage point share of women founders.

I also include a set of controls that help compare across deals where GPs face similar pre-investment costs. To start, I address two major sources of cost variation prior to investment: the geographic distance between the investing GP and the start-up's headquarters and gender differences in technological specialization. To address these costs I include start-up specific technology area fixed effects TA_s , δ_c city fixed effects, and λ_t year fixed effects. I also control for number of GPs in a city X_{ct} in order to control for any gender concordance correlated change with the size of the GP pool a city.

My method estimates the effect of a change in a city's share of GPs who are women on the deal share of women who are founders within the set of start-ups in the same city and technology category over time. I choose these factors because each can impose substantial costs on GPs who do not share a geographic location or technological specialization with a start-up. Given the high capital requirements (e.g., laboratory space) and technical complexity (e.g., PhD-level science) inherent in biomedical ventures, these two factors are especially likely to create meaningful cost barriers to investing.

Beyond this intuition, however, empirical evidence supports the importance of geographic distance and life-science specialization in shaping VC investment decisions. A substantial literature shows that distance-related frictions impede investments outside a VC's local region (Chen et al., 2010). Likewise, research demonstrates that specialized VCs tend to outperform generalist funds, remain active in markets for longer periods, and better overcome barriers such as foreignness (Gompers et al., 2009; Nörthemann, 2023). Further, nearly 40% of investments in my sample are made between GPs and start-ups based in the same city.

One challenge with my setting is that I do not observe potential founders that go unfunded. For example, if both GPs and potential founders who are women are simultaneously moving to the same cities then my estimate of homophily would be subject to upward bias where I would be overestimating a homophily effect. To control for unobserved changes in the gender composition of the supply of potential founders, I add a variable for the city-year share of life science patent inventors SWI_{ct}. If the gender composition of life science patent inventors is representative of the set of qualified potential founders, then, this variable can be used to control for the unobserved set of potential founders.

Another challenge with my setting is that I do not observe pre-existing GP-founder networks that may facilitate search and start-up quality verification. For example, if network formation is subject to gender homophily itself, then even within a city and technological specialty it may be cheaper, on average, for a GP to invest in a founder of the same gender

due to lower network frictions biasing my gender homophily estimate upwards.

While I have no way to directly control for the unobserved networks between GP and founder, I move away from previous measures of gender homophily, where homophily is estimated at the deal level and decouple whether the deal itself was homophilic. I rely solely on the within city and within technology gender homophily agnostic to whether the deals themselves were made in the city or were homophilic. The intuition behind this choice is that an observed deal is bound to experience selection on all variables, observed and unobserved. This deal level selection is less likely to be driving a city level effect.

Regression Results

Table 3 shows regression results for my estimation of gender homophily comparing first-round investments to follow-on investments. Regression 1 presents estimates of gender homophily without controlling for ex-ante costs to investing. Regression 2 estimates gender-driven homophily with full demand side controls including city, year, and technology fixed effects and clustering standard errors at the city level. Finally, regression 3 includes a control for gender changes in the supply of potential founders using the city-year share of patent inventors who are women as a proxy for gendered supply changes.

Estimates of gender homophily in first-round VC investments are consistently positive across all three regressions specifications. Considering the preferred coefficient, the coefficient in regression 3, a one standard deviation increase in the city share of GPs who are women is associated with a 2.6 percentage point increase (22% of the mean) in the deal share of founders who are women.

Table 3: Estimates of gender homophily controlling for ex-ante costs to investing

Dependent var: Deal share of founders women			
	(1)	(2)	(3)
City share of GPs	0.079	0.112	0.113
who are women	(0.031)	(0.049)	(0.049)
City share of inventors			-0.080
who are women			(0.249)
Mean share of founders	12.2	12.2	12.2
who are women			
Year, City, Technology FE		x	x
Cluster		City	City
R^2	.030	.055	.069
Observations	2121	2098	2098

Note: Table 3 estimates the relationship between city-year changes in the share of GPs who are women on the deal share of founders who are women. Table 3.1 gives the estimate with no controls. Table 3.2 controls for demand side cost differences such as geographic location and technology area. Table 3.3 adds an additional control for supply side changes in the potential founder pool using patent inventors as a proxy.

Robustness to Omitted Variable Bias

Since this paper's methodology relies on a fixed effects regression absent an exogenous shock or experiment we may still be worried that the estimated homophily effect is affected by omitted variable bias where an unobserved variable may be driving gender concordance related pre-investment cost differences. To test the sensitivity of my gender homophily estimate in regression 3 of Table 3, I implement the sensitivity analysis proposed by Oster (2019), which extends the coefficient stability logic of Altonji et al. (2005) by incorporating changes in both the coefficient and the R^2 across specifications, as well as a context-specific value for R^2_{Max}, the maximum attainable R^2 if all relevant controls were observed. Following Oster's recommendation, I set $R^2_{\text{Max}} = 1.3 \times R^2_{\text{Full}}$. Oster's delta statistic, δ^*, measures the relative strength of selection on unobservables (compared to observables) needed to reduce the coefficient to the target value of zero. Her formula for the required level of unobserved selection is:

$$\delta^* = \frac{\beta_{\text{Full}} - \beta_{\text{Target}}}{\beta_{\text{Short}} - \beta_{\text{Full}}} \times \frac{R^2_{\text{Full}} - R^2_{\text{Short}}}{R^2_{\text{Max}} - R^2_{\text{Full}}}. \tag{2}$$

Using $\beta_{\text{Target}} = 0$, the corresponding coefficients from regressions 1 and 3, and $R^2_{\text{Max}} = 0.0897$, I obtain:

$$\delta^* = \frac{0.113 - 0}{0.079 - 0.113} \times \frac{0.069 - 0.03}{0.0897 - 0.069} = 6.26. \tag{3}$$

This estimate implies that selection on unobservables would need to be more than six times stronger than selection on observables in order to eliminate the estimated effect. Under Oster's framework, such a large δ^* provides evidence that the homophily estimate is unlikely to be driven entirely by omitted variable bias. As a complementary check, Appendix D reports the simpler Altonji et al. (2005) coefficient-stability ratio, which yields the same conclusion.

The takeaway from the relatively insensitive, positive and statistically significant coefficient on city share of GPs who are women is that gender homophily is likely not driven solely by differences in gender concordance related pre-investment costs. Given this result I turn to the three other possible drivers of the observed same-gender investment: gender concordance related productive synergies, mistaken beliefs about gender concordant related synergies, and preference for gender concordance.

5.B Test for productive synergies due to gender concordance

The second step in quantifying the effect that profit-forgoing gender bias has on the biomedical founder gender disparity is to test for the possibility that there are productive synergies in gender-concordant investments. Without random assignment of GP to founder, it is challenging to disentangle the synergies component from other gender bias components even after controlling for pre-investment costs. To address the lack of randomization within my research context, I integrate an adapted outcomes test alongside the homophily framework. The premise is, if I find that gender-concordant investments are, on average, not more productive while controlling for pre-investment costs, then I can infer that gender homophily is not due to *accurate* GP beliefs that concordant investments are more likely to be profitable. To test for differences in realized productive synergies I estimate the difference in likelihood that gender-concordant investments participate in an M&A or IPO with the likelihood that discordant investments will M&A or IPO.

In this setting, the model of GP-founder gender homophily asserts that gender homophily can be the product of accurate GP assessment that GP-founder gender concordance is as-

sociated with higher likelihood of in investment participating in an IPO or an acquisition. Rejection that GP-founder gender concordance is associated with higher average returns, then, implies that GPs are not choosing same gender founders due to accurate predictions that gender concordance should lead to higher sell value in expectation.

To retrieve average differences in productivity for gender concordant and discordant investments, I run the following regression. For GP i, start-up founder j, deal d, city c, and time of founding deal t:

$$I(Exit_{ijdct}) = \beta_1 \times I(Discordant_{ijdct}) + X_d + \lambda_t + \delta_c + \epsilon_{jdct} \tag{4}$$

The outcome of interest, $I(Exit)$, is an indicator variable for whether start-up j successfully IPOs or is acquired for start-ups that received their first investment before 2015. The dependent variable, $I(Discordant)$, is an indicator equal to one when a first round investment is gender discordant. To define a deal as gender concordant or discordant, I separate start-ups and GPs into two categories either having all men or having at least one woman. An example of discordance is if all founders are men, but at least one GP investing in the first round is a woman. β_1 on $I(Discordant)$ estimates the relative likelihood a start-up will participate in an IPO and/or M&A if the first round deal was made where founder and GP gender categories did not match. A positive coefficient on β_1, then, can imply that there are no true gender concordance related synergies that GPs are accurately using to motivate disproportionate same-gender investment.

To interpret β_1 as evidence that GPs are forgoing profit β_1 should not be biased by differences in pre-investment costs between gender concordant and discordant investments. For example, while gender discordant investments may have higher returns, on average, if pre-investment costs for gender discordant investments is also higher then profitability can still be equal. While my first empirical step aims to establish that not all of the gender concordance observed is due to these pre-investment costs I include the same set of controls from Table 3 including city, year, and technology area fixed effects as well as the number of GPs associated with that deal.

Traditional outcome tests face the problem of inframarginality: researchers observe average differences in outcomes, not the marginal differences that determine investment decisions. As (Hull, 2021) shows, average outcome gaps are informative about marginal expected returns only when decision makers apply group-specific thresholds and when selection is monotone. Take the example where gender concordant investments face a lower threshold for being invested in such as in the case where I observe gender homophily that is unexplained by pre-investment costs. We, then, know that start-ups that exceed the higher threshold for being a discordant investment also exceed that of the lower threshold for concordant investments.

Given I have shown that GPs hold different investing thresholds for gender concordant and discordant investments I need only assume that GPs invest in gender-concordant founders over gender discordant ones when they (weakly) believe expected returns are higher. Under this monotonicity condition, the observed average difference in IPO or M&A rates between concordant and discordant investments provides a *lower bound* on the difference in marginal expected returns that rationalizes these threshold shifts.

Table 4: Difference in likelihood to successfully exit for gender concordant vs. discordant investments (2005-2015)

	Dependent var:	
	I(IPO)	I(M&A)
Gender discordant	0.040	0.019
	(0.014)	(0.038)
Concordant mean	0.090	0.242
Year, City, Technology FE	x	x
Cluster	City	City
Observations	1570	1570

Note: Table 4 presents estimates of the difference in likelihood for gender discordant investments to participate in an IPO or M&A relative to gender concordant investments. 4.1 presents results an IPO outcome and 4.2 presents results for an M&A outcome. Gender discordance is defined as either (i) at least one woman founder and all men GPs or (ii) all men founders and at least one woman GP. Controls include city, year, and technology fixed effects, and number of GPs at the deal level.

I find that gender-discordant investments are 4.0 percentage points more likely to IPO than gender-concordant investments, a 44% increase relative to the concordant IPO rate of 9.0%. There is no statistically significant M&A effect. When I disaggregate by GP gender (Appendix Table 8), the result holds for both men and women GPs: for deals with only men GPs, start-ups with a woman founder IPO at a rate 4.6 percentage points higher than start-ups with only male founders; for deals with at least one woman GP, start-ups with at least one woman founder are 15.2 percentage points less likely to IPO than start-ups with only men founders. Both men and women GPs thus appear to leave money on the table by disproportionately investing in founders of their own gender. These estimates are sufficient to reject the hypothesis that gender-concordant investments yield positive productive synergies in IPO likelihood. This result suggests that gender homophily is not driven by accurate GP

predictions that gender concordant investments will have higher ROI.

Together I now have two empirical observations. First, gender homophily is present in GP investment decisions even when controlling for pre-investment costs where unobservable variables would have to explain six times more of the estimated effect than observed variables to move my estimate to zero. Second, gender homophily is not likely driven by accurate, empirically motivated predictions that gender concordant investments are more likely to IPO or be acquired. In sum, there is gender homophily that is not explained by accurate statistical discrimination where same-gender investing is profit maximizing. Given this unexplained gender homophily I investigate the possible non profit maximizing reasons that gender homophily may be observed in my data.

6 Stereotyping or Taste for Discrimination?

The final challenge with identifying the underlying driver of gender homophily in VC investment in biomedicine is distinguishing between two forms of profit-forgoing gender bias - mistaken beliefs (stereotyping) and a preference for gender concordance (taste for discrimination). An outcomes test, alone, does not provide enough information to separate the two, as both mechanisms could result in the same observed differences in the likelihood to IPO for gender concordant and discordant investments.

To disentangle gender homophily due to mistaken priors from a preference for gender concordant investments I test the theoretical prediction that mistaken priors or stereotypes can attenuate in the face of new information (Bordalo et al., 2016). I test this theoretical prediction by examining what happens to the gender homophily effect when signals on start-up quality are more clear. To do this, I re-run the regression analysis from step 1 where I estimate the effect of changes in the city share of GPs who are women on the deal share of founders who are women, across three comparisons in which the information available about start-up quality differs: first-round versus follow-on rounds of investment, first-time versus repeat founders, and companies without versus with a prior public research award. Table 5 reports the homophily coefficient for each subsample.

The first comparison uses the funding round. Instead of using the sample of first round investments I estimate this regression on all follow-on rounds of investment. If GPs receive more informative signals on start-up quality as time goes on either due to information from GPs who have already invested or from observable metrics of success, then investing in follow-on rounds should be less impacted by gender homophily. I find that, unlike in first round investments, there is no statistically significant or positive relationship between changes in the share of GPs who are women and the share of founders who are women in follow on

Table 5: Gender homophily by information available about start-up quality

	Dep var: Deal share of founders women					
	Funding round		Start-up in series		NIH/SBIR award	
	First	Follow-on	First	Follow-on	Non-awardee	Awardee
	(1)	(2)	(3)	(4)	(5)	(6)
City share of GPs	0.113	−0.027	0.476	0.028	0.114	0.042
who are women	(0.049)	(0.027)	(0.188)	(0.056)	(0.055)	(0.084)
Year, City, Technology FE	x	x	x	x	x	x
Cluster	City	City	City	City	City	City
N	2098	3883	209	855	1,755	354

Note: Each column reports the homophily coefficient from the specification of Table 3 estimated on the indicated subsample. Columns (1)–(2) compare first-round investments to all follow-on rounds. Columns (3)–(4) conditions on having a repeat founder with more than one start-up in the sample where companies are classified by whether the funding round is for the founder's first start-up or subsequent start-up. Columns (5)–(6) classify companies by whether a founder has ever received a public NIH or SBIR/STTR award.

rounds. This result is suggestive that the conditions in follow-on rounds of funding do not support gender homophily in VC investment in biomedical start-ups and consistent with a story that information on start-up quality in later rounds lead to attenuation of bias due to stereotypes.

While consistent with a story where decreased asymmetry of information leads to reduction of gender homophily due to mistaken priors, there are potential alternative explanations. Follow-on rounds already go through one round of selection where start-ups that do not meet the investing threshold in the first round do not show up in the set start-ups available for follow-on rounds of investing. If follow-on investors share the same gender concordance for gender concordance related investing thresholds, then the selected sample of start-ups that receive first round funding may already surpass the investing threshold, leading to no more selection based on preference in follow-on rounds. In addition, if conditions under which market level taste-based discrimination attenuates are correlated with follow-on rounds of funding (such as more competition in for VC funds), then the regression result may still be interpreted as consistent with a story of taste-based discrimination.

To corroborate the information story I test a second comparison using founders' own histories rather than the funding round. Founders of sample companies are matched to their own founding histories across all industries, and each company is classified by whether the

founder is a first and only time founder, a first-time but future repeat founder, or a serial founder with at least one start-up already in their history. From there I compare gender homophily for serial founders between their first company and subsequent companies. If homophily attenuates with information, then once a founder is validated as higher quality homophily should disappear when founders raise funds for their future start-ups. I find that gender homophily is concentrated on founders the market has not yet learned about strongly where the effect nearly disappears for their subsequent companies.

The third comparison uses external certification. Companies are matched by name to public NIH and SBIR/STTR award records, and classified by whether the company ever received an award. Homophily is concentrated in never-awarded companies and attenuates on certified ones. These three complementary tests support the idea that gender homophily is driven by mistaken beliefs which attenuate with information on quality rather than a taste for gender concordance.

7 Founder Gender and Gender Specific Technologies

One potential consequence of bias-driven gender homophily is that certain biomedical technologies may be underfunded, particularly those developed by start-ups with women founders. Although I find symmetric gender homophily for both men and women GPs, the relatively small share of GPs who are women can still result in lower funding for women-founded areas of innovation if the gender distribution across therapeutic or technology types differs meaningfully.

To investigate whether gender-biased homophily contributes to missing technologies for women, I estimate the following linear probability model, where j indexes start-ups:

$$I(WHT_j) = \beta \times I(WF_j) + X_j + \lambda_t + \delta_c + \epsilon_j \tag{5}$$

This regression estimates the likelihood that a start-up with a woman founder is working on women's healthcare technology. $I(WHT)$ is an indicator for whether the start-up works on a women's healthcare technology, and $I(WF)$ equals one if the start-up has at least one woman founder. I include year fixed effects λ_t, city fixed effects δ_c, and a control for the number of GPs on the deal X_j. Technology fixed effects are omitted by construction, since the outcome is itself a technology direction; within-technology estimates are similar. Women's health is classified from company descriptions by a keyword classifier validated against 200 hand-coded companies; 4.5% of start-ups are in women's health.

Table 6 reports the results. In regression (1), which is unconditional, 8.8% of start-ups

with at least one woman founder work on women's health technologies, such as treatments for ovarian cancer or therapies related to maternal health, compared with 3.5% of start-ups founded only by men. Funded women founders are therefore roughly 2.5 times as likely to develop women's-health technologies, a difference of 5.4 percentage points. Regression (2) adds year and city fixed effects and yields a similar result of 5.8 percentage points. Regression (3) uses the deal share of founders who are women in place of the indicator where moving a founding team from all men to all women raises the probability of working in women's health by 12.2 percentage points. Across all three specifications, women-founded start-ups are significantly more likely to work on women's healthcare technologies.

Combining the homophily coefficient from Table 3 (0.113) with the women's-health coefficient in regression (3) (0.122), I calculate that each 10 percentage point increase in a city's share of women GPs raises the probability that a funded start-up works in women's health by about 0.14 percentage points. Raising the share of women GPs to parity with men, an increase of roughly 40 percentage points, would move the women's-health rate from 4.5% to about 5.1%, a 12% increase relative to the base rate. In light of this paper's gender bias results, this pattern suggests that venture capital may be misallocating resources away from women's healthcare technologies, given the low representation of women among general partners.

Table 6: Likelihood that a woman founded start-up works on women's health

	Dep var: Start-up is in women's health		
	(1)	(2)	(3)
Has a Woman Founder	0.054	0.058	
	(0.014)	(0.014)	
Deal share of founders who are women			0.122
			(0.028)
Year, City FE		x	x
Cluster		City	City
N	2641	2609	2084

Note: Table 6 presents linear probability estimates of the relative likelihood that a woman founded start-up works on women's health, for first-round investments. Women's health is defined as technologies that directly affect women's health (i.e. pregnancy, ovarian cancer, etc.); 4.5% of start-ups in the sample work in women's health, 3.5% of start-ups founded only by men and 8.8% of start-ups with at least one woman founder. Regression (1) is unconditional; regressions (2)–(3) include year and city fixed effects and a control for the number of GPs on the deal. Regression (3) replaces the woman-founder indicator with the deal share of founders who are women. Technology fixed effects are omitted because the outcome is itself a technology direction. Standard errors clustered by city in parentheses.

8 Conclusion

Venture capital plays an outsized role in shaping which biomedical technologies reach patients. In an industry defined by scientific uncertainty, long development timelines, and regulatory risk, investors often make decisions with incomplete information. This paper shows that under these conditions, gender shapes early-stage biomedical investment in ways that are difficult to rationalize with profit maximization alone.

Using PitchBook data on U.S. biomedical start-ups from 2005 to 2024, I first document persistent underrepresentation of women among both investors and funded founders. Women constitute 13.8% of GPs and 12.2% of funded founders, with little change over time, despite near parity in the upstream life-science PhD pipeline. I then show that biomedical VC exhibits gender homophily: places with higher shares of women GPs fund higher shares of women founders. Importantly, this relationship remains after controlling for key drivers of pre-investment costs, including geography and technological specialization, and after proxying for gendered shifts in the supply of potential founders using patent inventor

composition. Sensitivity analyses further indicate that unobserved confounding would need to be implausibly large to eliminate the estimated homophily effect.

Next, I test whether this residual homophily can be explained by productive synergies or accurate statistical discrimination, where gender-concordant investments are more likely to succeed. I find the opposite. Gender-discordant investments are more likely to IPO than gender-concordant investments, and there is no corresponding evidence of higher M&A rates for concordant investments. Under weak monotonicity assumptions, these outcome differences imply that observed homophily reflects, at least in part, investment decisions that leave money on the table. Moreover, the homophily effect attenuates in follow-on rounds, consistent with a mechanism in which biased beliefs diminish as more information about start-up quality becomes available, rather than a stable preference for gender concordance.

Finally, I show that women-founded start-ups are more likely to work on technologies that address women's healthcare needs, both across and within technology categories. Given the low share of women among GPs, even symmetric bias can generate asymmetric technological consequences if the gender distribution of founders differs across disease areas or technology types. The results therefore raise a concern that bias-driven allocation may distort not only who receives funding, but also which biomedical needs are prioritized, potentially skewing investment away from women's healthcare technologies.

These findings contribute to research on decision-making under uncertainty by showing that gender stereotypes can shape capital allocation even in settings where investors claim to rely primarily on science and product quality. They also refine the literature on gender and entrepreneurship by documenting a symmetric pattern of profit-forgoing behavior among both men and women investors, pointing to upstream constraints in who becomes a GP and who enters the founder pipeline as critical margins for policy and institutional attention. More broadly, the results suggest that efforts to improve gender representation among biomedical investors may have returns beyond equity considerations, by improving allocative efficiency and reducing the likelihood that socially valuable technologies are underfunded.

Several questions remain. Understanding how gender interacts with specific technological domains, and whether capital shortfalls translate into slower development or reduced entry in women-relevant therapeutic areas, are natural next steps. More generally, mapping the link between investor demographics and the direction of innovation is a promising path for future work, particularly in biomedical markets where private capital plays a central role in determining which ideas become therapies.

Bibliography

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

Altonji, J. G. and C. R. Pierret (2001). Employer learning and statistical discrimination. *Quarterly Journal of Economics 116*(1), 313–350.

Anwar, S. and H. Fang (2006). An alternative test of racial prejudice in motor vehicle searches: Theory and evidence. *American Economic Review 96*(1), 127–151.

Argyle, B., S. Indarte, B. Iverson, and C. Palmer (2025). Racial disparities and bias in consumer bankruptcy. Working paper.

Arnold, D., W. Dobbie, and P. Hull (2022). Measuring racial discrimination in bail decisions. *American Economic Review 112*(9), 2992–3038.

Arnold, D., W. Dobbie, and C. S. Yang (2018). Racial bias in bail decisions. *Quarterly Journal of Economics 133*(4), 1885–1932.

Arrow, K. J. (1973). The theory of discrimination. In O. Ashenfelter and A. Rees (Eds.), *Discrimination in Labor Markets*, pp. 3–33. Princeton University Press.

Ayres, I. (2002). Outcome tests of racial disparities in police practices. *Justice Research and Policy 4*(1–2), 131–142.

Bahlmann, M. D. (2023). Attractiveness, ethnicity, and stage financing: Exploring heuristics in venture capital staging. *Industry and Innovation 30*(3), 392–421.

Baker, S. P. and C. Koedel (2024). Diversity trends among faculty in STEM and non-STEM fields at selective public universities in the U.S. from 2016 to 2023. *Humanities and Social Sciences Communications 11*(1), 1–9.

Bartlett, R., A. Morse, R. Stanton, and N. Wallace (2022). Consumer-lending discrimination in the FinTech era. *Journal of Financial Economics 143*(1), 30–56.

Becker, G. S. (1957). *The Economics of Discrimination*. Chicago: University of Chicago Press.

Bohren, J. A., P. Hull, and A. Imas (2025). Systemic discrimination: Theory and measurement. *Quarterly Journal of Economics 140*(3), 1743–1799.

Bordalo, P., K. Coffman, N. Gennaioli, and A. Shleifer (2016). Stereotypes. *Quarterly Journal of Economics 131*(4), 1753–1794.

Bordalo, P., K. Coffman, N. Gennaioli, and A. Shleifer (2019). Beliefs about gender. *American Economic Review 109*(3), 739–773.

Brooks, A. W., L. Huang, S. W. Kearney, and F. E. Murray (2014). Investors prefer entrepreneurial ventures pitched by attractive men. *Proceedings of the National Academy of Sciences 111*(12), 4427–4431.

Calder-Wang, S. and P. A. Gompers (2021). And the children shall lead: Gender diversity and performance in venture capital. *Journal of Financial Economics 142*(1), 1–22.

Calder-Wang, S., P. A. Gompers, and P. Sweeney (2022). Venture capital's "Me Too" moment. NBER Working Paper 28679, National Bureau of Economic Research.

Canay, I. A., M. Mogstad, and J. Mountjoy (2024). On the use of outcome tests for detecting bias in decision making. *Review of Economic Studies 91*(4), 2135–2167.

Chen, H., P. Gompers, A. Kovner, and J. Lerner (2010). Buy local? The geography of venture capital. *Journal of Urban Economics 67*(1), 90–102.

Coffman, K. B., C. L. Exley, and M. Niederle (2021). The role of beliefs in driving gender discrimination. *Management Science 67*(6), 3551–3569.

Einiö, E., J. Feng, and X. Jaravel (2026). Social push and the direction of innovation. *American Economic Review 116*(10).

Ewens, M. (2023). Gender and race in entrepreneurial finance. In B. E. Eckbo, G. M. Phillips, and M. Sørensen (Eds.), *Handbook of the Economics of Corporate Finance: Private Equity and Entrepreneurial Finance*, Volume 1, pp. 239–296. Elsevier.

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

Gompers, P. A., W. Gornall, S. N. Kaplan, and I. A. Strebulaev (2020). How do venture capitalists make decisions? *Journal of Financial Economics 135*(1), 169–190.

Gompers, P. A., A. Kovner, J. Lerner, and D. Scharfstein (2009). Specialization and success: Evidence from venture capital. *Journal of Economics & Management Strategy 18*(3), 817–844.

Gompers, P. A., V. Mukharlyamov, E. Weisburst, and Y. Xuan (2022). Gender gaps in venture capital performance. *Journal of Financial and Quantitative Analysis 57*(2), 485–513.

Gompers, P. A., V. Mukharlyamov, and Y. Xuan (2016). The cost of friendship. *Journal of Financial Economics 119*(3), 626–644.

Greenberg, J. and E. Mollick (2017). Activist choice homophily and the crowdfunding of female founders. *Administrative Science Quarterly 62*(2), 341–374.

Gupta, A., S. Batra, and V. K. Gupta (2022). Gender, culture, and implicit theories about entrepreneurs: A cross-national investigation. *Small Business Economics 58*(2), 1073–1089.

Guzman, J. and A. O. Kacperczyk (2019). Gender gap in entrepreneurship. *Research Policy 48*(7), 1666–1680.

Hébert, C. (2025). Gender stereotypes and entrepreneur financing. *Review of Financial Studies*. Advance access, hhaf049.

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

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

Huang, L. (2018). The role of investor gut feel in managing complexity and extreme risk. *Academy of Management Journal 61*(5), 1821–1847.

Huang, X., Z. Ivković, J. X. Jiang, and I. Y. Wang (2023). Angel investment and first impressions. *Journal of Financial Economics 149*(2), 161–178.

Huayamares, S. G., M. P. Lokugamage, A. J. Da Silva Sanchez, and J. E. Dahlman (2022). A systematic analysis of biotech startups that went public in the first half of 2021. *Current Research in Biotechnology 4*, 392–401.

Hull, P. (2021). What marginal outcome tests can tell us about racially biased decision-making. Working paper, Brown University.

Kanze, D., L. Huang, M. A. Conley, and E. T. Higgins (2018). We ask men to win and women not to lose: Closing the gender gap in startup funding. *Academy of Management Journal 61*(2), 586–614.

Kerr, W. R., R. Nanda, and M. Rhodes-Kropf (2014). Entrepreneurship as experimentation. *Journal of Economic Perspectives 28*(3), 25–48.

Knowles, J., N. Persico, and P. Todd (2001). Racial bias in motor vehicle searches: Theory and evidence. *Journal of Political Economy 109*(1), 203–229.

Koning, R., S. Samila, and J.-P. Ferguson (2021). Who do we invent for? Patents by women focus more on women's health, but few women get to invent. *Science 372*(6548), 1345–1348.

Kozlowski, D., V. Larivière, C. R. Sugimoto, and T. Monroe-White (2022). Intersectional inequalities in science. *Proceedings of the National Academy of Sciences 119*(2), e2113067119.

Lassébie, J., S. Sakha, T. Kozłuk, C. Menon, S. Breschi, and N. Johnstone (2019). Levelling the playing field: Dissecting the gender gap in the funding of start-ups. OECD Science, Technology and Industry Policy Paper 73, OECD Publishing.

Lerner, J. and R. Nanda (2020). Venture capital's role in financing innovation: What we know and how much we still need to learn. *Journal of Economic Perspectives 34*(3), 237–261.

McPherson, M., L. Smith-Lovin, and J. M. Cook (2001). Birds of a feather: Homophily in social networks. *Annual Review of Sociology 27*, 415–444.

National Science Foundation, NCSES (2017). Doctorate recipients from U.S. universities: 2016. Report NSF 18-304, National Center for Science and Engineering Statistics, Alexandria, VA.

National Science Foundation, NCSES (2019). Women, minorities, and persons with disabilities in science and engineering: 2019. Report NSF 19-304, National Center for Science and Engineering Statistics, Alexandria, VA.

Nielsen, M. W., J. P. Andersen, L. Schiebinger, and J. W. Schneider (2017). One and a half million medical papers reveal a link between author gender and attention to gender and sex analysis. *Nature Human Behaviour 1*(11), 791–796.

Nörthemann, A. (2023). Industry-specific specialization in venture capitalists' internationalization decisions. *Journal of Business Economics 93*, 891–927.

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

Phelps, E. S. (1972). The statistical theory of racism and sexism. *American Economic Review 62*(4), 659–661.

PitchBook Data (2025). PitchBook 2025 life sciences outlook. PitchBook Industry Report.

Raina, S. (2019). VCs, founders, and the performance gender gap. Working paper, University of Alberta.

Russo, E. (2003). Special report: The birth of biotechnology. *Nature 421*(6921), 456–457.

Snellman, K. and I. Solal (2023). Does investor gender matter for the success of female entrepreneurs? Gender homophily and the stigma of incompetence in entrepreneurial finance. *Organization Science 34*(1), 154–177.

Sorenson, O. and T. E. Stuart (2001). Syndication networks and the spatial distribution of venture capital investments. *American Journal of Sociology 106*(6), 1546–1588.

Truffa, F. and A. Wong (2025). Undergraduate gender diversity and the direction of scientific research. *American Economic Review 115*(7), 2414–2448.

Tyebjee, T. T. and A. V. Bruno (1984). A model of venture capitalist investment activity. *Management Science 30*(9), 1051–1066.

1 Appendix A: Data construction

1.A GP categorization

To identify variation in gender composition of GPs, I use the following classification system in order to identify investment decision makers in Pitchbook. I classify the following under my GP umbrella term if the individual has one of the following position level titles at a VC fund or investment firm:

Primary decision makers:

- Managing Partner
- General Partner
- Managing General Partner
- Partner
- Founding Partner
- Managing Director
- Investment Partner
- Investment Director
- Senior Partner
- Senior Managing Director

Deal Execution & Diligence Leads:

- Principal
- Investment Manager
- Senior Investment Manager
- Vice President
- Senior Vice President
- Associate Partner
- Associate Director

- Associate
- Senior Associate

1.B Defining therapeutic classes by start-up description

To flexibly control for the expected cost and projected revenue across start-ups I classify start-ups by their start-up description. A typical length start-up description may look like: "Developer of a disposal surgical tool kit designed to make left ventricular assist device implantations easily reproducible. The company's disposal surgical tool kit and products facilitate surgical procedures on a beating heart which eliminates the need and added cost of cardiopulmonary bypass and lowers surgical complications by utilizing less-invasive surgical procedures, enabling patients to recover faster from heart diseases and reducing the chances of facing a heart failure."

From this description I use the US FDA documentation on therapeutic areas to create keywords associated with each therapy class for textual matching with start-up description. For example, the above description would match to the therapeutic category "Cardiovascular" where it would be identified as such through key words: "heart", "cardio" and "vascular". For technologies that are not identified as one of the therapeutic areas such as some general drug discovery technologies are classified as "Non-therapeutic".

The key therapeutic classes are as follows:

1. Cardiovascular
2. Respiratory
3. Oncology
4. Infectious Disease
5. Gastrointestinal
6. Endocrine
7. Orthopedic
8. Dermatological
9. Ophthalmic
10. Genetic

11. Dental
12. Pain
13. Immunological
14. Non-therapeutic

1.C Constructing city-year level patent inventor gender composition

2 Appendix B: VC investment trends

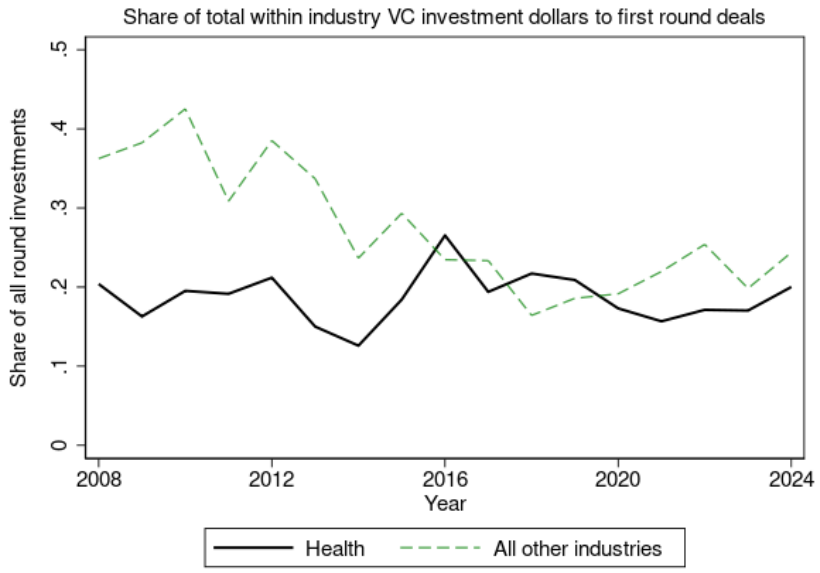
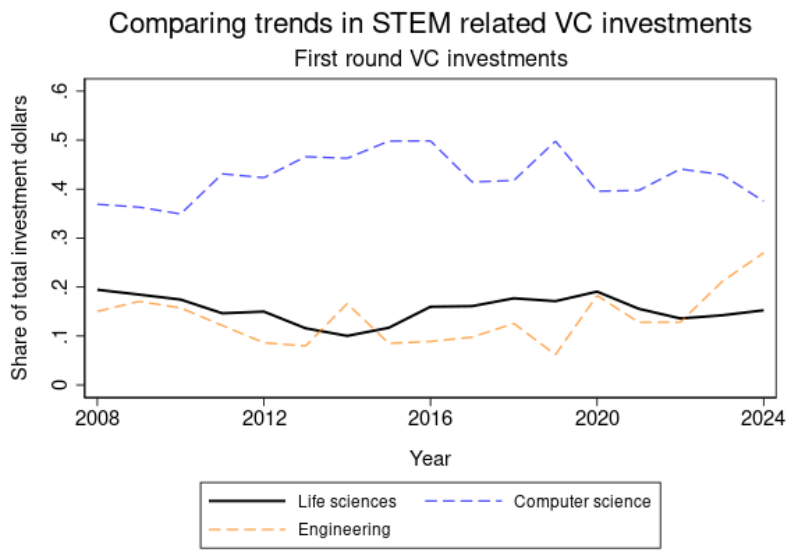
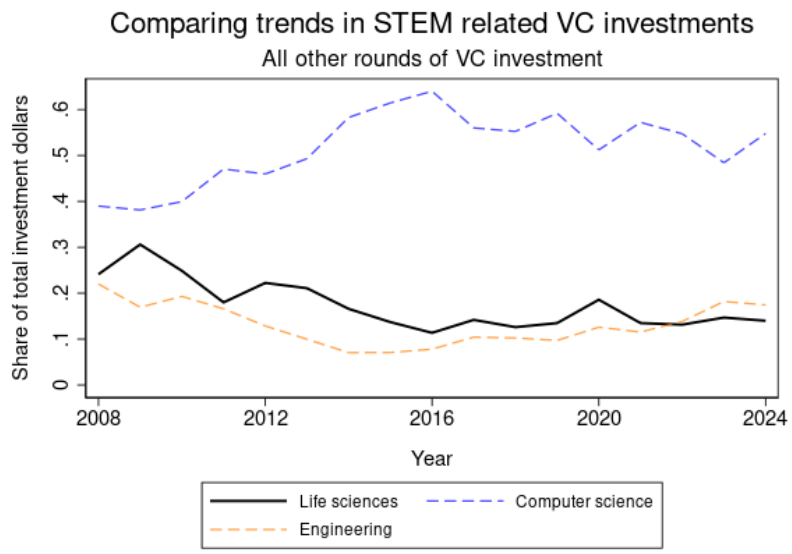


Figure 3: Share of VC investment dollars to first-round vs follow-on round deals.



(a) first-round



(b) Follow-on rounds

Figure 4: Comparing STEM related investments as a share of all VC investments

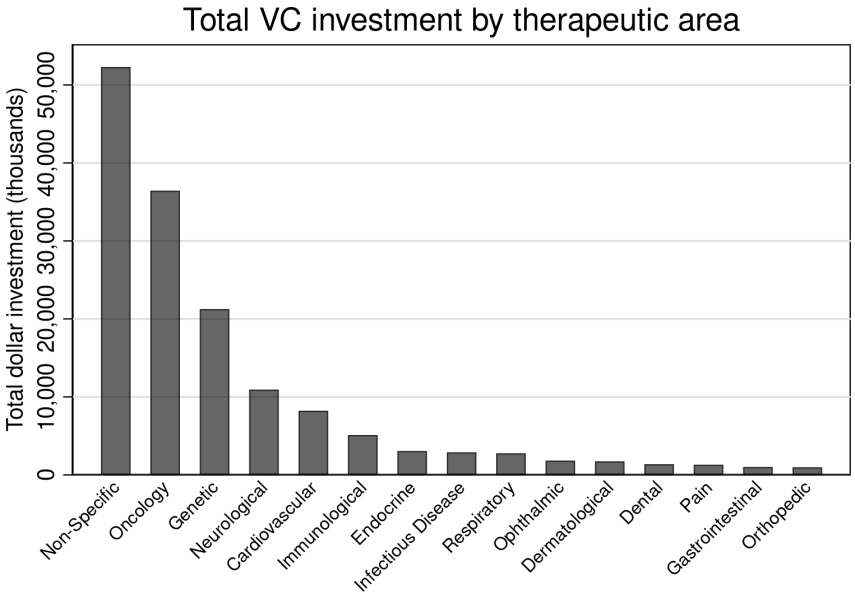


Figure 5: Total VC investment dollars to start-ups by therapeutic areas.

Appendix C: Model derivation of econometric approach

This appendix maps the model of Section 2 into the econometric specification. To economize on notation, I index pairings directly by GP gender $g \in \{W, M\}$ and founder gender $f \in \{W, M\}$, so the utility U_{gf} corresponds to U_{ijq} with $q = C$ when $g = f$ and $q = N$ otherwise. A GP invests if utility exceeds the reservation utility of zero. For a given pool of start-ups, the probability that a GP of gender g invests in a firm with a founder of gender f is $P(\text{invest}|g, f) = P(U_{gf} > 0)$.

Gender homophily, as modeled, implies that GPs are more likely to invest in founders of their own gender. This means:

1. $P(\text{invest}|W, W) > P(\text{invest}|M, W)$
2. $P(\text{invest}|M, M) > P(\text{invest}|W, M)$

These conditions follow from the model: substituting the subjective expected return into the investment condition, a GP invests when the start-up's true quality clears the pairing-specific threshold

$$\rho_{jq} > \rho^*_{ijq} \equiv \frac{I + C_{ijq} - D_{iq} - (1 - \lambda)\left(\bar{r}_q + \nu_{iq}\right)}{\lambda},$$

so the investment probability is $P(\text{invest}|g, f) = P(\rho_{jq} > \rho^*_{ijq})$. A positive concordance advantage ($\Delta U_i > 0$) corresponds to a lower threshold for concordant than discordant pairings

$(\rho^*_{ijC} < \rho^*_{ijN})$, with gap $\rho^*_{ijN} - \rho^*_{ijC} = \left[(1-\lambda)(\nu_{iC} - \nu_{iN}) + (D_{iC} - D_{iN}) + (\bar{C}_{iN} - \bar{C}_{iC})\right]/\lambda$ when true type means are equal, which raises the probability of investing in same-gender founders and delivers conditions 1 and 2. Define the homophily gap in the likelihood to invest for women and men founders, respectively, as:

$$\Delta_W = P(\text{invest}|W,W) - P(\text{invest}|M,W) > 0 \tag{6}$$

$$\Delta_M = P(\text{invest}|M,M) - P(\text{invest}|W,M) > 0 \tag{7}$$

Now, consider a city with a large number of GPs and potential start-ups. Let S^G_W be the share of GPs in the city who are women, and let S^P_W be the share of potential start-ups that have women founders. For simplicity, I assume the supply of potential start-ups with women founders, S^P_W, is exogenous to the share of women GPs - enforced by my empirical approach.

The number of investments or deals with women-founded firms is proportional to the number of women founders considered by all GPs. This can be expressed as:

$$\text{Deals}_W \propto S^P_W \times [S^G_W \cdot P(\text{invest}|W,W) + (1 - S^G_W) \cdot P(\text{invest}|M,W)] \tag{8}$$

Similarly, the number of deals with men-founded firms is:

$$\text{Deals}_M \propto (1 - S^P_W) \times [S^G_W \cdot P(\text{invest}|W,M) + (1 - S^G_W) \cdot P(\text{invest}|M,M)] \tag{9}$$

The share of *funded* companies with women founders, which is the outcome variable Y_{ict} in the empirical model, is the ratio of the investment Deals to women founders over the total investment Deals:

$$S^F_W = \frac{\text{Deals}_W}{\text{Deals}_W + \text{Deals}_M} \tag{10}$$

where P_{gf} stand in for $P(\text{invest}|g,f)$. I simplify the expressions inside the brackets of the deals equations:

$$\begin{aligned} S^G_W P_{WW} + (1 - S^G_W) P_{MW} &= S^G_W (P_{WW} - P_{MW}) + P_{MW} = S^G_W \Delta_W + P_{MW} \\ S^G_W P_{WM} + (1 - S^G_W) P_{MM} &= S^G_W (P_{WM} - P_{MM}) + P_{MM} = -S^G_W \Delta_M + P_{MM} \end{aligned}$$

Substitute back into the expression for S^F_W:

$$S^F_W(S^G_W) = \frac{S^P_W (S^G_W \Delta_W + P_{MW})}{S^P_W (S^G_W \Delta_W + P_{MW}) + (1 - S^P_W)(-S^G_W \Delta_M + P_{MM})} \tag{11}$$

To find the effect of changing the share of women GPs, I differentiate S_W^F with respect to S_W^G. Let the numerator be $N(S_W^G)$ and the denominator be $D(S_W^G)$. $\frac{\partial S_W^F}{\partial S_W^G} = \frac{N'D - ND'}{D^2}$.

$$N'(S_W^G) = S_W^P \Delta_W$$
$$D'(S_W^G) = S_W^P \Delta_W - (1 - S_W^P)\Delta_M$$

So, the numerator of the derivative is:

$$(S_W^P \Delta_W)D - N(S_W^P \Delta_W - (1 - S_W^P)\Delta_M)$$
$$= S_W^P \Delta_W (D - N) + N(1 - S_W^P)\Delta_M$$

Note that $D - N = \text{Deals}_M$ and $N = \text{Deals}_W$.

$$= S_W^P \Delta_W (\text{Deals}_M) + (1 - S_W^P)\Delta_M (\text{Deals}_W) \tag{12}$$

Since all probabilities, shares, and number of deals are non-negative, and the homophily gaps Δ_W and Δ_M are strictly positive under the model's assumptions, this expression is positive. Therefore, $\frac{\partial S_W^F}{\partial S_W^G} > 0$.

3 Appendix D: Robustness to Different Specifications

For my Table 3 I make several choices on how to define my primary control variables. To assure robustness, the following regressions use alternative definitions of technology.

3.A Alternate Technology Categories: Pitchbook Sub-Industry Categories

My alternate definition of technology controls uses the Pitchbook, identified subindustry classifications. These include:

1. Biotechnology (22.3%)
2. Diagnostic Equipment (7.3%)
3. Discovery Tools (2.7%)
4. Drug Delivery (1.8%)
5. Drug Discovery (28.6%)

6. Medical Supplies (2.1%)
7. Monitoring Equipment (5.1%)
8. Other Devices and Supplies (5.8%)
9. Other Pharmaceuticals and Biotechnology (4.0%)
10. Pharmaceuticals (6.5%)
11. Surgical Devices (5.0%)
12. Therapeutic Devices (8.74%)

Running my regression specification using these categories as technology category fixed effects I get the following results.

Table 7: Estimates of gender homophily controlling for ex-ante costs to investing

	(1)	(2)	(3)
City share of GPs	0.079	0.101	0.101
who are women	(0.031)	(0.049)	(0.049)
City share of inventors			-0.046
who are women			(0.221)
Year, City, Technology FE		x	x
Cluster		City	City
Observations	2121	2098	2098

Note: Table 6 presents estimates the magnitude of gender homophily for first round investments. Table 6.1 gives the estimate with no controls. Table 6.2 controls for demand side cost differences such as geographic location and technology area. Table 6.3 adds an additional control for supply side changes in the potential founder pool using patent inventors as a proxy.

3.B Altonji–Elder–Taber Coefficient Stability

As a complement to the Oster (2019) sensitivity analysis reported in the main text, I apply the coefficient stability test described in Altonji et al. (2005). This approach assesses how much stronger selection on unobservables would need to be, relative to selection on

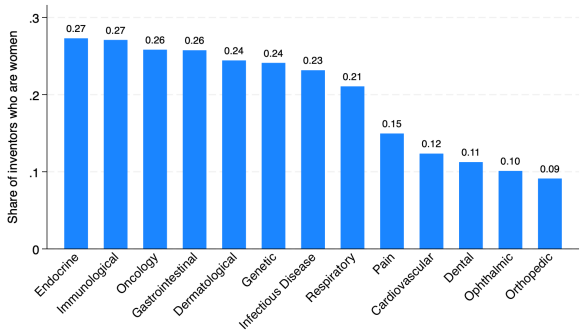
observables, to drive the estimated coefficient to zero. The method uses movements in the regression R^2 between the short specification and the full specification to infer the implied strength of unobserved confounding. Using regression 1 of Table 3 as the base equation and regression 3 as the full specification, I compute:

$$\frac{R^2_{\text{Full}}}{R^2_{\text{Short}} - R^2_{\text{Full}}} = \frac{0.069}{0.03 - 0.069} = -1.769. \tag{13}$$

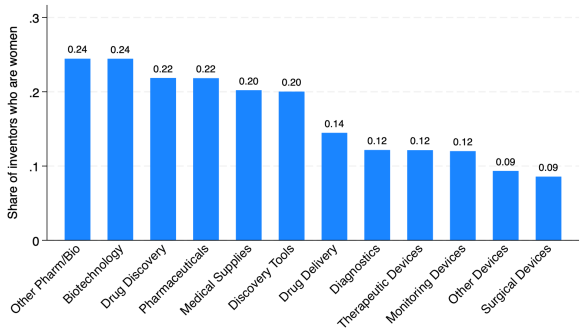
Taking the absolute value, the implied selection ratio indicates that unobserved variables would need to be 1.769 times more explanatory than the observed covariates to eliminate the estimated homophily effect. Ratios greater than one are typically interpreted as evidence of robustness, since it is often implausible that selection on unobservables dominates selection on observables to such a degree.

4 Appendix E: Gender Distribution of Patent Inventors Across Technologies

Figure 6: Gender distribution of patent inventors across technologies



(a) Share of inventors who are women, by therapeutic category



(b) Share of inventors who are women, by industry category

Notes: This figure summarizes variation in the gender composition of patent inventors across biomedical technology categories. Panel A plots the share of inventors who are women within therapeutic category. Panel B plots the share of inventors who are women within industry categories.

5 Appendix F: Exit Outcomes Test by GP Gender

Table 8: Exit outcomes test by whether a deal has a woman GP (2005–2015)

	IPO		M&A	
	Men GPs	Has woman GP	Men GPs	Has woman GP
Has woman founder	0.046	-0.152	-0.033	-0.130
	(0.024)	(0.073)	(0.035)	(0.100)
Baseline mean	0.086	0.241	0.240	0.430
(no women founder or GP)				
Observations	1371	177	1371	177

Note: This table disaggregates the pooled outcome test (Table 4) by GP gender. Columns (1) and (3) restrict the sample to deals with only men GPs; columns (2) and (4) restrict to deals with at least one woman GP. The dependent variable is an indicator for IPO (columns 1–2) or M&A (columns 3–4). "Has woman founder" is an indicator equal to one if the start-up has at least one woman founder. The baseline mean reports the exit rate for deals with no women founders within each GP gender subsample. Controls include city, year, and technology fixed effects, and number of GPs at the deal level. The sample is restricted to first-round investments made before 2015.