Discrimination in Two-sided Matching Market: Experimental and Theoretical Evidence in Entrepreneurial Finance *

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Abstract

This paper investigates discrimination within two-sided matching markets, focusing specifically on the entrepreneurial financing market. Through an experiment involving real US startup founders, we identify the presence of statistical gender discrimination against female investors among startup founders. Specifically, female investors' signals are perceived as less informative compared to those of male investors. This discrimination is predominantly driven by male founders and disproportionately affects high-quality female investors, indicating the presence of both gender homophily and a glass ceiling effect for women in this domain. Interestingly, Asian investors do not face similar levels of discrimination. Building upon these experimental findings, we develop a novel search and matching model with endogenously information aggregation and belief formation. This theoretical framework demonstrates how statistical discrimination arises endogenously within two-sided matching markets, leading to the observed glass ceiling effect and perpetuating a persistent low female participation rate in entrepreneurial financing. Overall, this paper offers novel insights into the nature and distinct characteristics of discrimination within two-sided matching markets.

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1 Introduction

Studying discrimination in two-sided matching processes is crucial, given that various important markets, such as labor market, college admissions, and housing rentals market, often involve such matching processes. The complex interaction between agents during search and matching can lead to unique equilibrium settings that profoundly impact minority groups (Craig, Fryer et al., 2017). This paper aims to explore the nature and distinct characteristics of discrimination within such markets, offering theoretical insights into when and how discrimination emerges and its effects on two-sided matching market participants. We specifically focus on gender discrimination in the entrepreneurial financing market due to its importance in high-impact entrepreneurship and innovation within the US economy.[1] As a representative two-sided matching market (Sørensen, 2007), abundant anecdotal evidence suggests implicit gender bias exists on both the investor and startup sides and it is documented that women's participation in this market remains consistently lower than in other high-skilled and well-paid occupations (Gompers and Wang, 2017).[2] While gender or racial discrimination on the investor side has been widely studied (Ewens, 2022), the potential presence and nature of such discrimination among startup founders, who possess significant bargaining power to shape equilibrium outcomes (Ebrahimian and Zhang, 2024; Ewens, Gorbenko and Korteweg, 2022), still remains underexplored.

To fill in this gap, our paper first conducts an experiment with US startup founders to mainly explore the potential presence of gender discrimination among founders together with its nature and characteristics. Combining experimental results with US venture capitalists (VCs) in Zhang (2020), our experiment reveals symmetric gender discrimination patterns across both investors and startups by completing an experimental system.[3] Leveraging these experimental findings, we develop a theoretical model that explains the conditions under which statistical discrimination arises in a two-sided matching market. We further explore how it leads to observed phenomena like the glass ceiling and long-lasting low participation

[1]While this paper also examines whether racial discrimination against Asian investors exists among US startup founders, it is not the primary focus of the study

[2]see "What are some reasons why there are fewer female venture capitalists (VCs)?" on Quora

[3]An experimental system is a framework within which individual experiments are conducted. It usually contains a series of experiments that complement each other. The concept is widely used in biology, and "the choice of an appropriate experimental system is often seen as critical for a scientist's long-term success." For more discussions of this concept, see Ebrahimian and Zhang (2024).

rates among women.

In total, 141 real US startup founders who are seeking VC funding participated in our study through two waves of recruitment and collectively evaluated 2,820 randomly generated VC profiles. Following the design in Kessler, Low and Sullivan (2019), participating founders evaluate multiple hypothetical VC profiles with randomly assigned first names highly indicative of their genders and last names highly indicative of their races. We compile a comprehensive global VC database and develop a matching algorithm to offer personalized investor recommendation services for participating founders. This algorithm generates a list of matched *real* VCs for each founder. While founders are aware that the VC profiles are hypothetical, they are incentivized to provide truthful evaluations due to a matching incentive: the more honest their evaluations, the more effective and beneficial the generated list will be. In addition to evaluating each VC profile based on investor quality, investment likelihood, and informativeness, founders also express their interest in contacting each VC and establishing potential collaboration opportunities with them.

Compared to alternative experimental designs, our design offers multiple advantages in providing deeper insights into discrimination theory. Beyond avoiding deception, this design uncovers nuanced belief-driven mechanisms, particularly regarding whether minority group signals are perceived noisier compared to majority group signals by evaluators. This information-related mechanism is crucial for verifying information-based discrimination theories but is challenging to capture with other methods. Additionally, by simultaneously randomizing a rich set of VC characteristics, this design reveals how discrimination affects candidates of varying qualities. This distributional effect informs the unique features of discrimination in a matching context, which guides relevant theory development.

The experiment first identifies the presence of gender discrimination against female VCs among US startup founders. When comparing female VC profiles to similar male VC profiles, startup founders rate female VCs, on average, 3.46 percentage points (p.p.) lower in contact interest ratings. This decrease corresponds to a 5.8% drop from the average rating level and remains statistically significant at the 1% level even after adjusting for multiple hypothesis testing. The magnitude of this effect is approximately 47.40% of the effect of VCs' entrepreneurial experience on the ratings, which is considered one of the most crucial human capital characteristics of VCs (Bottazzi, Da Rin and Hellmann, 2008; Gompers and Mukharlyamov, 2022). However, we do not observe any significant racial discrimination against Asian VCs.

Secondly, the experiment further indicates that startup founders' discrimination behaviors are closely related to belief-driven mechanisms. Consistent with statistical discrimination, founders perceive female VCs as 3.17 p.p. less likely to contribute to higher startup profitability and 3.20 p.p. less likely to express investment interest in their startups. An important and novel finding is that founders view female VC profiles as 5.25 p.p. less informative compared to similar male VC profiles. This serves as a crucial empirical validation for information-based discrimination theories (Che, Kim and Zhong, 2020), suggesting that signals from underrepresented groups (i.e., the minority group) are inherently perceived as noisier than those from the majority group. As illustrated in our model, these beliefs can arise endogenously within a matching context, even when different groups possess identical quality distributions and evaluators utilize identical rating technologies.

Thirdly, we document the presence of gender homophily in startup founders' fundraising endeavors. Male founders, on average, assign significantly lower contact interest ratings to female VCs, with a reduction of 4.84 percentage points, and this difference is statistically significant at the 1% level. Similarly, male founders also hold more negative beliefs about female VCs' value added to their profitability and investment intentions in their startups compared to their perceptions of similar male VCs. However, compared to male founders, female founders exhibit a significantly higher propensity to engage with female VCs and hold more positive beliefs about their value added and investment intentions. While our study identifies gender homophily, we do not find any evidence of racial homophily. The discovered presence of gender homophily and the absence of racial homophily offer crucial empirical insights for our model, elucidating the circumstances under which discrimination emerges in a matching market.

Lastly, we further discover a novel "glass ceiling" phenomenon wherein statistical discrimination disproportionately hurts *high-quality* female VCs. Using other orthogonally randomized VC characteristics as proxies for VC quality, we find that founders assign 3.71 p.p. lower contact interest ratings to high-quality female VCs compared to similar high-quality male VCs. Similarly, negative perceptions about female VCs also predominantly impact high-quality ones. However, when evaluating low-quality VCs, founders rate female VCs slightly more positively compared to similar VCs, leading to a weak "discrimination reversion" phenomenon. Consistent with the "glass ceiling" phenomenon, we also observe that while implicit gender discrimination influences startup founders' fundraising behaviors, such implicit discrimination particularly hurt female VCs in *senior* positions.[4]

To explain the stark empirical findings above, we develop a novel search and matching model with endogenously information aggregation. In a matching market, founders search for VCs and a successful matching leaves an informative, albeit imperfect, rating about the VC's quality. The model features a seemingly level playing field for VCs from different identity groups: different groups have identical quality distribution and access to the same rating technology. Yet, the opportunity of getting evaluated is determined endogenously by the matching frequency of each group by entrepreneurs, leading to a feedback loop: a more frequently matched group has ratings perceived as more reliable, resulting in even more matching of the group (specifically, those with good ratings). However, our model shows that this feedback loop alone is not sufficient for generating discrimination: the information from the ratings eventually corrects initial biases, resulting in a unique non-discriminatory equilibrium. This justifies the absence of racial discrimination against Asian VCs.

The crucial insight from our model is that the feedback loop, combined with homophily in the matching market, leads to persistent statistical discrimination against the minority group. This is because homophily creates a "payoff wedge" only across different identity groups. Hence, since the majority group has a larger population, their interaction with the minority group dictates the equilibrium evaluations, leading to under-sampling of minorities. Notably, this discrimination against the minority group features both a "glass ceiling" and a "glass basement" effect: the rational belief from the ratings "discriminates" against high ratings from the minority group but potentially favors low ratings from the minority group, as homophily hurts the high ratings disproportionally.[5]

The key theoretical novelty of our model is that it is based on endogenous "statistical discrimination", where different identity groups have identical quality and the same rating technology, yet the search and match process endogenously leads to different rating qualities across groups. This enables us to endogenize the key channel of belief formation in our paper. Traditional models of discrimination, on the other hand, take the asymmetric beliefs

[4] Similar observations are also documented in Zhang (2020), which demonstrates that VCs' implicit gender discrimination primarily affects *high-quality* female startup founders using a symmetric IRR experiment with US VCs.

[5] The combination of the "glass basement" and "glass ceiling" effect may lead to a distributional effect, such as the "discrimination reversion" phenomenon.

as an assumption, due to either intrinsic quality difference (exogenous difference in Phelps (1972), and endogenous difference in Arrow et al. (1973); Coate and Loury (1993); Craig et al. (2017)) or heterogeneous observable information about different groups (Phelps (1972)). However, in our framework, we demonstrate that even with identical intrinsic quality and observable information across different groups, the presence of homophily in matching and imbalanced representation among groups is sufficient to endogenously generate rational statistical discrimination and creates an equilibrium where minority participation in the market consistently remains low.

The contribution of this paper is both empirical and methodological. First of all, we make several contributions to the empirical gender and racial discrimination literature. Beyond detecting statistical discrimination against women in an under-explored context (i.e., startup founders seek funding from VCs), we uncover several key empirical insights highly informative to discrimination theories. Firstly, we reveal that evaluators (i.e., founders) perceive signals from minority groups (i.e., female VCs) as less informative compared to majority groups (i.e., male VCs), empirically confirming an important assumption in discrimination theories (Morgan and Várdy, 2009). Secondly, in this two-sided matching market, we observe that gender discrimination disproportionately affects *high-quality* female candidates, leading to a glass ceiling phenomenon. This suggests that minority candidates sending high-quality signals are more likely to face discrimination in a matching context.[6] Thirdly, while gender homophily has been observed in VCs' investment processes (Raina, 2021; Zhang, 2020), our paper documents its presence in startup founders' fundraising behaviors (i.e., the capital demand side). Lastly, while we observe gender discrimination against female VCs, we do not detect similar racial discrimination against Asian VCs. These distinct patterns of discrimination contribute to theories explaining the differing participation trends of women and Asians in high-impact entrepreneurial communities in the US. Overall, these empirical findings provide crucial insights into the emergence and characteristics of discrimination in two-sided matching markets.

Additionally, the paper also contributes to the literature explaining the persistent gender gap in US entrepreneurial activities. Previous research has noted that women's participation rates in high-impact entrepreneurial activities have been consistently low and also lagged be-

[6] A similar phenomenon is also observed in Zhang (2020), where VCs tend to implicitly discriminate against *high-quality* female startup founders.

hind those in other high-skilled occupations (Gompers and Wang, 2017). Multiple potential explanations have been proposed. On the capital demand side, women are documented as more risk-averse and less likely to participate in risky entrepreneurial activities (Croson and Gneezy, 2009). On the capital supply side, multiple papers have discovered empirical evidence that venture capitalists (VC) have gender bias against female entrepreneurs (Ewens and Townsend, 2020; Guzman and Kacperczyk, 2019; Hebert, 2023; Zhang, 2020).[7] Unlike previous studies, we aim to explain this gender gap by considering the two-sided matching nature and imperfect evaluations of agents' quality in the entrepreneurial financing process. Given that women's participation rate is essentially a matching equilibrium outcome and VCs' discrimination behaviors have been well studied on the capital supply side, we first examine the capital demand side by investigating the characteristics and nature of startup founders' gender discrimination. Taking these experimental results as building blocks, we provide a theoretical framework that sheds light on how two-sided discrimination may emerge in a matching context and trap women, both as founders and investors, in a long-lasting "low participation rate" equilibrium outcome.

Lastly, this paper contributes directly to the theoretical literature explaining discrimination behaviors. Classical models of discrimination theories attribute discrimination to either coordination failure and the resulting heterogeneity in agents' qualities (Arrow et al., 1973; Arrow, 1998,7; Coate and Loury, 1993) or the heterogeneity in the observable information about different agents with the same quality (Aigner and Cain, 1977; Phelps, 1972). Craig et al. (2017) extend these models to a two-sided matching labor market to investigate the effect of several anti-discrimination policies. Unlike these models, our model endogenizes the information about agents' true quality via a channel of informative but imperfect ratings in a two-sided matching financing market. The informational quality of ratings is determined by the endogenous frequency of a specific group of agents being considered for a collaboration opportunity. This model offers novel explanations for several important findings, such as the persistent gender gap in entrepreneurship and why statistical discrimination would predominantly affect candidates receiving *higher* ratings in a two-sided matching context.

[7] However, it should be noted that VCs' gender bias alone cannot fully explain the unique aspects of the gender gap in entrepreneurship compared to other occupations where gender discrimination also exists but women's participation rates steadily increase over time (Egan, Matvos and Seru, 2022). Similarly, while VCs have also been found to have implicit biases against Asian founders (Zhang, 2020), the participation of Asians has improved over the past two decades.

The paper is organized as follows. Section 2 outlines the experimental design and implementation details. Section 3 examines startup founders' discrimination behaviors and uncovers the underlying mechanisms. 4 develops a theoretical framework that explains our experimental findings. Section 5 discusses policy implications and the broad relevance of our findings. Section 6 concludes.

2 Experimental Design

In this section, we outline the design and implementation details of the IRR experiment. Beyond identifying potential discrimination by US startup founders against female or Asian VCs during their fundraising, this experiment also aims to uncover underlying mechanisms, examine homophily, and assess distributional effects. These empirical insights provide crucial foundations for our theoretical framework explaining the enduring gender gap in the US entrepreneurial financing landscape.

Real-world Setting We design the IRR experiment to simulate a real-world startup fundraising environment. It provides founders with a personalized real investor recommendation service, utilizing a data-driven matching tool and a comprehensive individual-level VC database. Commercial firms like SuperWarm.AI and dealroom.co offer a similar data-driven matchmaking service for startups and investors aimed at reducing search frictions for startup founders.

Recruitment and Sample Selection In total, this experiment recruits 141 US startup founders, providing 2,820 VC evaluations through two waves of recruitment. The first wave (i.e., Wave 1) recruited 45 founders between February 2021 and March 2021. The second wave (i.e., Wave 2) recruited the remaining 96 founders between January 2024 and March 2024. Recruitment process details are available in Online Appendix Section A. All startup founders participating in the same recruitment wave received identical recruitment emails and were allotted the same amount of time to complete the survey.[8]

[8]For the recruitment emails, please see Online Appendix Figure A1 and Figure A2. For the instruction poster, please see Online Appendix Figure A3.

The overall response rate is approximately 5%. Table 1 summarizes the background information for participating founders. Among the recruited founders, 19.86% are female, and 26.24% are from minority groups. Notably, a majority (83.69%) are in the seed stage, consistent with the fact that early-stage startups value the provided "matching incentives" more than later-stage startups. These founders also span various industries typically targeted by VC firms, with 48.23% in Information Technology, 19.86% in the Consumer sector, and 13.48% in Healthcare.

It's important to recognize that standard commercial databases typically track completed deals and *funded* startups. However, subjects of interest for our study encompass *all* startups seeking VC funding, including those that may be ultimately rejected by VCs. Hence, comparing our recruited sample with VC-backed startups is not very meaningful. To shed light on the potential sample selection issues during recruitment, Table 1 also reports available background information on startups listed on Crunchbase. It's worth noting that startups listed on Crunchbase tend to be IT startups, mature and large companies, and male-led startups, indicating that they might also not be representative of the broader spectrum of all startups seeking VC funding on the market. Despite this limitation, given the absence of a perfect benchmark database in the entrepreneurial finance literature, this approach is the best available option for us at present.

[Insert Table 1 here]

Upon receiving the recruitment email and reading the consent form, the founders who choose to participate in the experiment enter the Qualtrics-based matching tool. Before the profile evaluation section starts, we require the founders to provide background information about their startups, such as industry, stage, number of employees, and fundraising goals. These preliminary questions follow standard practice in other investor recommendation services. During the evaluation process, founders assess 20 randomly generated hypothetical VC profiles. The experiment instructs the founders to assume that all hypothetical VCs they evaluate would invest in their startup's industry and funding stage. While the founders understand these profiles are hypothetical, they are aware that by providing candid VC evaluations they enable the matching algorithm to generate more accurate investor recommendations, therefore incentivizing them to rank the investors' profiles honestly.

Investor Profile Creation and Variation To generate hypothetical VC investors' profiles, we simultaneously and independently randomize individual-level and fund-level VC characteristics across multiple investors. Similar to Kessler et al. (2019), the experiment dynamically populates each VC characteristic from a pool of options, and the matching tool combines these randomly selected characteristics together to create an investor profile. The detailed randomization process of VC characteristics is described in Online Appendix Table A1, and an example VC profile is provided in Online Appendix Figure A4.

Names Indicating Gender and Race Following Fryer Jr and Levitt (2004) and Gornall and Strebulaev (2020), we compile a list of commonly used first names strongly indicative of investors' gender (Male vs Female) and last names strongly indicative of race (Asian vs White).[9] Each assigned name is predominantly displayed at the beginning of the profile and mentioned multiple times in evaluation questions to increase its saliency with ample use of gender pronouns in the description. For the complete randomized list of all potential investor names see Online Appendix Table A2.

Evaluation Questions To evaluate each VC profile, participating founders need to answer three theory-based mechanism questions and two decision questions. A sample evaluation question page is provided in Online Appendix Figure A5, and participating founders will face the same questions in the same order following each of the twenty VCs they are presented with.

Regarding the mechanism-based questions, Q_1 is a quality evaluation question that assesses an investor's potential to improve a startup's profitability. Q_2 is an availability rating question, which requires participants to evaluate the likelihood of each investor showing interest in their startups and capture the matching channel. Q_5 is an informativeness question that tests whether each VC profile provides enough information for founders to make their evaluations. Specifically, Q_5 provides crucial insights for our theoretical framework.

Regarding the decision-based questions, Q_3 is the fundraising amount question and per-

[9]Given that Asian VCs are the largest minority group in the US VC industry and contribute significantly to the US entrepreneurial community, this study mainly focuses on this minority group. Also, due to similar first name patterns between Asian Americans and white Americans, we utilize last names to indicate race. However, this method may not work when studying racial discrimination against African VCs or Hispanic VCs, as these groups share similar last-name patterns with white Americans.

tains to the intended fundraising amount that reflects startup founders' plans for fundraising with each investor. Another crucial decision-based question, Q_4, concerns the contact interest rating, gauging the likelihood of founders to initiate contact with each investor. The contact interest rating holds substantial importance in an IRR experiment, which serves as a pivotal metric for conducting distributional effect analysis, as demonstrated in Kessler et al. (2019). Moreover, research employing similar IRR experiments on the VC side has consistently shown that contact interest ratings exhibit stronger correlations with real-world investment decisions by VCs compared to other ratings (Zhang, 2020,2). Thus, this metric serves as a fundamental measure of candidates' overall appeal, factoring in their quality, availability, and informativeness.

Incentive Since the entrepreneurial financing market is a two-sided matching market, the experiment adopts the standard "matching incentive" used in Kessler et al. (2019). Specifically, after evaluating multiple VC profiles, each startup founder will receive the contact information of the ten most-matched real VCs, recommended by our matching algorithm based on a large comprehensive global VC database collected in Zhang (2020). Since startup founders generally need to purchase similar recommendation services on the market and our investor recommendation service is free of charge, the experiment provides real benefits to participants without deception. Details of the matching algorithm are provided in Online Appendix Section A.

Background Questions To explain the enduring gender gap in the US entrepreneurial community, we further collect startup founders' *individual-level* demographic information and conduct corresponding heterogeneous effects, such as testing gender or racial homophily. For this reason, the experiment also asks several standard background questions about participants' gender, race, entrepreneurial experience, educational level, and their startups' goals.

Lessons in IRR Experiment Implementation As the IRR experiment adopts a non-deceptive experimental design, participants generally receive a consent form outlining the experimental purpose and researcher background. Hence, despite existing discrimination, various factors may obscure evidence of discrimination and lead to overly pro-social behaviors from subjects. Here, we share key lessons learned from practical experience regarding the effective detection of discrimination in an IRR experiment.

Consent Form — In the consent form, researchers typically disclose their names and affiliations. During recruitment, we indeed observed increased traffic to researchers' websites. Hence, posting discrimination-related papers on researchers' websites heightens the risk of priming subjects and impeding evidence of discrimination. Similarly, recruiting through researchers' personal networks requires vigilance to prevent social desirability bias or the Hawthorne effect due to subjects' awareness of discrimination detection.

Candidate Characteristics — Overloading candidate profiles with numerous characteristics complicates discrimination detection. Excessively detailed profiles often dilute participants' attention on candidates' gender and race, impeding discrimination detection.[10] Additionally, rich information hinders the detection of belief-driven discrimination, which generally stems from limited candidate information. Moreover, the inclusion of gender- or race-related traits, such as the fraction of women in senior management teams, can prime subjects for the experimental purpose. Thus, maintaining an appropriate number of non-sensitive characteristics is vital.

Sample Recruitment — This paper comprises two waves of experiments, both offering the standard matching incentive as per Kessler et al. (2019). In Wave 1, monetary awards were also provided as required by Qualtrics Panel. Despite the presence of implicit discrimination evidence, the aggregate-level evidence of discrimination was weaker, partially due to the additional noise introduced when participants joined the study primarily for monetary incentives rather than the matching incentive.

Subjects' Background Questions — Standard background questions, such as inquiries about subjects' gender and race, may inadvertently prime subjects with the experimental purpose of testing discrimination. This concern is heightened if some questions directly relate to subjects' attitudes toward women and minorities. Therefore, it's crucial to place all such questions after the formal evaluation section. Additionally, researchers may consider prohibiting subjects from altering their evaluation results after entering the background information section.

[10] Compared to similar experiments conducted on the startup side in Ebrahimian and Zhang (2024) or Zhang (2022), we intentionally include fewer VC characteristics in this experiment to prevent attention dilution issues.

3 Results

In this section, we investigate gender and racial discrimination among US startup founders during fundraising. To provide crucial empirical support for our theoretical framework, we further examine the underlying mechanisms of gender and racial homophily and delve into its corresponding distributional effects.

3.1 Detection of Gender Discrimination

Table 2 tests how VCs' gender and race influence founders' evaluations in the IRR experiment. The dependent variable is the perceived investor's quality (i.e., Q_1 profitability rating), investment likelihood (i.e., Q_2 availability rating), amount of information available for evaluations (i.e., Q_5 informativeness ratings), the relative amount of funding to be raised (i.e., Q_3 fundraising plan), and founders' willingness to contact the VC (i.e., Q_4 contact interest ratings), respectively. We regress each dependent variable on the gender and racial dummies, as well as other orthogonally randomized VC characteristics in the experiment. All the regressions include subject-fixed effects, which account for the possibility that founders have different rating levels. Standard errors in parentheses are clustered within each experimental subject.

Column (5) of Table 2 demonstrates the existence of gender discrimination against female VCs among startup founders. However, we do not detect significant racial discrimination against Asian VCs. When evaluating female VCs with similar male VCs, startup founders, on average, assign 3.46 p.p. lower contact interest ratings to female VCs. This effect corresponds to a 5.8% decrease compared to the average contact interest rating level and is statistically significant at the 1% level even after adjusting for multiple hypothesis testing with Westfall-Young stepdown adjusted p-values. The magnitude of the gender discrimination captured is approximately 47.40% (calculated as 3.46 divided by 7.30) of the effect of VCs' entrepreneurial experience- one of the most important human capital characteristics of VCs (Bottazzi et al., 2008; Gompers and Mukharlyamov, 2022). However, as all the coefficients for "Asian Investor" stay insignificant across all columns, we do not detect racial discrimination against Asian VCs.

[Insert Table 2 here]

3.2 Statistical Discrimination and Informativeness of VC Profiles

Columns (1) and (2) of Table 2 further demonstrate that gender discrimination is primarily influenced by statistical discrimination, which involves belief-driven mechanisms such as quality and investment likelihood concerns. On average, founders assign female VCs 3.17 p.p. lower quality ratings and 3.20 p.p. lower availability ratings. This indicates that founders perceive female VCs as less likely to enhance their profitability or show investment interest in their startups. Importantly, since founders are required to assume all evaluated VCs would invest in their industries and stages, they essentially compare male VCs and similar female VCs *within the same industry*. Hence, the observed gender discrimination is not driven by industry match considerations.

Rational Beliefs? Table 2 reveals that the gender discrimination among startup founders stems from their perception of female VCs providing less value to their startups' profitability and lower investment likelihood compared to similar male VCs. Then, a natural follow-up question is whether such beliefs are rational. As documented in Gompers, Mukharlyamov, Weisburst and Xuan (2014), female VCs are associated with lower financial performance compared to their male counterparts. Additionally, gender homophily has been documented in VCs' investment process (Raina, 2021; Zhang, 2020), indicating that female VCs are more skilled and willing to evaluate women-led startups and providing them emotional support. Hence, if the majority of participating founders are male, their perceptions about female VCs' value-added and investment intentions appear to be rational and consistent with previous empirical findings at first glance. However, the findings documented in the literature could be self-fulfilling, and the belief formation process can also be endogenous. As shown in Section 4, even when female and male VCs have an identical distribution of inherent qualities or abilities, founders may still form negative beliefs about female VCs compared to their male counterparts. Due to this endogenously generated statistical discrimination, these VCs would suffer from worse portfolio performance as they struggle to attract high-quality deals from men-led startups. Moreover, suppose male founders are more inclined to work with male VCs due to their endogenously formed perceptions. In that case, female VCs may logically show less interest in male-led startups, expecting lower collaboration.

Informativeness of VC Profiles An important finding in Table 2 is that founders deem female VCs' profiles as less informative compared to similar male VCs' profiles, as demonstrated in Column (3). On average, founders assign 5.25 p.p. lower informativeness ratings to female VCs compared to similar male VCs, which is statistically significant at the 1% level. This observation confirms a crucial prediction in our model and assumptions used in other discrimination theories, such as Morgan and Várdy (2009). That is, deciphering signals from the minority group is often more challenging for evaluators to interpret compared to those from the majority group.

3.3 Detection of Gender Homophily

Table 3 tests gender and racial homophily, examining whether the influence of VCs' gender and race on founders' evaluations varies depending on the gender and race of the founder.[11] "Female Investor × Female Founder" and "Asian Investor × Asian Founder" are both interaction terms. All regressions include subject-fixed effects, with standard errors in parentheses clustered at the startup founder level.

Table 3 reveals that male startup founders predominantly drive gender discrimination against female VCs. Based on Column (5), when male founders evaluate female VCs versus male VCs, the contact interest ratings assigned to female VCs are, on average, 4.84 p.p. lower than those assigned to similar male VCs, with 1% statistical significance. This result indicates that male founders prefer collaborating with male VCs. However, the coefficient for "Female Investor × Female Founder" is significantly positive and equal to 5.97 p.p., suggesting that female founders rate female VCs more positively than male founders do. Additionally, Columns (1) and (2) demonstrate that founders' aggregate-level negative perceptions of female VCs are also mainly driven by male founders' evaluations. The coefficients for "Female Investor × Female Founder" across these columns indicate that female founders hold significantly more positive perceptions of female VCs' value-added and investment likelihood compared to male founders. In Online Appendix Section B, we further demonstrate that implicit gender discrimination also primarily exists among male startup founders. Hence, Table 3 provides empirical evidence supporting the existence of gender

[11] Homophily refers to the tendency of individuals to be attracted to those who are similar to themselves. Homophily can manifest based on gender and race (e.g., male founders prefer male VCs, white founders prefer white VCs).

homophily.

Regarding the results on racial homophily, Columns (1) and (2) reveal only slight discrimination against Asian VCs among non-Asian founders, which becomes insignificant after adjusting for multiple hypotheses testing. Importantly, Column (5) indicates that white founders or Asian founders do not significantly differ in their contact interest ratings for Asian VCs compared to similar white VCs. Consequently, we do not observe any similarly notable racial homophily phenomenon.

3.4 Glass Ceiling: Discrimination Against High-Quality VCs

"Glass Ceiling" refers to the phenomenon where discrimination concentrates at the higher echelons of an organization, around senior positions or among top-tier candidates Hegde, Ljungqvist and Raj (2022). In this section, we offer empirical evidence to substantiate a "glass ceiling" hypothesis as it pertains to the VC entrepreneurship setting, particularly in the context of gender discrimination. Although this finding may seem counter-intuitive given the evidence of statistical discrimination, our model developed in Section 4 elucidates how this distributional effect arises as an equilibrium outcome within a two-sided matching framework.

Summarizing our first piece of evidence in Table 4, we examine whether the effects of VCs' gender and race are different among high-quality VCs and low-quality VCs. To proxy for each VC's quality, we assume that investor quality is an unknown linear single index of other orthogonally randomized VC characteristics that are uncorrelated with VCs' gender and race.[12] We then regress contact interest ratings (Q_4) on these characteristics and use the fitted value (i.e., $\hat{Q}_4$) as a proxy for this quality index. By design, these VC characteristics are independent of gender and race. Hence, the estimate is consistent even though the regression does not include gender and race dummies. To make the final results easy to interpret, we discretize the estimated quality index by defining "High-Quality Investor" as investors whose $\hat{Q}_4$ is above 50.

Column (5) of Table 4 reveals that the degree of gender discrimination varies depending on VC quality. Specifically, the coefficient for "Female Investor" is 2.53 p.p. with statistical

[12]These VC characteristics include "Very Selective School," "Graduate Degree," "Senior Investor," "Angel Investor," "Large Fund," "Entrepreneurial Experience," "ESG Fund," and "Years of Investment Experiences."

significance at the 10% level. This result indicates that for low-quality VCs, startup founders exhibit no gender discrimination against female VCs. However, the coefficient for "Female Investor × High-Quality Investor" is -6.24 p.p., which is statistically significant at the 5% level, suggesting that startup founders assign 3.71 p.p. lower contact interest ratings to high-quality female VCs compared to similar high-quality male VCs. Similar findings are observed in Columns (1) and (2), indicating that founders' negative perceptions of female VCs' value-added on profitability and investment likelihood mainly influence high-quality female VCs and not their less-accomplished counterparts.

To confirm the presence of the "glass ceiling" phenomenon, we further extend our analysis to quantile regressions as shown in Table 5. We assume that the quantile function of $Q4$ (i.e., contact interest ratings) for each VC profile j varies based on the VC's gender and race. All regressions control for startup founders' rating levels, measured by the "leave-one-out median of Q_4" to account for the possibility that some startup founders might be more generous in their ratings. Standard errors in parentheses are clustered at the startup founder level.

In Column (10) of Table 5, the coefficient for "Female Investor" is -3.35 p.p., indicating that when VCs' contact interest ratings are high enough (i.e., ranked within the top 5% among female investors), they receive 3.35 p.p. lower contact interest ratings compared their top 5% male counterparts. Similar negative coefficients are also observed across Columns (3)-(10), indicating that high contact interest ratings are more common for male investors compared to similar-quality female investors. Consequently, even if some female VCs possess equally appealing characteristics compared to their male counterparts, they are less likely to receive high Q_4 ratings. However, the coefficient for "Female Investor" becomes 8.17 p.p., which is positive and statistically significant at the 5% level, suggesting that when evaluating low-quality VCs, founders slightly favor female VCs.

Additional analysis of the glass ceiling phenomenon is available in Online Appendix Table B2. When dividing the sample into senior investors in Panel A and junior investors in Panel B, we find that founders exhibit larger implicit gender discrimination against senior female VCs, corroborating the notion that high-quality female VCs suffer more from founders' negative perceptions about them.

Finally, and similar to previous subsections, in both Tables 4 and 5, the coefficient "Asian Investor" is mostly insignificant. This suggests that the experiment does not discover systematic discrimination against Asian investors in terms of contact interest ratings or other evaluations by founders, neither at the aggregate level, nor directed at high-quality Asian investors (glass ceiling).

3.5 Detection of Implicit Discrimination

Building on previous findings of statistical discrimination, we investigate the role of implicit discrimination in founders' fundraising decisions.[13] Given the ambiguous and potentially stressful nature of fundraising, which entails subjective evaluations of opportunities, implicit discrimination may play a role by impacting founders' decisions.

Following Kessler et al. (2019) and Zhang (2020), Table 6 investigates the presence of implicit discrimination by comparing founders' ratings in the second half of the study with their ratings in the first half of the study.[14] Column (1) shows that, on average, founders spent 21.96 seconds less evaluating profiles in the second half of the study compared to the first half. This result is statistically significant at the 1% level, indicating that subjects may have felt more rushed or fatigued in the second half of the study. Online Appendix Figure B1 confirms the finding in Column (1) by illustrating a decreasing trend in founders' evaluation time as the study progresses to the end.

In Columns (2), (3), (4), and (6) of Table 6, the coefficients for "Female Investor" are insignificant, indicating that female VCs do not receive significantly different evaluations compared to male VCs in the first half of the study. However, the coefficients for the interaction term "Female Investor $\times$ Second Half of Study" are significantly negative. Also, when analyzing founders' evaluations in the second half of the study, the coefficients for "Female Investor" are also significantly negative with a p-value lower than 0.01. This change demonstrates that the detected gender discrimination primarily arises from founders' evaluations in the second half of the study. Overall, Table 6 finds that implicit gender discrimination influences founders' fundraising decisions. However, we do not find any evidence of implicit

[13] Implicit discrimination involves unconscious attitudes or stereotypes that influence evaluators' decisions. As highlighted by Bertrand, Chugh and Mullainathan (2005), factors such as ambiguity, stress, cognitive load, and inattention to the task at hand may render individuals susceptible to implicit biases, even in situations where their behaviors are controllable.

[14] The rationale behind this method is based on the idea that implicit discrimination is more likely to influence individuals' behaviors when they feel rushed or fatigued (Bertrand et al., 2005). We have preregistered this method on the AEA RCT Registry.

racial discrimination against Asian VCs.

Online Appendix Figure B2 provides additional empirical evidence supporting the presence of implicit gender discrimination. It examines whether the impact of VCs' genders on founders' evaluations turns more negative as the profile evaluations progress to the end of the study. The graph displays point estimates of the coefficient on gender and the corresponding 95% confidence intervals. From the figure, it is evident that founders' ratings of female investors decline significantly compared to their ratings of male investors as they evaluate more profiles. This trend indicates that although founders initially aim to be politically correct, their discriminatory perceptions of female VCs gradually surface over the course of the experiment. Given that real-world fundraising environments are more stressful and demanding in terms of cognitive workload, this detected gender discrimination likely influences founders' fundraising processes. Conversely, as depicted in Figure B4, similar patterns regarding racial discrimination are not observed.

Discussion of Alternative Interpretations One alternative interpretation of the previous findings is a "learning story." According to this narrative, as founders become more familiar with the evaluation process, they act on their discriminatory tendencies against female VCs more. However, this explanation is not likely, given the simplicity and intuitiveness of our evaluation interface, which takes just a couple of minutes to understand. Contrary to the expectations of the "learning story," the evaluation time of founders does not sharply decrease after the first four profiles (see Figure B1). Yet, the decline of founders' ratings of female VCs continues among the last few profile evaluations (see Figure B2). This suggests that factors beyond this narrative are at play. Moreover, even if the "learning story" were to dominate, it would simply indicate a more severe situation where founders explicitly discriminate against women.

Another alternative interpretation is the "balance the profile" hypothesis. To increase the experimental power, we intentionally skewed the gender distribution of investors to 40% female and 60% male, differing from the real-world distribution of approximately 20% female and 80% male. The higher proportion of female VCs in our randomization process may lead to two potential issues. Firstly, it could prime subjects to our experimental objectives, making it more difficult to uncover evidence of gender discrimination. Secondly, suppose subjects perceive an overrepresentation of female VCs in the first half of the study. In that case, they might seek to "balance the profile" by contacting more male investors in the second half of the study. In Online Appendix Section B, we rule out this "balance the profile" hypothesis by demonstrating that evaluating more female VCs in the first half of the study does not result in significantly lower ratings of female VCs in the second half of the study.

4 Theoretical Framework

In this section, we develop a theoretical model that explains the stark empirical findings using a theory of statistical discrimination. Specifically, the model prediction addresses three critical questions by leveraging an endogenous informational mechanism:

1. When does discrimination arise?
2. Who is the subject of the discrimination?
3. What generates the discrimination?

Our model considers a frictional search market in which entrepreneurs (E) search for unknown types of venture capital investors (VC).

Players. There is a unit mass of VC in the market. VC are indexed by two characteristics, *type* and *group*. The type of VC represents any payoff-relevant information of the VC. At a given moment, a VC is either of high type (H) or low type (L). Each VC's type, however, changes according to a continuous-time Markov process. Specifically, each type turns into the other type at rate $\delta > 0$. The group of a VC describes her payoff-irrelevant identity, such as her gender, ethnic or racial identity. Each VC belongs to either group 1 or 2, with $\ell = 1, 2$ being used as the generic index. Unlike her type, a VC's group does not change over time. We assume that both groups have the same total size (i.e., each group has a mass of 1/2).

On the other side of the market, there is mass $Q(> 0)$ of E. They search for VC based on public information about VC. Specifically, they condition their search on VC's two observable characteristics, rating $j = G, B$, and group identity $\ell = 1, 2$. Each E also belongs to either of the two groups, indexed by $\iota = 1, 2$. Let Q_ι denote the mass of each E group. Throughout the analysis, we assume $Q_1 > Q_2$.[15]

The VC who share the same observable characteristics, (j, ℓ), and the E that search for them constitute a "submarket." Clearly, each submarket can be indexed by (j, ℓ). Sellers are assigned to those submarkets according to their (perfectly persistent) group identity and (evolving) ratings, while buyers choose which submarket to enter.

Matching. We adopt the canonical search-and-matching framework to model an interaction between VC and E. Let λ denote the ratio of E to VC in the submarket. We let $\psi(\lambda)$ denote VC's matching rate and $\phi(\lambda)$ denote E's matching rate. Note that consistency requires that $\psi(\lambda) = \lambda\phi(\lambda)$ for all $\lambda > 0$.

For expositional clarity, we focus on the parametric case where $\psi(\lambda) = \lambda^k$ for some $k \in (0, 1)$. This case corresponds to the constant-returns-to-scale Cobb-Douglas matching function and, therefore, satisfies various natural and desirable properties. In particular, $\psi(0) = 0$, $\lim_{\lambda\to\infty} \psi(\lambda) = \infty$, $\psi'(\lambda) > 0$, and $\psi''(\lambda) < 0$. In addition, $\phi(0) = \infty$, $\lim_{\lambda\to 0} \phi(\lambda) = 0$, $\phi'(\lambda) < 0$, and $\phi''(\lambda) > 0$. As it becomes clear later, most of our results require only these standard properties of the matching function and, therefore, can easily be generalized beyond our parametric case.

In the case when there exhibits **homophily** in the market, the matching breaks at rate $\kappa > 0$ per E whose identity $\ell \neq \iota$ without reaching a transaction.

Investment. Once a VC and an E meet, they transact instantaneously and go back to the market. The transaction yields surplus $u_H(u_L)$ if the VC's type is $H(L)$, where $u_H > u_L \geq 0$. After the transaction, E pays a return p to the VC.

Ratings. The market accumulates information about sellers through simple summary indices called "ratings." There are two possible ratings: G (as in "good") and B (as in "bad"). After a matching being formed, the VC's rating may be updated to reveal her type. Specifically, with probability $\alpha \in (0, 1]$, a B-rated VC with type H receives G rating, and a G-rated VC with type L receives G rating. A VC with the correct rating keeps the same rating after

[15] While the absolute group size does not matter for either E or VC, the key assumption is that type 1 is more represented among E than among VC.

a transaction. With the remaining probability $1-\alpha$, the VC's rating remains unchanged. Note that due to the changing environment (or changing type), a correct rating may turn inaccurate.

E's beliefs about a VC's type will depend on the rating and the (equilibrium) behavior of all players in the system. In particular, the belief may depend on the group identity. If the two groups of agents are treated differently, the inference a buyer makes on a seller with a given rating depends nontrivially on her group identity.

Solution Concept. We consider a steady state of the economy in terms of the distribution of types, ratings, and group identity and the beliefs that the E holds for each submarket. Specifically, an equilibrium is a tuple $\{(P^{\ell}_{ij}, \lambda^{\ell}_{j}, Q^{\ell\iota}_{j}, \mu^{\ell}_{j})\}^{\ell,\iota=1,2}_{i=H,L,j=G,B}$ in the stationary distribution, where P^{ℓ}_{ij} is the mass of VC of type i with rating j and group ℓ, λ^{ℓ}_{j} is the ratio of E to VC in submarket (j,ℓ), Q^{ι}_{j} is the mass of E of group ι in market λ, j, and $\mu^{\ell}_{j} \in [0,1]$ is the public belief on the VC in submarket (j,ℓ), i.e., the probability that they are of type H. We say the tuple constitutes an equilibrium if:

- **Stationarity**:

$$\begin{aligned}
P^{\ell}_{HG}\delta =& P^{\ell}_{LG}\delta + P^{\ell}_{HB}\psi^{\ell}_{B}\alpha,\\
P^{\ell}_{LG}(\delta + \psi^{\ell}_{G}\alpha) =& P^{\ell}_{HG}\delta,\\
P^{\ell}_{HB}(\delta + \psi^{\ell}_{B}\alpha) =& P^{\ell}_{LB}\delta,\\
P^{\ell}_{LB}\delta =& P^{\ell}_{HB}\delta + P^{\ell}_{LG}\psi^{\ell}_{G}\alpha,
\end{aligned}$$

  where

$$\psi^{\ell}_{j} = \left(\frac{Q^{\ell 1}_{j} + Q^{\ell 2}_{j}}{P^{\ell}_{Hj} + P^{\ell}_{Lj}}\right)^{k}$$

- **Optimality**:

$$\left[\left(\frac{Q^{\ell 1}_{j} + Q^{\ell 2}_{j}}{P^{\ell}_{Hj} + P^{\ell}_{Lj}}\right)^{k-1} - \kappa 1_{\ell\neq\iota}\right]\left(\frac{P^{\ell}_{Hj}u_H + P^{\ell}_{Lj}u_L}{P^{\ell}_{Hj} + P^{\ell}_{Lj}} - p\right)$$

is the same among all j, ℓ for each ι, when $Q_j^{\ell\iota} > 0$.

4.1 Equilibrium without homophily

Note that in this setting, E's group becomes irrelevant for payoffs and $\kappa = 0$. Hence, the model reduces to the one studied in Che et al. (2020).

We begin with characterizing the non-discriminatory equilibrium, where no decision conditions on VC/E's group identities. Therefore, effectively, there are only two submarkets indexed by rating $j = G, B$. We drop all indices ℓ, ι for notational simplicity. For each $j = G, B$, let q_j denote the measure of E that join submarket j and P_{ij} denote the measure of type $i = H, L$ VC with rating $j = G, B$. Then, the ratio of E to VC ("queue length") in submarket $j = G, B$ is given as follows:

$$\lambda_j \equiv \frac{q_j}{P_{Hj} + P_{Lj}}.$$

In steady state, P_{ij}'s must satisfy the following system of equations:

$$\begin{aligned}
P_{HG}\delta &= P_{LG}\delta + P_{HB}\psi_B\alpha, \\
P_{LG}(\delta + \psi_G\alpha) &= P_{HG}\delta, \\
P_{HB}(\delta + \psi_B\alpha) &= P_{LB}\delta, \text{ and} \\
P_{LB}\delta &= P_{HB}\delta + P_{LG}\psi_G\alpha.
\end{aligned}$$

The above equalities implies:

Lemma 1 (Steady-state Distribution)**.** *In steady state, the measure of sellers with type $i = H, L$ and rating $j = G, B$ is given as follows:*

$$\begin{aligned}
P_{HG} &= \frac{\psi_B(\delta + \psi_G\alpha)}{2\left(\delta(\psi_G + \psi_B) + \alpha\psi_G\psi_B\right)}, \; P_{LG} = \frac{\psi_B\delta}{2\left(\delta(\psi_G + \psi_B) + \alpha\psi_G\psi_B\right)}, \\
P_{HB} &= \frac{\psi_G\delta}{2\left(\delta(\psi_G + \psi_B) + \alpha\psi_G\psi_B\right)}, \; P_{LB} = \frac{\psi_G(\delta + \psi_B\alpha)}{2\left(\delta(\psi_G + \psi_B) + \alpha\psi_G\psi_B\right)}.
\end{aligned}$$

Letting $\mu_j \equiv P_{Hj}/(P_{Hj}+P_{Lj})$ *for each* $j = G, B$,

$$\mu_G = 1 - \frac{\delta}{2\delta + \psi_G \alpha} \text{ and } \mu_B = \frac{\delta}{2\delta + \psi_B \alpha}.$$

E's Expected Payoffs Let u_j denote an E's flow expected payoff when he targets j-rated VCs (i.e., searches in submarket j). Given the steady-state queue length λ_j and the fraction μ_j of type H VCs, u_j is given by:

$$u_j = \phi_j(\mu_j u_H + (1-\mu_j)u_L - p).$$

Recall that $\phi_j = \phi(\lambda_j)$ and in steady state, μ_j is also a function only of λ_j (see Lemma 1). Therefore, u_j also can be interpreted as a function of λ_j. A non-discriminatory equilibrium is characterized by

$$u_G(\lambda_G) = u_B(\lambda_B).$$

Equilibrium Characterization We are now ready to characterize the non-discriminatory steady-state equilibria of our model.

Proposition 1. *If* $(u_H + u_L)/2 \leq p$, *then it is the unique non-discriminatory equilibrium outcome that E does not search for VC, regardless of their ratings (i.e.,* $\lambda_G = \lambda_B = 0$*). Conversely, if* $(u_H + u_L)/2 > p$, *then there always exists a non-discriminatory equilibrium in which* $\lambda_G > \lambda_B > 0$. *Moreover, there exists* $(\underline{\beta}, \bar{\beta})$ *such that there exists only non-discriminatory equilibrium if and only if*

$$k \leq \frac{1 + \sqrt{1 - \frac{u_H - u_L}{2(u_H - p)}}}{2} \ \underline{\text{or}}\ \frac{\alpha}{\delta} \in (\underline{\beta}, \bar{\beta}).$$

Proposition 1 is a rephrase of the main result of Che et al. (2020).

4.2 Equilibrium with homophily

In this setting, we focus on the case where $(u_H + u_L)/2 > p_1$ and $k \leq \frac{1+\sqrt{1-\frac{u_H-u_L}{2(u_H-p_1)}}}{2}$. Per Proposition 1, the gain from trade is large enough to sustain a non-trivial equilibrium and

k is sufficiently small to rule out discrimination without homophily. In this case, $u_G(\lambda_G)$ $(u_B(\lambda_B))$ is a strictly decreasing(increasing) function (for either $p = p_0/p_1$).

In this subsection, we distinguish the two groups with $\ell = 1, 2$ and $\iota = 1, 2$. For each $\ell = 1, 2$, the proportion of type H VC in submarket $j\ell$ is given as follows:

$$\mu_G^\ell \equiv \mu_G(\lambda_G^\ell) = 1 - \frac{\delta}{2\delta + \psi(\lambda_G^\ell)\alpha} \text{ and } \mu_B^\ell \equiv \mu_B(\lambda_B^\ell) = \frac{\delta}{2\delta + \psi(\lambda_B^\ell)\alpha}.$$

In addition, E's expected payoffs are determined as follows:

$$u_j^{\ell\iota}(\lambda_j^\ell) = (\phi(\lambda_j^\ell) - \kappa 1_{\ell \neq \iota})(\mu_j^\ell u_H + (1 - \mu_j^\ell)u_L - p).$$

Key observation: Since $\kappa > 0$, then it is straightforward that $\mu_G^\ell > \mu_B^\ell$ implies

$$\begin{aligned} u_G^{11}(\lambda_G^1) - u_B^{11}(\lambda_B^1) &> u_G^{12}(\lambda_G^1) - u_B^{12}(\lambda_B^1); \\ u_G^{22}(\lambda_G^2) - u_B^{22}(\lambda_B^2) &> u_G^{21}(\lambda_G^2) - u_B^{21}(\lambda_B^2). \end{aligned}$$

In words, for any given VC group ℓ, only one E group may find it indifferent when searching for both G and B rated VC. Moreover, if an E searches for VC of *different* group identity, he always favors those with B ratings. Based on this payoff order, we say an equilibrium is *regular* if either group of E enters the market following the order of

$$(\ell = \iota \& G) \succ (\ell = \iota \& B) \succ (\ell \neq \iota \& B) \succ (\ell \neq \iota \& G).$$

In other words, $Q_j^{\ell\iota} = 0$ implies $Q_{j'}^{\ell'\iota} = 0$ in all lower ranked markets.

Theorem 1. *There exist only three types of regular equilibria under homophily:*

1. *VC markets:* $\overbrace{G1 - - - - B1 - -}^{\textit{Group 1 E}}\underbrace{- - B2 - - - - G2}_{\textit{Group 2 E}}.$

2. *VC markets:* $\overbrace{G1 - - - - B1 - - \rlap{$\underbrace{- - B2 - - - - G2}_{\textit{Group 2 E}}$}}^{\textit{Group 1 E}}.$

3. *VC markets:* $\overbrace{G1 - - - - B1 - - - - B2 - - \underbrace{- - G2}_{\textit{Group 2 E}}}^{\textit{Group 1 E}}.$

Moreover, in all regular equilibria, $\mu_G^2 < \mu_G^1$ *and* $\mu_B^2 > \mu_B^1$.

Proof. See appendix C.1. □

4.3 Discussions

When does discrimination arise? Our results (Proposition 1 and Theorem 1) suggest that when market congestion is moderate ($k \le \frac{1+\sqrt{1-\frac{u_H-u_L}{2(u_H-p)}}}{2}$), discrimination arises if and only if entrepreneurs exhibit homophily. This prediction exactly explains our empirical evidence that the lack of race-based homophily coincides with the lack of race-based discrimination (let the group's identity ℓ, ι represent ethnicity). While gender-based discrimination is accompanied by statistically significant gender homophily (let the group's identity ℓ, ι represents gender).

Since our model characterized the stationary equilibrium, we can also interpret it as a long-run prediction: even though statistical discrimination may prevail in the short run, whether the market corrects itself through information revelation crucially depends on the existence of homophily.

Who is discriminated against? When the group identity ℓ, ι represents gender, we interpret group 1 as "men" and group 2 as "women". This interpretation is consistent with the empirical findings that women are "under-represented" among entrepreneurs. Different from the ethnicity-based discrimination case, there is strong empirical evidence that entrepreneurs exhibit homophily based on gender.

Our results (Theorem 1) then predict potential gender-based statistical discrimination and a "glass ceiling" for females. We say a gender group is (not) discriminated against if the quality ratings of the group that is searched do (not) vary with the gender of entrepreneurs.

1. *Men are never discriminated against.* In all three types of equilibria, men are always searched by men and never searched by women, independent of their quality ratings.

2. *Women are discriminated against when significantly under-represented.* When Q_1 and Q_2 are "close" and male VC market and female VC market can "absorb" each gender's entrepreneurs, there is no discrimination. Of course, empirical evidence suggests that this is not the case in practice; hence, women are always discriminated against.

3. *Men discriminates high rating women.* When women are sufficiently under-represented among entrepreneurs, we show a consistent pattern for the direction of discrimination.

   When there are not too many male entrepreneurs, female entrepreneurs actively search for female VCs of all ratings. However, male entrepreneurs only reach out to low-rated female VC. This leads to highly rated female VC being under-sampled. The key intuition for this phenomenon is that the gain from matching is the matching probability scaled by a potential gain from matching. Therefore, the failure of matching caused by homophily is more severe in a market with a lower matching rate & higher average quality. In other words, homophily "hurts" high-rated females more from male entrepreneurs' perspective.

   When there are way too many male entrepreneurs, male entrepreneurs actively search for female VCs of all ratings. However, female entrepreneurs only reach out to female VCs with high ratings. The same intuition from the previous case applies, but with a twist: homophily "benefits" highly rated females more from female entrepreneurs' perspective.

What generates the discrimination? Note that in our model, different groups have identical distribution of quality and identical rating technology. Hence, this novel approach enables us to endogenize the "statistics" that lead to statistical discrimination. The key mechanism that drives the theoretical results is the endogenous formation of the entrepreneurs' beliefs. This is illustrated by the equilibrium condition (1):

$$u_j^{\ell\iota}(\lambda_j^\ell) = \underbrace{(\phi(\lambda_j^\ell) - \kappa 1_{\ell\neq\iota})}_{\substack{\text{(Adjusted)}\\ \text{Matching rate}}}(\underbrace{\mu_j^\ell(\lambda_j^\ell)}_{\text{Belief}}(u_H - u_L) + u_L - p). \tag{1}$$

The belief μ_j^ℓ depends on the "congestion" parameter λ_j^ℓ differently for the good ratings versus the bad ratings: the more popular VC group (with higher λ) gets sampled more often; hence, the rating quality is higher, leading to higher posterior belief from a good rating but lower posterior belief from a bad rating.

Notably, the beliefs convert to the entrepreneurs' payoffs via successful matching: only when a match is formed is the expected payoff from the investment realized. Therefore, a loss of matching opportunities caused by homophily leads to different impacts on VCs with different ratings: Since the lower-rated female VCs are more "costly" to search than male VCs by male entrepreneurs, the "required return" has to be higher. This means, from the analysis in the last paragraph, that female VCs should necessarily be less popular in order to make low ratings more attractive. However, this under-sample of female VCs hurts the highly rated ones: their ratings are endogenously noisier; hence, a high rating from female VCs leads to lower perceived quality than male VCs.

5 Discussion

Policy Implications Given the importance of homophily in our theoretical framework, any initiatives that raise awareness about explicit and implicit discrimination across different groups may help mitigate its effects in shaping discriminatory equilibrium. Additionally, considering that evaluators' negative beliefs about minority groups can form endogenously in the matching context, it is important to adopt objective evaluation measures that rely less on subjective beliefs or expectations of evaluators. Furthermore, considering that the information accumulation gap between different groups plays a key role in our framework, any strategies to increase the representation or matching rates of minority groups, particularly high-type candidates, are essential to disrupt the feedback loop perpetuated by homophily and promote fairer outcomes in two-sided matching markets.

Experimental Setting In this experiment, we primarily focus on the *pre-selection* stage of startup founders' fundraising process. Usually, founders choose which investors to approach and initiate contact, influencing potential deal flows for VCs and subsequently impacting VC financial performance. If the relevant data or field experimental opportunities are available, future research could also explore other scenarios where startup founders receive multiple offers from different VCs and analyze the criteria founders use to select which VC to collaborate with.

Result Applicability While our study focuses on the entrepreneurial financing market, our empirical and theoretical insights extend to the broader context of women's under-representation in other two-sided matching scenarios. For instance, research shows that women hold a small percentage of board positions or CEO positions in the US. Given that board and CEO recruitment involves a two-sided matching process and often relies on networks where homophily may prevail, our findings shed light on the potential presence of statistical discrimination in such settings. Furthermore, considering the infrequent matches and high overall candidate quality in these areas, our model offers explanations for the observed glass ceiling phenomenon in boardroom and CEO appointments.

6 Conclusion

This paper delves into discrimination within a two-sided matching market, providing insights into its unique features, emergence, and impact on participants. We primarily focus on gender discrimination in the entrepreneurial financing market, given its pivotal role in innovation and its two-sided matching nature. By conducting an experiment with real US startup founders, we first examine the nature and characteristics of gender discrimination against female VCs among founders. Alongside findings from a parallel experiment with US VCs (Zhang, 2020), this study completes an experimental system that documents symmetric gender discrimination on both the startup side and the investor side.

Apart from detecting gender discrimination among US startup founders, our experiment shows that statistical discrimination drives this observation. Founders perceive female VCs as less helpful in enhancing startup profitability and consequentially less likely to invest in their companies compared to their male counterparts. Notably, founders perceive female VC profiles as less informative, consistent with information-based discrimination theory. Additionally, we observe gender homophily and the glass ceiling effect as powerful forces that drive these matching decisions, resulting in disproportionate discrimination against high-quality female VCs.

To explain the experimental findings above, we develop a novel search and matching model with endogenous information aggregation and belief formation. This information-based discrimination theory demonstrates that homophily in matching and imbalanced representation among different groups are sufficient to generate statistical discrimination and lead to an equilibrium where women (an underrepresented group) experience a low participation rate in the entrepreneurial financing market. The model also explains why the glass ceiling effect would persist, mainly affecting female VCs.

Researchers can replicate our experiments across different countries and timeframes. Besides examining the presence and features of discrimination in other two-sided matching markets, researchers can also develop more sophisticated experimental systems to explore equilibrium outcomes when discrimination exists among multiple market players. Any innovations in experimental methods that enhance discrimination detection would also be particularly valuable in advancing this area of research.

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Table 1: Summary Statistics of Recruited Startup Founders

	N	Fraction (%)	Fraction (%) Crunchbase
Panel A: Founder-level Stated Background Information			
Female Founder	28	19.86%	15.27%
Minority Founder	37	26.24%	37.32%
Serial Founder	88	62.41%	N/A
Democratic Founder (Only for Wave 2)	27	28.12%	N/A
Panel B: Startup-level Background Information			
Distribution of Sectors			
Information technology	68	48.23%	43.94%
Consumers	28	19.86%	15.33%
Healthcare	19	13.48%	14.33%
Clean technology	2	1.42%	2.63%
Finance	12	8.51%	11.54%
Media	6	4.26%	16.26%
Energy	2	1.42%	2.35%
Education	3	2.13%	6.25%
Life sciences	5	3.55%	4.62%
Transportation & Logistics	6	4.26%	4.19%
Manufacture & Construction	10	7.09%	5.15%
Distribution of Stage			
Seed Stage (developing products or services)	20	14.18%	N/A
Seed Stage (mature products, no revenue)	31	21.99%	N/A
Seed Stage (mature products, positive revenue)	67	47.52 %	N/A
Series A	15	10.64%	N/A
Series B	6	4.26%	N/A
Series C or later stages	2	1.42 %	N/A
Startups' Goals			
Financial Gains	129	91.49%	N/A
Promote Diversity	73	51.77%	N/A
Positive Environmental Impact	48	34.04%	N/A
Number of Employees (Only for Wave 2)			
0-5 employees	54	56.25%	N/A
5-20 employees	33	34.38%	N/A
20-50 employees	8	8.33 %	N/A
$>$ 50 employees	1	1.04 %	20.84%

Notes. This table reports descriptive statistics for the recruited startup founders who participated in the experiment. In total, 141 US startup founders provided 2,820 VC evaluations. Among these subjects, 45 founders participated in the Wave 1 experiment, and 96 participated in the Wave 2 experiment. Panel A reports the founder-level background information. Panel B reports the startup-level background information. "Female Founder" equals one if the founder is a female and zero otherwise. "Minority Founder" equals one if the founder is an Asian, Hispanic, Middle Eastern, Native American, Pacific Islander, or African American, and zero otherwise. "Serial Founder" equals one if the founder is a serial entrepreneur and zero otherwise. "Democratic Founder" equals one for Democrat founders and zero otherwise. Startups' number of employees and founders' political affiliations are collected only from the Wave 2 experiment. Founders can choose multiple sectors and only one stage option that best fit their startups. For information on startups' goals, each founder can choose multiple startup missions, from aiming for financial returns and promoting diversity in the entrepreneurial community to caring about positive environmental impact.

Table 2: Aggregate-level Gender and Racial Discrimination (Average Treatment Effect)

Dependent Variable	Q1 Quality (1)	Q2 Availability (2)	Q5 Informativeness (3)	Q3 Funding (4)	Q4 Contact (5)
Female Investor	-3.17***	-3.20***	-5.25***	-0.17	-3.46***
	(0.82)	(0.75)	(0.91)	(0.62)	(0.93)
Asian Investor	-0.98	-0.71	0.40	-0.11	-0.14
	(0.77)	(0.64)	(0.60)	(0.54)	(0.70)
Very Selective School	1.74*	1.18	0.31	-0.00	1.15
	(0.94)	(0.86)	(0.72)	(0.65)	(0.97)
Graduate Degree	0.85	-0.20	-0.16	0.30	1.02
	(0.94)	(0.92)	(0.73)	(0.74)	(0.97)
Senior Investor	8.11***	3.82**	1.69	0.82	7.42***
	(1.55)	(1.30)	(1.11)	(1.04)	(1.64)
Angel Investor	4.82***	3.41**	1.71*	-2.79**	4.11**
	(1.26)	(1.10)	(0.92)	(0.95)	(1.38)
Large Fund	7.57***	4.35***	1.64**	7.07***	7.65***
	(1.13)	(1.08)	(0.81)	(1.13)	(1.26)
Entrepreneurial Experience	8.49***	4.86***	1.66**	0.21	7.30***
	(0.99)	(0.77)	(0.61)	(0.65)	(0.93)
ESG Fund	-1.67*	-2.26**	0.24	0.50	-2.10**
	(0.86)	(0.96)	(0.53)	(0.65)	(0.94)
Years of Investment Experiences	0.35***	0.22***	0.16***	0.11**	0.35***
	(0.06)	(0.05)	(0.05)	(0.05)	(0.06)
Subject FE	Yes	Yes	Yes	Yes	Yes
Mean of Dependent Variables	59.09	54.95	67.36	48.71	60.15
Observations	2820	2820	2820	2820	2820
R-squared	0.504	0.583	0.669	0.698	0.531

Notes. This table reports the regression results about how investors' gender and race influence different dimensions of startup founders' evaluations. The sample includes 2,820 profile evaluations from both the Wave 1 experiment (i.e., pilot experiment) and the Wave 2 experiment. The dependent variable is investors' received quality or profitability ratings (i.e., Q_1) in Column (1), availability ratings (i.e., Q_2) in Column (2), informativeness ratings (i.e., Q_5) in Column (3), fundraising plan (i.e., Q_3 relative amount of funding to be raised) in Column (4), and contact interest ratings (i.e., Q_4) in Columns (5). "Female Investor" is a dummy variable that is equal to one if the investor has a female first name, and zero otherwise. "Asian Investor" is a dummy variable that is equal to one if the investor has an Asian last name, and zero otherwise. "Very Selective School," "Graduate Degree," "Senior Investor," "Angel Investor," "Larger Fund," "Entrepreneurial Experience," and "ESG Fund" are all indicator variables which equal to one for startup founders who have graduated from very selective US schools, obtained graduate degrees, hold senior positions (refer to Table A3), are angel investors, work in larger VC funds, possess entrepreneurial experiences, and work in VC funds with a focus on positive environmental, social, and governance (ESG) impact. "Years of Investment Experiences" refers to the years of investment experience. All regressions include subject fixed effects, and standard errors in parentheses are clustered at the startup founder level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 3: Heterogeneous Effects Based on Founders' Gender and Race (Homophily)

Dependent Variable	Q1 Quality (1)	Q2 Availability (2)	Q5 Informativeness (3)	Q3 Funding (4)	Q4 Contact (5)
Female Investor	-4.39***	-4.08***	-6.52***	-0.59	-4.84***
	(0.96)	(0.82)	(1.03)	(0.69)	(1.05)
Female Investor ×	5.24**	3.63*	5.89**	1.70	5.97**
Female Founder	(2.26)	(2.00)	(2.12)	(1.56)	(2.27)
Female Founder	-1.72	-43.04***	11.74***	-38.79***	-35.43***
	(1.44)	(1.28)	(1.33)	(0.99)	(1.44)
Asian Investor	-1.57*	-1.37*	0.11	-0.42	-0.86
	(0.94)	(0.71)	(0.71)	(0.61)	(0.86)
Asian Investor ×	2.28	3.22*	1.13	1.91	3.29
Asian Founder	(2.47)	(1.93)	(1.33)	(1.21)	(2.11)
Asian Founder	-7.42***	29.82***	-21.85***	27.67***	26.64***
	(1.33)	(1.14)	(0.92)	(0.80)	(1.20)
Subject FE	Yes	Yes	Yes	Yes	Yes
Mean of Dependent Variables	59.09	54.95	67.36	48.71	60.15
Observations	2820	2820	2820	2820	2820
R-squared	0.388	0.547	0.660	0.674	0.444

Notes. This table investigates the presence of gender and racial homophily in the startup fundraising process by analyzing whether the impact of investors' gender and race on founders evaluations also vary depending on startup founders' gender and race. The sample includes 2,820 profile evaluations from both the Wave 1 experiment (i.e., pilot experiment) and the Wave 2 experiment. The dependent variable is investors' received quality or profitability ratings (i.e., Q_1) in Column (1), availability ratings (i.e., Q_2) in Column (2), informativeness ratings (i.e., Q_5) in Column (3), fundraising plan (i.e., Q_3 relative amount of funding to be raised) in Column (4), and contact interest ratings (i.e., Q_4) in Columns (5). "Female Investor" is a dummy variable that is equal to one if the investor has a female first name, and zero otherwise. "Asian Investor" is a dummy variable that is equal to one if the investor has an Asian last name, and zero otherwise. "Female Founder" is a dummy variable that is equal to one if the startup founder is female, and zero otherwise. "Asian Founder" is a dummy variable that is equal to one if the startup founder is Asian, and zero otherwise. "Female Investor × Female Founder" and "Asian Investor × Asian Founder" are both interaction terms. All regressions include subject fixed effects, and standard errors in parentheses are clustered at the startup founder level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 4: Heterogeneous Effects Based on Investor Quality (Distributional Effect)

Dependent Variable	Q1 Quality (1)	Q2 Availability (2)	Q5 Informativeness (3)	Q3 Funding (4)	Q4 Contact (5)
Female Investor	2.19	0.14	-4.56**	0.52	2.53*
	(1.61)	(1.26)	(1.47)	(0.92)	(1.51)
Female Investor × High-Quality Investor	-5.73**	-3.33**	-0.11	-0.42	-6.24**
	(1.90)	(1.62)	(1.41)	(1.32)	(1.90)
Asian Investor	-1.50	0.20	2.25**	0.50	-0.03
	(1.63)	(1.27)	(1.10)	(0.89)	(1.47)
Asian Investor × High-Quality Investor	0.49	-1.49	-2.81**	-0.87	-0.38
	(1.82)	(1.51)	(1.25)	(1.20)	(1.74)
High-Quality Investor	30.87***	24.22***	13.02***	9.22***	36.95***
	(2.20)	(1.95)	(1.55)	(1.48)	(2.29)
Subject FE	Yes	Yes	Yes	Yes	Yes
Mean of Dependent Variables	59.09	54.95	67.36	48.71	60.15
Observations	2820	2820	2820	2820	2820
R-squared	0.570	0.651	0.695	0.690	0.663

Notes. This table tests whether investors' gender and race affect startup founders' evaluations differently when participants evaluate high-quality investor profiles and low quality investor profiles. The sample includes 2,820 profile evaluations from the Wave 1 experiment (i.e., pilot experiment) and the Wave 2 experiment.. The dependent variable is investors' received quality or profitability ratings (i.e., Q_1) in Column (1), availability ratings (i.e., Q_2) in Column (2), informativeness ratings (i.e., Q_5) in Column (3), fundraising plan (i.e., Q_3 relative amount of funding to be raised) in Column (4), and contact interest ratings (i.e., Q_4) in Columns (5). "Female Investor" is a dummy variable that is equal to one if the investor has a female first name, and zero otherwise. "Asian Investor" is a dummy variable that is equal to one if the investor has an Asian last name, and zero otherwise. "High-Quality Investor" is an indicator variable that equals one if investors' received "objective" quality measure (i.e., $\hat{Q}_4$) is above 50, and zero otherwise. The $\hat{Q}_4$ values are predicted using OLS models based on other orthogonally randomized investor characteristics in Table 2, which include "Very Selective School," "Graduate Degree," "Senior Investor," "Angel Investor," "Larger Fund," "Entrepreneurial Experience," "ESG Fund," and "Years of Investment Experiences." All regressions include subject fixed effects, and standard errors in parentheses are clustered at the startup founder level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 5: Quantile-Regression Estimates for Startup Founders' Discrimination (Distributional Effect)

	5th	15th	25th	35th	45th	55th	65th	75th	85th	95th
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
Female Investor	8.17**	-0.35	-2.94**	-3.84***	-2.71***	-1.94**	-2.75**	-3.38***	-4.76***	-3.35***
	(3.61)	(1.77)	(1.48)	(1.08)	(0.96)	(0.89)	(1.13)	(1.15)	(1.44)	(1.21)
Asian Investor	0.87	0.19	0.77	0.74	0.06	-0.47	-0.60	-0.42	-0.56	-0.23
	(2.38)	(1.44)	(1.20)	(0.86)	(0.57)	(0.62)	(0.84)	(0.84)	(0.99)	(0.88)
Leave-one-out Median	0.39***	0.71***	0.89***	0.95***	0.97***	0.96***	0.85***	0.72***	0.56***	0.26***
of Q_4 Ratings	(0.08)	(0.06)	(0.04)	(0.03)	(0.01)	(0.02)	(0.04)	(0.04)	(0.05)	(0.06)
Quantile of Dep. Var.	6	29	44	51	60	66	74	82	90	100
Observations	2,820	2,820	2,820	2,820	2,820	2,820	2,820	2,820	2,820	2,820
R-squared	0.24	0.34	0.34	0.34	0.34	0.34	0.34	0.34	0.34	0.33

Notes. This table reports the effects of investors' gender and race on different conditional quantiles of investors' received contact interest ratings after controlling for startup founders' rating levels. The dependent variable is the investors' received contact interest rating (i.e., Q_4). In Columns (1)–(10), the reported coefficient of "Female Investor" (or "Asian Investor") represents the effect of investors' gender (or race) on the kth conditional percentile ($k \in 5, 15, 25, ..., 95$) of investors' received contact interest ratings (i.e., Q_4). "Female Investor" is a dummy variable that is equal to one if the investor has a female first name, and zero otherwise. "Asian Investor" is a dummy variable that is equal to one if the investor has an Asian last name, and zero otherwise. "Leave-one-out Median of Q_4 Ratings" is generated for each investor profile j that is evaluated by each startup founder i after dropping Q_{4ij}. Standard errors in parentheses are clustered at the startup founder level. $*p < 0.10, **p < 0.05, ***p < 0.01$

Table 6: Implicit Gender and Racial Discrimination

Dependent Variable	Response Time (Unit: Second) (1)	Q1 Quality (2)	Q2 Availability (3)	Q5 Informativeness (4)	Q3 Funding (5)	Q4 Contact (6)
Second Half of Study	-21.96***	4.49**	3.88**	2.76**	-0.97	3.45**
	(1.34)	(1.44)	(1.28)	(0.95)	(1.00)	(1.47)
Female Investor	-0.19	-0.02	-0.87	-3.94***	0.24	-1.51
	(1.12)	(1.13)	(0.99)	(0.96)	(0.82)	(1.20)
Female Investor ×		-6.51***	-4.88***	-2.65**	-0.98	-4.15**
Second Half of Study		(1.54)	(1.44)	(1.04)	(1.25)	(1.67)
Asian Investor	2.67**	-0.26	-0.05	0.80	-0.54	0.05
	(1.20)	(1.07)	(0.89)	(0.83)	(0.71)	(1.12)
Asian Investor ×		-1.80	-1.59	-1.03	0.93	-0.80
Second Half of Study		(1.57)	(1.32)	(1.11)	(1.14)	(1.61)
p-value of Female Investor in the second half of study		0.00	0.00	0.00	0.47	0.00
p-value of Asian Investor in the second half of study		0.26	0.19	0.91	0.29	0.65
Subject FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean of Dependent Variables	43.82	59.09	54.95	67.36	48.71	60.15
Observations	2820	2820	2820	2820	2820	2820
R-squared	0.40	0.39	0.55	0.66	0.67	0.44

Notes. This table tests implicit gender and racial discrimination in the IRR experiment by examining how startup founders' response time and evaluation results respond to an investor's gender and race in the first and second half of the study. "Female Investor" is equal to one if the investor has a female first name, and zero otherwise. "Asian Investor" is equal to one if the investor has an Asian last name, and zero otherwise. "Second Half of Study" is an indicator variable for investor profiles shown among the last half of the study viewed by a startup founder. In column (1), the dependent variable is startup founders' response time, which is defined as the number of seconds spent before each page submission, winsorized at the 95th percentile (43.82 seconds on average). The dependent variable is investors' received quality or profitability ratings (i.e., Q_1) in Column (2), availability ratings (i.e., Q_2) in Column (3), informativeness ratings (i.e., Q_5) in Column (4), fundraising plan (i.e., Q_3 relative amount of funding to be raised) in Column (5), and contact interest ratings (i.e., Q_4) in Columns (6), respectively. The "p-value of Female Investor (or Asian Investor) in the second half of study" provides the p-value of the coefficient of "Female Investor" (or "Asian Investor") when we only include the evaluation results in the second half of the study. All the regressions add subject fixed effect. R-squared is indicated for each OLS regression. Standard errors in parentheses are clustered within each experimental subject. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

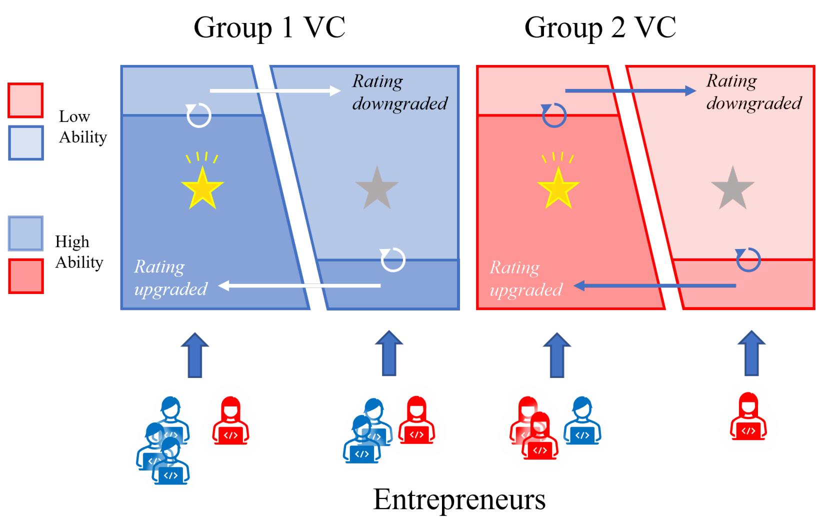


Figure 1: Ratings-guided matching market

Online Appendix

A Experimental Design and Implementation

A.1 Recruitment and Sample Selection

The recruitment process was implemented in two waves. The first wave ran (i.e., Wave 1) from February to March 2021 via Qualtrics, a third-party recruitment company that enables reach out to US startup founders and small business owners. To recruit startup founders, this company sent recruitment emails with the survey link (see Figure A1). After completing the main experiment, participants received both customized investor recommendation lists by logging into the experimental website and obtained approximately $50 as monetary compensation.

In Wave 1, we include several filter questions and additional screeners to select founders who meet the following criteria: (1) are a startup founder or business owner planning to raise VC funding for their company, (2) understand the designed incentive, and (3) pass various attention checks, including an evaluation–time assessment, inserted attention-check questions, and Qualtrics' Bot Detection algorithms.[16] Similar to Kessler et al. (2019), the consent form mainly emphasizes the matching purpose of our "investor–startup" matching tool without mentioning the research purpose of testing discrimination. Also as required by the recruitment company, Wave 1 cannot collect any identifiable information about participants. This precondition helps to mitigate potential Hawthorne effects or observer bias when examining participants' socially sensitive behaviors.

Since participants in Wave 1 are also provided with monetary compensation, this may introduce additional noise into their evaluations, as some participants may only value this payment rather than the matching incentive. For participants primarily motivated by this monetary compensation, their optimal strategy would be to complete the study quickly to receive payment. We employ the following standard pre-registered noise reduction techniques to ensure careful participant recruitment and mitigate the impact of noisy participants in the experiment. In total, 45 valid founders' evaluations are collected through Wave 1 and

[16] If participants fail any of these criteria, the Qualtrics system will automatically terminate the experiment and inform the participants that they no longer qualify for this study. Unqualified participants do not have a second chance to join the study.

the response rate of Wave 1 is about 6.5%.

a. Use Attention Check Questions. We insert one attention check question and several other background questions requiring participants to manually enter the answer. If participants fail the attention check question, the Qualtrics system will terminate their evaluation process and inform them that they are unqualified for this study. If participants type in some irrelevant answers, their responses are also removed from our formal data analysis.[17]

b. Enough Evaluation Time. We only include evaluation results from participants who satisfy the following criteria based on evaluation time: 1) spend at least 15 minutes on this study. 2) spend at least 50 (15) seconds on evaluating the first (second) profile.

c. Reasonable Rating Variations. If participants' evaluation results almost have no variations for Q_1 (i.e., profitability evaluation) or Q_4 (i.e., likelihood of contacting the investor), we also remove their responses in our formal data analysis. We create the following three measures for each subject i to detect such situations using their evaluation ratings Y_{ij}^k for the k^{th} question of j^{th} profile: i) sample variance of Q_1 (i.e., $Var_i(Q_1)$), $\frac{1}{20-1}\sum_{j=1}^{j=20}(Y_{ij}^k - \frac{1}{20}\sum_{k=1}^{k=20} Y_{ij}^k)^2$ where $k = 1$. ii) sample variance of Q_4 (i.e., $Var_i(Q_4)$), $\frac{1}{20-1}\sum_{j=1}^{j=20}(Y_{ij}^k - \frac{1}{20}\sum_{k=1}^{k=20} Y_{ij}^k)^2$ where $k = 4$. iii) sum of sample variance of Q_1 and sample variance of Q_4 (i.e., $Var_i(Q_1) + Var_i(Q_4)$). If any of the three measures for subject i falls below the $5th$ percentiles of the corresponding measures in the full sample, evaluation results of subject i will be removed. We do not apply this criteria to Q_2 (i.e., likelihood of being invested), Q_3 (i.e., funding to raise), or Q_5 (i.e., informativeness) because it is reasonable that participants give the same evaluation to these questions.[18]

If participants' evaluation results almost have no variations among Q_1, Q_2, Q_4, and Q_5 within the same profile, we also remove their data. To quantify this variation, we calculate the sample variance based on Q_1, Q_2, Q_4, and Q_5 for each subject i and profile j: $Var_{ij}^* = \frac{1}{4-1}\sum_{k\in\{1,2,4,5\}}(Q_{ij}^k - Mean_{ij})^2$ where $Mean_{ij} = \frac{1}{4}(Q_{ij}^1 + Q_{ij}^2 + Q_{ij}^4 + Q_{ij}^5)$. For each subject, if the percentage of profiles with "small sample variance" is more than 40%, we will remove the subject's evaluations. "Small sample variance" is defined as $Var_{ij}^* \leq 5$.

d. Reasonable Answers to Text Entry Questions. When the tool asks participants to

[17]For example, if the question asks participants to provide information about the detailed industry background of their startups and someone types in "1000", their responses become invalid and do not enter our sample pool.

[18]This can happen if participants find it hard to guess investors' decisions, have a determined amount of funding to raise, or believe that each profile has provided enough information.

enter their industry background, amount of funding needed, or general comments about the study, any answers containing gibberish lead to removal of subjects' evaluations.

e. Other Subsidiary Criteria In addition to the criteria mentioned above, we also take the following subsidiary criteria into consideration when identifying "noisy participants". These criteria include i) a reasonable amount of required funding; ii) time spent on evaluating profiles (i.e., "Timing - Last Click", "Timing - Page Submit", "Duration (in seconds)"); iii) distribution of rating variations; iv) the list of low-quality responses identified by Qualtrics team based on their designed "data scrub" algorithms.

It should be noted that these methods cannot fully eliminate all the noises, which biases our discovered results towards null results. However, these noise reduction techniques generally work well in terms of improving experimental power and detecting invalid responses in practice.

To increase the sample size of the experiment, we conducted the second wave of recruitment between January 2024 and March 2024 after collecting contact information of startups listed on Crunchbase. Unlike in Wave 1, we directly sent recruitment emails to these startups (see Figure A2) without providing any monetary compensation. While many emails listed on Crunchbase are essentially associated with help desks, this approach allowed us to recruit real startup founders interested in seeking VC funding. In cases where emails were sent to help desks, we were informed that the emails would be forwarded to their founders and fundraising teams due to the nature of our study. In total, 96 founders participated in the second wave (i.e., Wave 2).[19]

A.2 Profile Creation and Randomization of VC Characteristics

We make the following efforts to improve the realism of generated investors' profiles. First, the distribution of most displayed characteristics try to mimic the real-world situation. Specifically, we use investors' information collected by Pitchbook to generate our randomization parameters. Second, wording used to describe investors' working experiences and funds' investment philosophies are extracted from real world investors' experiences and funds' descriptions posted online. We remove relative information indicating the investor's interested

[19] We randomly selected 2,500 startups with valid email addresses listed on Crunchbase for the recruitment in the second wave. Hence, the response rate for Wave 2 is roughly 4% and the average response rate of the whole experiment (i.e., including both Waves 1 and 2) is roughly 5%.

industries and stages. Lastly, our profile is essentially a combination of investors' publicly available information rather than their resumes. Different from the job seeking process, investors rarely post their resumes online. Instead, startup founders do their due diligence on investors by collecting information from multiple online platforms, such as LinkedIn, personal websites, Crunchbase, AngelList, Pitchbook, etc. Therefore, the format of our investor profiles tries to mimic these platforms, displaying key points of investors' characteristics.[20]

All investor profiles contain three sections in the following order: i) individual-level characteristics, including first name, last name, title/position, investment experience, educational background, and previous entrepreneurial experience or other working experience. ii) fund-level sensitive characteristics, including the fund's investment philosophy and type (i.e., profit-driven funds or impact funds). iii) fund-level nonsensitive characteristics, including the fund's size measured by AUM (i.e., asset under management) and dry powder. We do not include important investor characteristics which are not publicly accessible online or available on mainstream startup fundraising platforms as such information is usually not used by typical investor recommendation algorithms on the market.

Titles and Positions. — We randomly assign 70% of investor profiles to VC institutional investors and the rest 30% profiles to angel investors. For the 70% institutional investors' profiles, half of them (i.e., 35% of total profiles) are randomly assigned to junior positions with titles like "Analyst", "Investment Analyst", "Associate", etc. The other half of them are randomly assigned to senior positions with titles like "Partner", "Investment Director", "Co-founding Partner", etc.

Entrepreneurial Experiences. — Venture capitalists' entrepreneurial experiences are documented as one of the human capital characteristics correlated with investors' investment decisions (Dimov and Shepherd, 2005; Zarutskie, 2010). This information is also generally available on investors' LinkedIn or their biography posted on personal websites. To increase the realism of hypothetical investors' experiences, we extract real venture capitalists' entrepreneurial experiences posted on Pitchbook, and remove any sensitive information which potentially reveals the investor's educational background or industry background. A

[20] To further enhance participants' experiences of participating in this study, we provide a progress bar and regularly report progress by inserting the breaks.

detailed description of used entrepreneurial experiences is provided in the Online Appendix.

Educational Background. — Educational background is another human capital characteristic which is correlated with investors' investment strategies. We independently randomize both investors' degrees (bachelor degree vs graduate degree) and graduated schools (from very selective universities or selective universities).[21] All selected schools have been verified to have alumni who are working in the US venture capital industry based on Google search. Detailed randomization process and school lists are provided in the Online Appendix.

Years of Experience and Total Number of Deals. — Venture capitalists with more experiences are more likely to be put in charge of investment activities (Bottazzi et al., 2008; Gompers, Kovner and Lerner, 2009). Therefore, we use both investors' years of investment and total number of involved deals to indicate their working experience. The total number of involved deals is positively correlated with investors' years of investment in our design. This design helps to avoid unrealistic cases where junior investors have completed extremely large numbers of deals.

Fund Type and Investment Philosophy. — Considering the recent rise of impact investing in the US VC industry, we also randomize each fund's investment type and philosophy (i.e., impact funds VS profit-driven funds). Impact funds generally focus on sustainable investment or green finance, and profit-driven funds usually aim to maximize financial returns. However, identifying impact fund and accurately estimating its distribution still face many difficulties. Different data sources and classification methods often provide different results. Based on the survey evidence from Botsari and Lang (2020), "approximately 7 in 10 VCs incorporate ESG criteria into their investment decision process". In Barber, Morse and Yasuda (2021), impact VC funds account for less 5% of their total sample. Given this inconsistency, we randomly assign half hypothetical investors into impact funds and the other half into profit-driven funds, which also helps to maximize the experimental power.

[21] Graduate degrees include MBA, JD, master, and PhD. Bachelor degrees include BA and BS. Very selective universities include Ivy League colleges, California Institute of Technology, Duke University, MIT, Northwestern University, Stanford University, University of California Berkeley, University of Chicago. Selective universities are defined as other universities which also foster real startup founders and venture capitalists.

Fund Size. — We use AUM (i.e., "asset under management") and dry powder to indicate the size of the VC firm that each investor works for.[22] This information exists on the Pitchbook platform and is summarized by annual National Venture Capital Association (NVCA) Yearbook. The information about fund size exists on the Pitchbook Platform and other standard databases. The distribution used in the randomization process mimics the fund size distribution of early-stage VC firms recorded by Pitchbook database.

In this paper, our research question mainly focuses on gender and race discrimination issues in entrepreneurs' fund-seeking process. The purpose of simultaneously and orthogonally randomizing other investor and fund characteristics is to introduce quality variations in the experiment and examine potential useful interaction effects between gender and other characteristics. The introduced quality variations are crucial to test the nature of discrimination and to investigate both gender's distributional effect and heterogeneous effect across the investor's attractiveness.[23]

[22]Dry powder refers to cash reserves kept on hand by a venture capital firm or individual to cover future obligations, purchase assets, or make acquisitions. AUM is calculated by adding a firm's total remaining value and its total dry powder. In general, these two measures are highly positively correlated.

[23]We realize that the impact of other investor-level and fund-level characteristics on entrepreneurs' fund-raising decisions is an important but under-explored question in the entrepreneurial finance literature. Therefore, we provide relevant results in a separate paper Ebrahimian and Zhang (2024).

Table A1: Randomization of Investor Profile Components

Profile Component	Randomization Description	Analysis Variable
Investor's individual-level characteristics		
First and Last Names	Drawn from list of 50 candidate names given randomly assigned race and gender. For detailed names, please see Online Appendix. Race randomly drawn (40% Asian, 60% White), Gender randomly drawn (40% Female, 60% Male)	White Female (24%) Asian Female (16%) White Male (36%) Asian Male (24%)
Position/Titles	Drawn randomly following the distribution VC Junior: VC Senior: Angel=35%:35%:30%. Within each category, uniformly drawn a detailed position according to Online Appendix Table A3.	Junior VC (35%) Senior VC (35%) Angel Investors (30%)
Entrepreneurial Experiences	Drawn from a list of entrepreneurial experience descriptions extracted from real venture capitalists' and angel investors' biography. For detailed wording used, please see Online Appendix Table A4.	With Entrepreneurial Experience (10/20)
Educational background		
Degree	Degree drawn randomly (50% Bachelor (BA/BS), 50% graduate school degrees (JD/MBA/Master/PhD)) For detailed list of degrees, please see Online Appendix Table A5.	Graduate Degree (10/20)
College	College drawn randomly (50% very selectove universities, 50% selective universities). For detailed list of schools, please see Online Appendix Table A5.	Very Selective College (10/20)
Investment experience		
Years of Investment Experience	Within each investor's type and seniority, years of investment experiences are randomized based on Table A6.	Years of investment experiences
Investor's fund-level characteristics		
Fund Size	Within each investor type (i.e., VC investor or angel investor), the fund size as measured by AUM and dray powder will be drawn based on the distribution shown in Table A7. To facilitate entrepreneurs to understand the relative size of each fund, we add a description of "relatively large VC fund", "relatively small VC fund" or "relatively large angel fund", "relatively small angel fund" in the profile.	Large Fund (10/20)
Investment Philosophy	Drawn randomly (50% profit-driven fund, 50% impact fund) No extra description is used to elaborate the meaning of impact funds and profit-driven funds.	Impact Fund (10/20)

Notes. This table provides the randomization of each investor profile's components and the corresponding analysis variables. Profile components are listed based on their categories. Weights of characteristics are shown as fractions when they are fixed across subjects (e.g., each subject saw exactly 10/20 profiles with larger funds) and percentages when they represent a draw from a probability distribution. Variables in the right-hand column are randomized to test how startup founders respond to these analysis variables.

Table A2: Full Names Populating Profile Tool

Asian Female	White Female	Asian Male	White Male
Allison Chung	Brittany Cooper	Phillip Wang	Jeremy Parker
Angela Wu	Tina Roberts	Brian Lin	Jeffrey Hall
Erica Cho	Amber Ward	Jared Chung	Justin Bennett
Laura Zheng	Catherine Thompson	Zachary Wong	Gregory Martin
Kayla Ngo	Theresa Baker	Jeffery Li	Thomas Cox
Amber Kwon	Kathleen Bennett	Patrick Tang	Jared Morris
Kara Luong	Melinda Taylor	Jason Le	Jeffery Allen
Jessica Cheung	Jenna Collins	Jared Zhou	James Evans
Natalie Yang	Sara Nelson	Paul Yoon	Richard Thompson
Katie Li	Monica Peterson	Erik Huynh	William Moore
Melissa Wong	Angela Murphy	Adam Luong	Philip Russell
Melanie Nguyen	Megan Fisher	Robert Hu	Jonathan Rogers
Catherine Wang	Sarah White	Kenneth Zhu	Scott Stewart
Megan Chen	Rebecca Anderson	Gary Zhang	Frank Bailey
Sarah Cheng	Emily Russell	John Zheng	Seth Wilson
Christine Luu	Cassandra Myers	Derek Hsu	Matt Campbell
Christina Huang	Jennifer Smith	Alan Nguyen	Kevin Ward
Jennifer Thao	Melanie Rogers	Joel Thao	Peter Peterson
Sandra Dinh	Amber Morris	Jeffery Yang	Derek Roberts
Tina Xu	Tara Cox	Christopher Lu	Jeffrey Cooper
Rebecca Hsu	Jacqueline Parker	Philip Hwang	Benjamin Cook
Katrina Ho	Nicole Hill	Frank Dinh	William White
Anna Truong	Amy Evans	Peter Kwon	Timothy Price
Alicia Tang	Natalie Hall	Steven Hoang	Mark Smith
Kathryn Jiang	Melissa Adams	Samuel Chan	Phillip Nelson
Lisa Zhu	Megan Bailey	Jeremy Duong	Nathan Phillips
Amanda Liang	Lisa Kelly	Dustin Huang	Ronald Wright
Melinda Lin	Kara Stewart	Richard Chen	Patrick Taylor
Samantha Tsai	Christine Campbell	Nicholas Tsai	Dustin Fisher
Victoria Choi	Christina Gray	Andrew Cheung	Donald Myers
Nicole Duong	Teresa Clark	Dennis Jiang	Christopher Sullivan
Tara Zhou	Linda Hughes	Anthony Ngo	Samuel Reed
Allison Lu	Allison Miller	Joel Yu	Joel Clark
Veronica Hu	Katrina Allen	Edward Truong	Erik Gray
Jacqueline Huynh	Veronica Moore	Nathan Choi	Stephen Hill
Mary Zhao	Patricia Wilson	Nathan Chang	Travis Miller
Brittany Pham	Laura Reed	Benjamin Ho	Marcus Collins
Linda Le	Jessica Sullivan	Matt Zhao	David Kelly
Patricia Yoon	Anna Cook	Thomas Liang	Jacob Baker
Jenna Hoang	Amber Phillips	Ronald Luu	Keith Adams
Julie Zhang	Samantha Price	Seth Cho	Zachary Hughes
Emily Yu	Allison Martin	Stephen Pham	Victor Anderson
Amber Liu	Erica Wright	Keith Xiong	Robert Murphy
Angela Chan	Kayla Cooper	Kevin Wu	Nicholas Parker
Kristy Yi	Tiffany Roberts	Timothy Xu	Anthony Hall
Sara Chang	Alicia Ward	James Liu	Brian Bennett
Cassandra Xiong	Mary Thompson	Travis Cheng	Dennis Martin
Theresa Hwang	Elizabeth Baker	Mark Yi	Andrew Cox
Megan Chung	Katherine Bennett	Marcus Wang	Edward Morris
Tiffany Wu	Valerie Taylor	Donald Lin	Adam Allen

Notes. This table presents the names used for the hypothetical VC profiles, with 50 names selected to represent each combination of race and gender. Due to the dominance of white and Asian individuals in VC and angel investment, only four combinations are listed: Asian Female, White Female, Asian Male, and White Male. First and last names are always paired together, and the combinations of first and last names are randomly generated. Asian and White Americans have very similar naming patterns, as documented by Fryer Jr and Levitt (2004). Therefore, we chose their first names from the same pool. We further checked these names to avoid those associated with famous investors. Notably, to make sure that US founders can associate these names with investors' gender and race correctly; we hired 107 MTurk workers located in the US to match candidate names with gender and race categories manually. Only highly indicative names are selected.

Table A3: Investor Title Categories Populating the Profile

Title Category	Title	Percentage
Venture Capital Investors		
Senior	Partner/Managing Partner/Venture Partner	35%
	Managing Director/Investment Director	
	Investment Partner/President	
	Co-founding Partner	
Junior	Analyst/Investment Analyst	
	Associate/Investment Associate	35%
Angel Investors		
Angel	Angel Investor	30%

Notes. The titles listed above represent common descriptions of early-stage investors in both venture capital companies and the angel investment community. During the randomization process, title categories are first selected randomly based on the following distribution: VC Senior, VC Junior, Angel = 35%, 35%, 30%, respectively. Within each title category, a specific title (e.g., Managing Partner) is then randomly chosen from a uniform distribution.

Table A4: Experience Description

Panel A: With Entrepreneurial Experience

Description Example
1. (Investor Name) was a successful entrepreneur himself earlier on in his career, cofounding 2 successful startups. Currently, he focuses on startup investment to promote more innovation in the world.
2. (Investor Name) was associated with a startup and served as the co-founder. Later he moved to a venture capital company, investing in early-stage startups and providing guidance.
3. (Investor Name) previously joined a consulting firm providing guidance and advice to startups. He later co-founded his own startup and became an early-stage investor.
4. When (Investor Name) was a student at college, she co-founded a startup during her undergraduate years. She later moved to a VC firm, helping startup founders develop their businesses.
5. Previously, (Investor Name) worked as a correspondent for a well known magazine and co-founded a successful startup later.
6. When (Investor Name) was at school, he was starting to ruminate on the idea of founding a company and co-founded a startup with his classmate after graduation.
7. Prior to joining the current position, (Investor Name) co-founded and sold a startup with utilizing his strategic, commercial and leadership skills.
8. An entrepreneur at heart, during his undergraduate years, (Investor Name) co-founded a startup and raised VC money. Later he decided to become an investor, helping more startups to grow.
9. (Investor Name) launched a startup project with his classmates at college before joining the current position. After selling his company, he decided to become an investor, focusing on startup investment.
10. Growing up, (Investor Name) was drawn to startups and technology-early on as a founder of a startup and later moved to a consulting company providing service to early stage companies.
11. (Investor Name) was previously part of the founding team at a startup, where he focused and led business development.
12. Prior to the current work, (Investor Name) worked within a B2B business and/or later moved to a technology firm to help open a new market.
13. (Investor Name) has expertise in overseeing product vision and corporate strategy. Before investing in startups, he himself was also a startup founder.
14. Previously, (Investor Name) founded a startup and a studio. Prior to that, He also served as a business and product developer in and around the SF area.
15. Besides serving as a fundraiser and early-stage investor, (Investor Name) was also a co-founder of a startup and responsible for investor relations.
16. (Investor Name) is experienced at the product design, marketing, community building and focuses on early-stage investing. He was a co-founder of a startup, overseeing its business development.
17. Before becoming an investor, (Investor Name) was also a innovation-focused entrepreneur. He is dedicated to introducing new levels of innovation and customer value to the global capital markets community.
18. (Investor Name) is also a startup founder with a strong background in financial management, sales, and strategy.
19. (Investor Name) had created and built start-up businesses resulting in accumulated connections with other investors. He is helping other startups develop innovative products and attract more investors.
20. (Investor Name) has diversified experience in various industries. He is one of the co-founders of a startup company in New York.

Panel B: Without Entrepreneurial Experience

Description Example
1. Previously, (Investor Name) was an analyst at a Capital Management firm, focusing on global growth equities. Later, he joined a private equity firm, conducting market analysis and due diligence.
2. Previously, (Investor Name) worked at a large online sales and operations company and later joined an investment bank. His investment experience spans a wide range of industries.
3. (Investor Name) performed in various executive roles and began her career as a product development engineer. She has experience in operations, budgeting, and strategic planning.
4. Previously, (Investor Name) worked in a consulting company and started his career in a global investment bank. His prior work experience includes consulting, investment banking and venture capital funds.
5. Prior to joining the current position, (Investor Name) was an equity research analyst and investor at an investment bank, covering publicly traded stocks.
6. (Investor Name) has diverse experience of working in tech companies, sales companies, and an investment bank.
7. (Investor Name) was specialized in corporate finance and M&A when working at the investment bank. Later, he moved to a venture capital firm, focusing on early-stage startup investment.
8. (Investor Name) started his career as a management consultant at a leading consulting company and later worked in a P&E fund.
9. After graduating from college, Investor Name worked in a management consulting company and joined a P&E company later.
10. Investor Name started his career as an institutional investment analyst at an asset management company, analyzing investments across asset classes from public equities to venture capital.
11. Investor Name started his career as an institutional investment analyst at an asset management company, analyzing investments across asset classes from public equities to venture capital.
12. Previously, (Investor Name) held a position in asset management company, executing fixed-income investment, FX trading, and cash management. He also worked on M&A transactions later.
13. After graduation, Investor Name worked in a research institution and later joined a consulting company.
14. Investor Name started working for an venture capital fund a s an (exit) analyst and responsible for investor relations, controlling and reporting. She keeps a constant eye on the latest M&A trend and market development.
15. (Investor Name) has diverse experience in the areas of marketing, finance and international relations. Prior to joining the current company, he was responsible for international relationship at an investment firm.
16. After graduation, (Investor Name) started working as an investment analyst for a private equity firm. Later, he joined the job, identifying additional opportunities for financial vehicles to further expand the investment.
17. (Investor Name) started his career as an investment analyst in a leading private equity investment firm. He held various operations and business development roles for the portfolio companies.
18. (Investor Name) began his career as a commercial banker on Wall Street and then joined a leading consulting company. After leaving consulting, (Investor Name) started investing in early-stage startups.
19. Prior to this position, (Investor Name) served as an investment analyst at a private equity firm and accumulated expertise in corporate debt and equities.
20. (Investor Name) was part of the go-to-market team, responsible for building, launching and scaling new business ventures. He specialized in enterprise growth strategy and business operations.

Notes. This table provides descriptions of investors' entrepreneurial experience in Panel A and non-entrepreneurial experience in Panel B. The descriptions are drawn from real venture capitalists' or angel investors' personal profiles. Specific company names have been omitted from the descriptions to ensure transferability across different investors and industries.

Table A5: Education Background (School List)

Panel A: Very Selective Schools

Undergraduate Programs(BA/BS)	Graduate Programs
Brown University	(No Business School)
Columbia University	MBA, Columbia Business School
Cornell University	MBA, Cornell University (Johnson)
Dartmouth College	
Harvard University	MBA, Harvard Business School
	JD, Harvard Law School
Princeton University	(No Business School)
University of Pennsylvania	MBA, University of Pennsylvania (Wharton)
Yale University	MBA, Yale School of Management
	Master of Arts, Yale School of Management
	MBA, University of California, Berkeley (Haas)
California Institute of Technology	
MIT	MBA, MIT (Sloan)
	Master of Science, MIT
Northwestern University	MBA, Northwestern University (Kellogg)
Stanford University	MBA, Stanford Graduate School of Business
	Master of Science, Stanford University
	Ph.D, Stanford University
University of Chicago	MBA, University of Chicago (Booth)

Panel B: Selective Schools

Undergraduate Programs	Graduate Programs
University of Puget Sound	MBA, La Salle University
University of Cape Town	MBA, University of Denve
University of Arizona	MBA, Syracuse University (Martin J. Whitman School)
Clemson University	Master of Science, SUNY Buffalo State College
Lehigh University	Master of Engineering, Stony Brook University–SUNY
Morehouse College	MBA, Rochester Institute of Technology
Clark University	Master of Arts, Villanova University
University of Oklahoma	Master of Science, New Jersey Institute of Technology
Hofstra University	Ph.D. University of Nebraska
CUNY-Hunter college	J.D, University of Louisville
Franklin and Marshall College	MBA, Georgia State University (J.Mack Robinson College)
Alfred University	MBA, Oregon State University
Northern Kentucky University	
Rutgers University–New Brunswick	
Kent State University	
Wheaton College	
Salisbury University	
Drexel University	
Occidental College	
DePauw University	

Notes. The schools and programs listed in the table are derived from the educational backgrounds of real venture capital (VC) investors or angel investors. This information was collected from publicly available platforms such as investors' personal websites, LinkedIn, Crunchbase, AngelList, and others.

Table A6: Investment Experience Randomization

Title	Investment Experience Description/Criteria	Percentage
Senior Position	years of experience: Uniform Distribution 12-30 (integer)	35%
Junior Position	years of experience: Uniform Distribution 1-6 (integer)	35%
Angel Investors	years of experience: Low: Uniform Distribution 1-6 (integer) High: Uniform Distribution 12-30 (integer)	30%

Notes. This table presents the randomization of investors' investment experiences in the experiment. The randomization process is conducted independently within each investor category.

Table A7: Randomization of Fund Size (AUM and Dry Powder)

Fund Size	AUM & Dry Powder	Percentage
VC Fund Size		
Large Fund	Description: relatively large VC fund	50%
	AUM: 100-250; Dry Powder: 40-80	(25%)
	AUM:250-500; Dry Powder: 80-160	(10%)
	AUM:>500; Dry Powder:>160	(15%)
Small Fund	Description: relatively small VC fund	50%
	AUM $<$ 10; Dry Powder: $<$ 4	(20%)
	AUM 10-25; Dry Powder: 4-6	(15%)
	AUM 25-50; Dry Powder: 6-16	(15%)
Angel Fund Size		
Large Fund	Description: relatively large angel fund Drawn Uniformly from [20, 50] to second decimal place	50%
Small Fund	Description: relatively small angel fund Drawn Uniformly from [1, 10] to second decimal place	50%

Notes. To introduce more variations within larger and smaller funds, we also randomize the Asset Under Management (AUM) and dry powder within each fund size category. AUM and dry powder are measured in $1 million units. The distribution of AUM follows the U.S. VC industry AUM distribution in 2018. Dry powder is set to range from 30% to 40% of the fund's AUM. Generally, AUM and dry powder are positively correlated, with larger funds expected to have greater AUM and dry powder.

Title: Invitation for Trying a Startup-Investor Matching Tool from [redacted]

Dear [Founder First Name],

Our research team learned about your entrepreneurial experience from the Pitchbook Database and would like to invite you to participate in a research project conducted by the Columbia University Economics Department. Given your startup fundraising experience, your insight would be indispensable to our research, which we hope would shed light on the global entrepreneurial financing process and help the recovery of entrepreneurial activities from recession.

The purpose of this research project is to understand the entrepreneurial financing process (for example, founders' preferences for future collaborative investors) and remove the frictions typically found in the fund-raising process using the matching algorithms we have developed (i.e., the "Nano-Search Financing Tool") that can match startup founders with the best potential investors from our Global Investor Database. The research project is supervised by [redacted]

Using the tool takes about 20 – 30 minutes and involves evaluating 20 hypothetical investor profiles. After evaluating these profiles, the tool uses a newly developed machine-learning algorithm to identify investors who could potentially be interested in your startups. Our research team will also use a completely anonymized version of your data to research broader trends in what startups value when looking for collaborators. We will be glad to share these insights with you when the research is complete.

In order to receive information on potential investors, at least one startup founder must complete the survey. If possible, having multiple individuals participate will further increase the accuracy of our algorithms' recommendations. The investor recommendation list and contact information will be delivered within one month so that you can reach out to these investors or institutions when you are ready. Based on our previous experience, the response rate is decent, and many investors give valuable feedback.

To access the tool, please click the link; we have also attached instructions for its use.

If you would like more detailed information about how the tool will enhance your startup's fund-raising process or have questions, please contact the tool developer and project investigator, [redacted]

Sincerely,

[redacted]

Figure A1: Recruitment Email (Wave 1)

[Email Subject Line] Identify Top Venture Capitalists for Your Firm

Dear member of ${m://CompanyName},

We discovered your startup company on Crunchbase and would like to invite you to participate in a research project in collaboration with researchers from [redacted] and [redacted]. Your insights would shed light on the investor-startup matching process in the U.S. and contribute to the post-recession entrepreneurial recovery.

We have developed a matching tool that can match US venture capitalists with the best-fit startup teams. Using the tool takes about 20 minutes and involves evaluating 20 hypothetical investor profiles in your industry. After the study, you will receive a customized investor recommendation list within two months, along with a few opportunities to participate in lotteries.

To share your insights, please click on the following link:
${l://SurveyLink?d=Share Your Insights}

Alternatively, you can copy and paste the URL below into your internet browser:
${l://SurveyURL}

Rest assured, your participation is completely anonymous, and the data collected is solely used for this project. For any inquiries or more information, please feel free to reach out to Prof. [redacted]

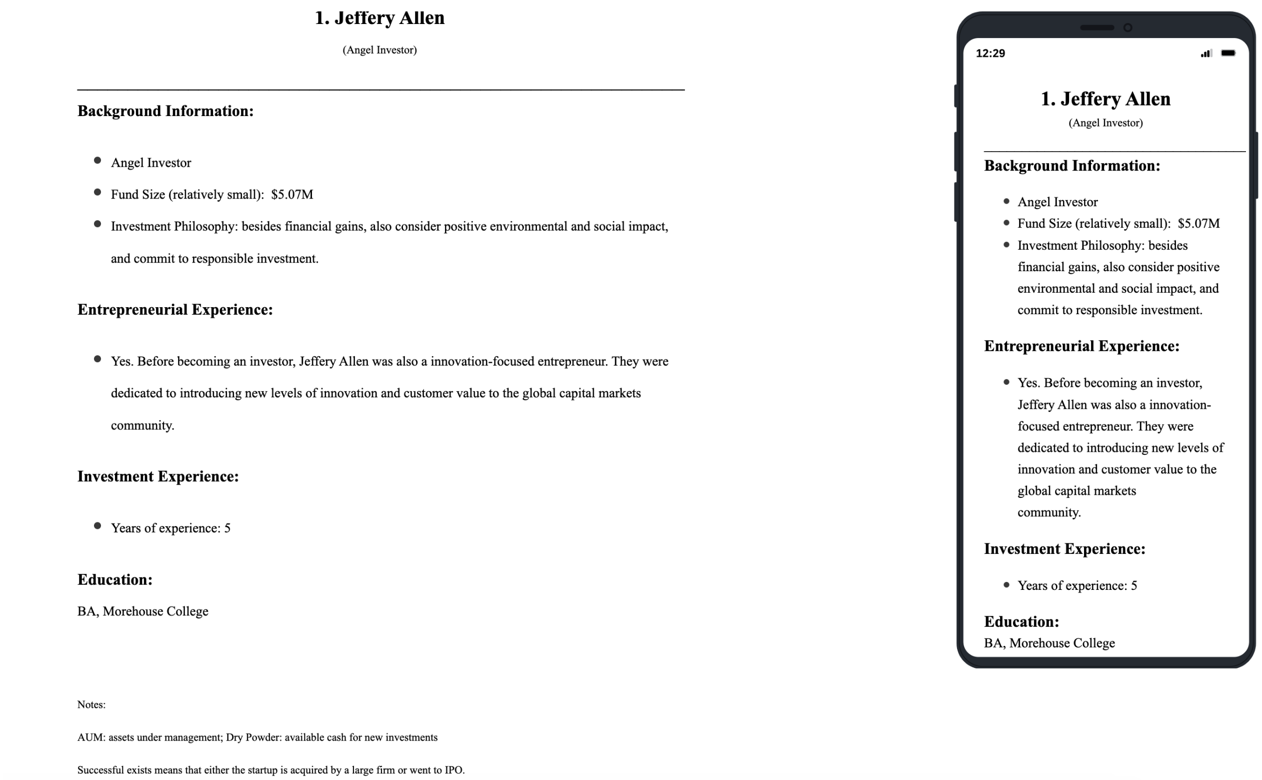
We greatly appreciate your time and look forward to your valuable contribution to our study.

Sincerely,
[redacted]

Follow the link to opt out of future emails:
${l://OptOutLink?d=Click here to unsubscribe}

Figure A2: Recruitment Email (Wave 2)

Figure A3: Instruction Poster



1. Jeffery Allen

(Angel Investor)

Background Information:

- Angel Investor
- Fund Size (relatively small): $5.07M
- Investment Philosophy: besides financial gains, also consider positive environmental and social impact, and commit to responsible investment.

Entrepreneurial Experience:

- Yes. Before becoming an investor, Jeffery Allen was also a innovation-focused entrepreneur. They were dedicated to introducing new levels of innovation and customer value to the global capital markets community.

Investment Experience:

- Years of experience: 5

Education:

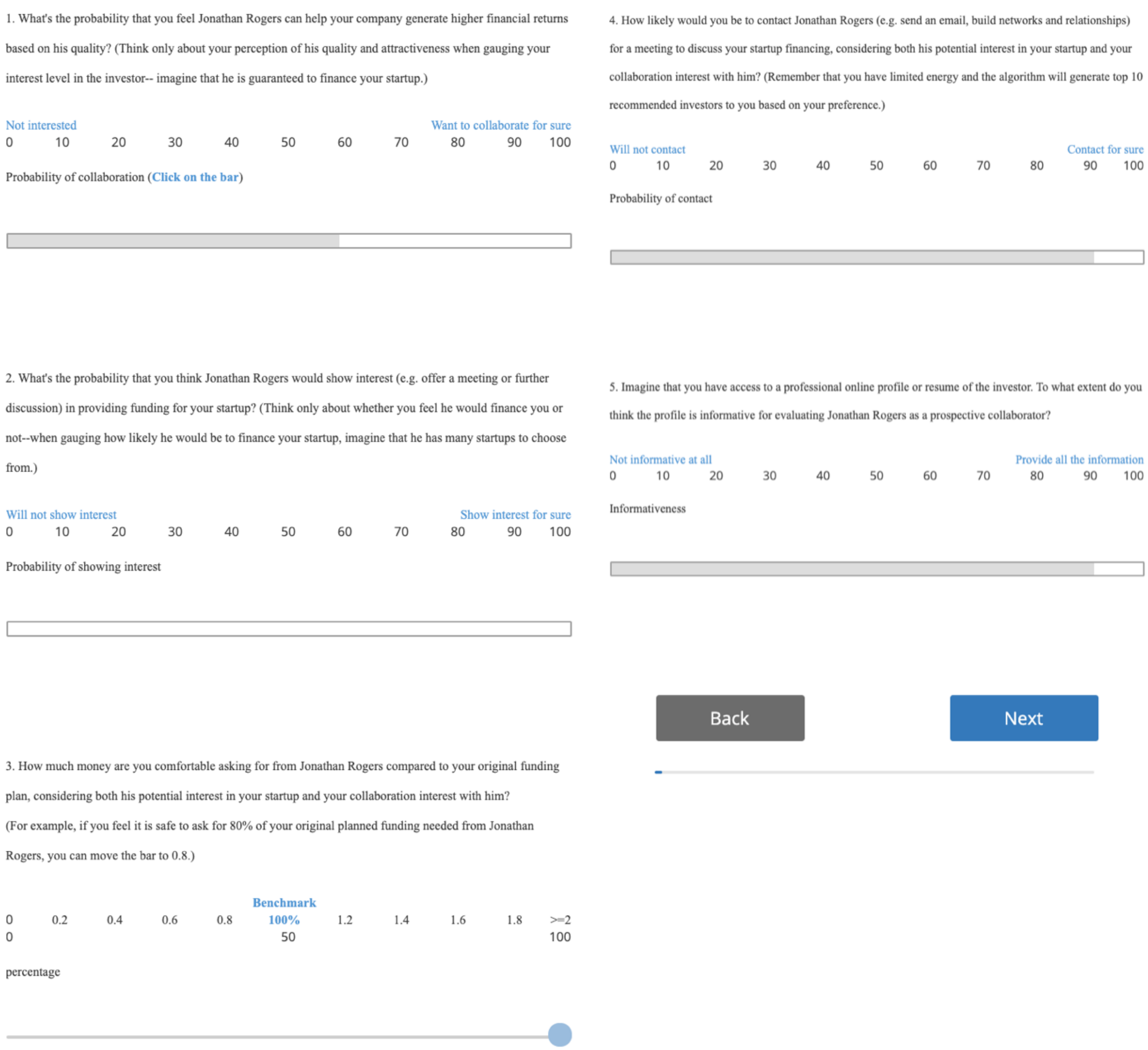
BA, Morehouse College

Notes:

AUM: assets under management; Dry Powder: available cash for new investments

Successful exists means that either the startup is acquired by a large firm or went to IPO.

Figure A4: Sample Investor Profile



1. What's the probability that you feel Jonathan Rogers can help your company generate higher financial returns based on his quality? (Think only about your perception of his quality and attractiveness when gauging your interest level in the investor-- imagine that he is guaranteed to finance your startup.)

Not interested | Want to collaborate for sure

0 10 20 30 40 50 60 70 80 90 100

Probability of collaboration (**Click on the bar**)

2. What's the probability that you think Jonathan Rogers would show interest (e.g. offer a meeting or further discussion) in providing funding for your startup? (Think only about whether you feel he would finance you or not--when gauging how likely he would be to finance your startup, imagine that he has many startups to choose from.)

Will not show interest | Show interest for sure

0 10 20 30 40 50 60 70 80 90 100

Probability of showing interest

3. How much money are you comfortable asking for from Jonathan Rogers compared to your original funding plan, considering both his potential interest in your startup and your collaboration interest with him? (For example, if you feel it is safe to ask for 80% of your original planned funding needed from Jonathan Rogers, you can move the bar to 0.8.)

Benchmark

0 0.2 0.4 0.6 0.8 **100%** 1.2 1.4 1.6 1.8 >=2

0 50 100

percentage

4. How likely would you be to contact Jonathan Rogers (e.g. send an email, build networks and relationships) for a meeting to discuss your startup financing, considering both his potential interest in your startup and your collaboration interest with him? (Remember that you have limited energy and the algorithm will generate top 10 recommended investors to you based on your preference.)

Will not contact | Contact for sure

0 10 20 30 40 50 60 70 80 90 100

Probability of contact

5. Imagine that you have access to a professional online profile or resume of the investor. To what extent do you think the profile is informative for evaluating Jonathan Rogers as a prospective collaborator?

Not informative at all | Provide all the information

0 10 20 30 40 50 60 70 80 90 100

Informativeness

Back | Next

Figure A5: Sample Evaluation Questions

B Complementary Results

Rule Out "Balance the Profile" Hypothesis To rule out this alternative interpretation of our experimental result, we empirically test whether subjects evaluating more female investors in the *first* half of the study give lower ratings to female investors in the *second* half of the study. Results are reported in Online Appendix Table B1. We find that evaluating one more female investor's profile among the first ten profiles is insignificantly associated with more positive attitudes towards female investors in the second half of the study. This goes against the "balance the profile" hypothesis. Moreover, according to the "balance the profile" hypothesis, we should also observe similar data patterns for the evaluation results of Asian investors. However, both Table 6 and Figure B4 in the Appendix show that investor's race does not influence entrepreneurs' evaluation results. Similarly, this "fatigue effect" phenomenon does not exist for the other nonsensitive investor characteristics. All of these results make us confident to conclude that the "balance the profile" hypothesis is not the driver of our "implicit discrimination" findings.

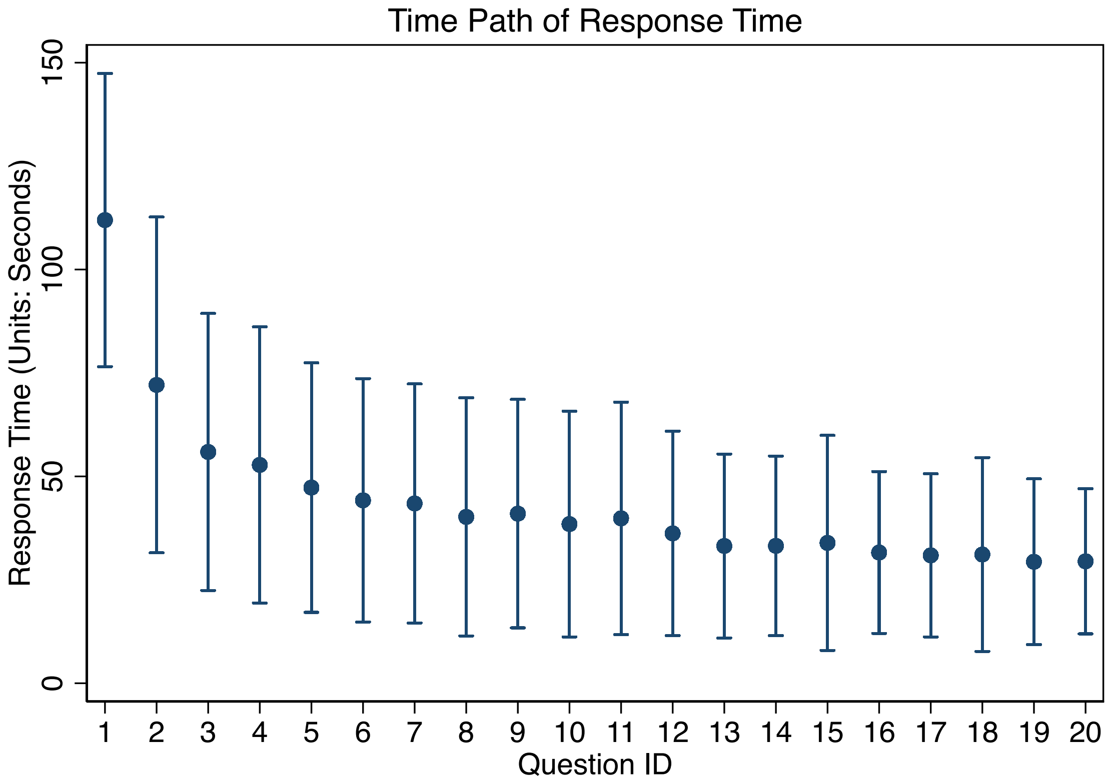


Figure B1: Time Path of Response Time

Notes. This figure demonstrates the time-path of startup founders' response time as the study progresses to the end. The x-axis is the profile ID, which indicates the order of profiles displayed to each startup founder. The y-axis reports the mean and standard deviation of startup founders' response time measured in seconds.

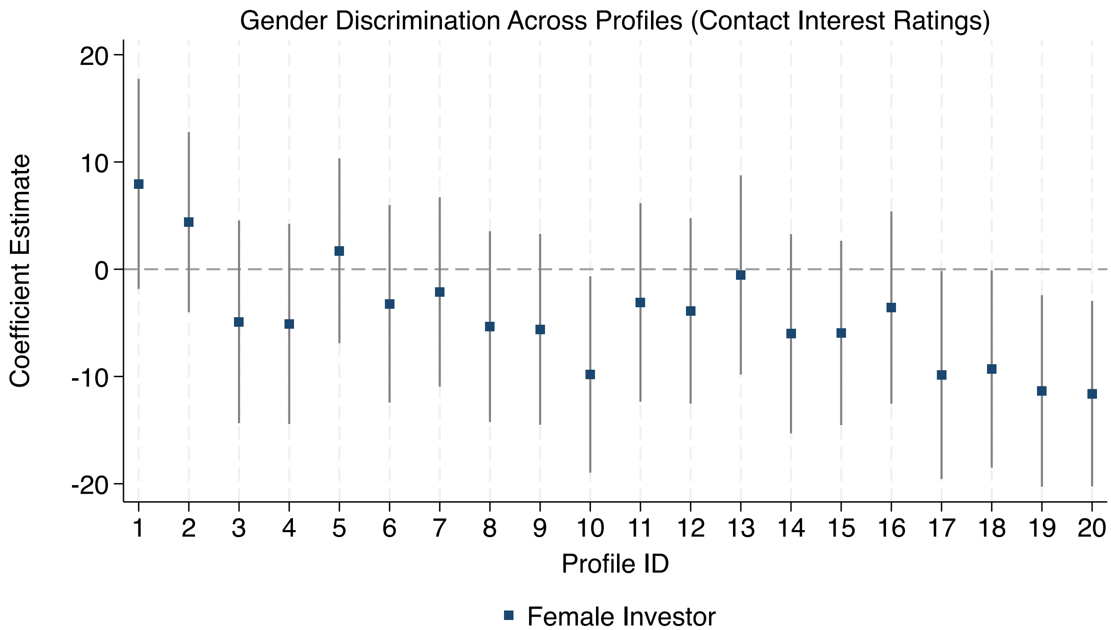


Figure B2: Gender Discrimination Across Profiles (Contact Interest Ratings)

Notes. This figure demonstrates how investors' gender affects recruited founders' contact interest ratings across profiles. It shows how founders' gender discrimination evolves as the study progresses to the end. The horizontal line describes the order of each investor profile displayed to the experimental subjects (i.e., the k^{th} displayed investor profile). The vertical line is the coefficient of "Female Investor" of the following regressions: $Q4_{ij} = \alpha + \beta_1$Female Investor$_{ij} +\ \beta_2$Asian Investor$_{ij} + \epsilon_{ij}$ for all subjects' evaluation results of the k^{th} displayed investor profiles, with 95% confidence interval. This represents the magnitude of gender discrimination as measured by startup founders' contact interest ratings (i.e., Q_4).

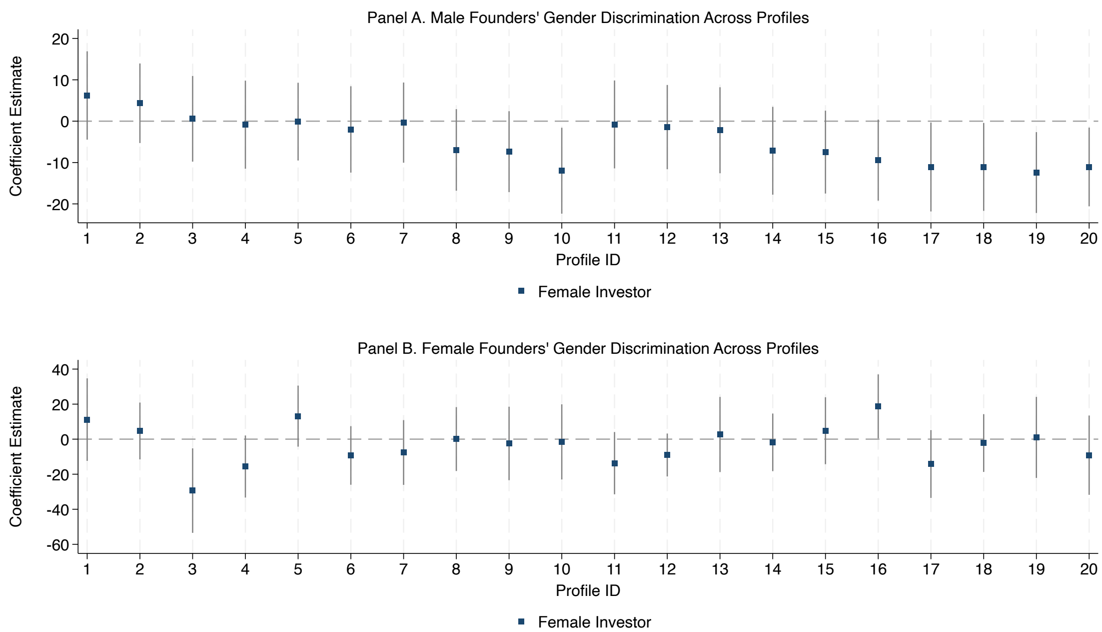


Figure B3: Gender Discrimination Across Profiles (Male Founders vs Female Founders)

Notes. This figure demonstrates how investors' gender affects the contact interest ratings of male startup founders and female startup founders as the study progresses to the end. Panel A uses evaluations of male startup founders. Panel B uses evaluations of female startup founders. The horizontal line describes the order of each investor profile displayed to the experimental subjects (i.e., the k^{th} displayed investor profile). The vertical line is the coefficient of "Female Investor" of the following regressions: $Q4_{ij} = \alpha + \beta_1 \text{Female Investor}_{ij} + \beta_2 \text{Asian Investor}_{ij} + \epsilon_{ij}$ for all subjects' evaluation results of the k^{th} displayed investor profiles, with 95% confidence interval. This represents the magnitude of gender discrimination as measured by startup founders' contact interest ratings (i.e., Q_4).

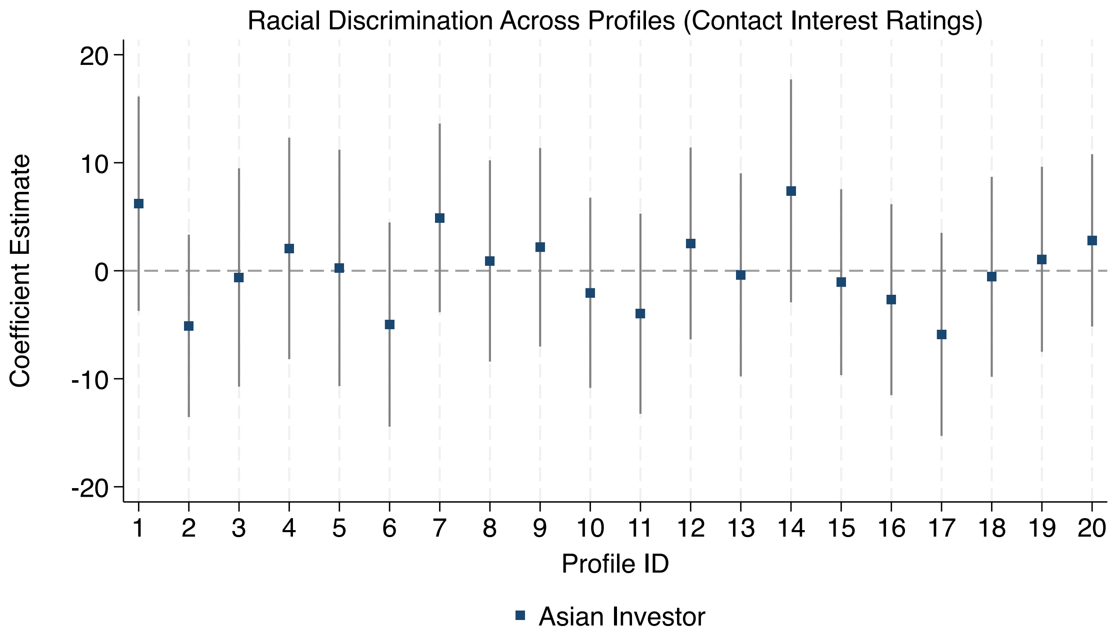


Figure B4: Racial Discrimination Across Profiles (Contact Interest Ratings)

Notes. This figure demonstrates how investors' race affects recruited founders' contact interest ratings across profiles. It shows how founders' racial discrimination evolves as the study progresses to the end. The horizontal line describes the order of each investor profile displayed to the experimental subjects (i.e., the k^{th} displayed investor profile). The vertical line is the coefficient of "Asian Investor" of the following regressions: $Q4_{ij} = \alpha + \beta_1 \text{Female Investor}_{ij} + \beta_2 \text{Asian Investor}_{ij} + \epsilon_{ij}$ for all subjects' evaluation results of the k^{th} displayed investor profiles, with 95% confidence interval. This represents the magnitude of racial discrimination as measured by startup founders' contact interest ratings (i.e., Q_4).

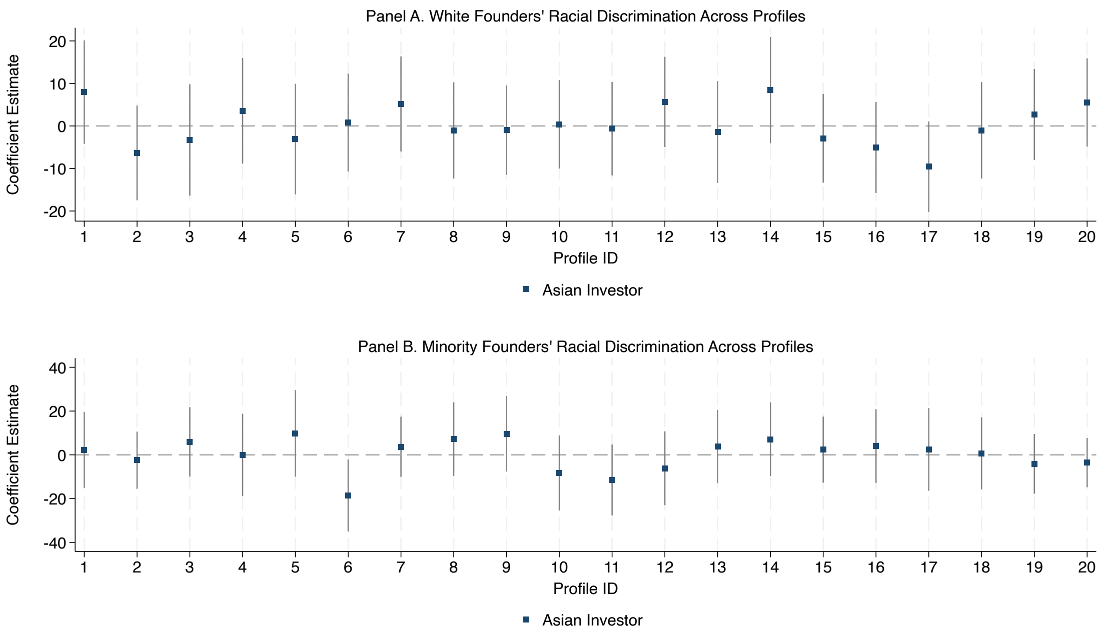


Figure B5: Racial Discrimination Across Profiles (White Founders vs Minority Founders)

Notes. This figure demonstrates how investors' race affects the contact interest ratings of white startup founders and minority startup founders as the study progresses to the end. Panel A uses evaluations of white startup founders. Panel B uses evaluations of minority startup founders. The horizontal line describes the order of each investor profile displayed to the experimental subjects (i.e., the k^{th} displayed investor profile). The vertical line is the coefficient of "Asian Investor" of the following regressions: $Q4_{ij} = \alpha + \beta_1 \text{Female Investor}_{ij} + \beta_2 \text{Asian Investor}_{ij} + \epsilon_{ij}$ for all subjects' evaluation results of the k^{th} displayed investor profiles, with 95% confidence interval. This represents the magnitude of racial discrimination as measured by startup founders' contact interest ratings (i.e., Q_4).

Table B1: Profiles in the First Half and Evaluations in the Second Half

This table tests whether startup founders' evaluations of the female or Asian VCs decrease in the second half of the study when they evaluate more female or Asian founders' profiles in the first half of the study. The dependent variable is the average profitability rating (i.e., Q_1), average availability rating (i.e., Q_2), average informativeness rating (i.e., Q_5), average fundraising plan (i.e., Q_3), and average contact interest rating (i.e., Q_4) in the second half of the IRR experiment in Columns (1), (2), (3), (4), and (5), respectively. "Fraction of Female VCs In the First Half" and "Fraction of Asian VCs In the First Half" represent the fraction of female VCs and Asian VCs in the first half profiles, respectively. These cross-sectional regressions use robust standard errors.

	Profitability (1)	Availability (2)	Informativeness (3)	Funding (4)	Contact (5)
Panel A. Gender					
Fraction of Female VCs	2.09	8.57	5.49	10.86	-1.31
In the first Half	(8.06)	(9.72)	(11.61)	(11.23)	(9.52)
Observations	141	141	141	141	141
R-squared	0.000	0.005	0.002	0.006	0.000
Panel B. Race					
Fraction of Asian VCs	12.48	7.55	18.48*	1.54	3.91
In the first Half	(9.07)	(10.50)	(10.32)	(12.17)	(10.47)
Observations	141	141	141	141	141
R-squared	0.014	0.004	0.024	0.000	0.001

Table B2: Implicit Discrimination Based on Investor's Seniority

Dependent Variable	Response Time (Unit: Second) (1)	Q1 Quality (2)	Q2 Availability (3)	Q3 Funding (4)	Q4 Contact (5)	Q5 Informativeness (6)
Panel A: Senior Investors						
Second Half of Study	-22.71***	5.39**	7.34***	3.84**	0.55	3.86*
	(1.97)	(2.08)	(2.02)	(1.62)	(1.59)	(2.08)
Female Investor	-2.67	0.58	0.03	-1.68	1.44	-1.71
	(1.98)	(1.84)	(1.62)	(1.57)	(1.56)	(2.05)
Female Investor × Second Half of Study		-8.51***	-9.34***	-6.03**	-1.77	-6.06**
		(2.43)	(2.39)	(2.03)	(2.06)	(2.85)
Asian Investor	1.60	-1.95	0.35	-1.39	-1.79	-3.24*
	(1.95)	(1.69)	(1.49)	(1.29)	(1.34)	(1.84)
Asian Investor × Second Half of Study		-1.00	-2.66	0.24	0.92	0.92
		(2.39)	(2.08)	(1.85)	(1.81)	(2.60)
p-value of Female Investor in the second half of study		0.00	0.00	0.00	0.76	0.01
p-value of Asian Investor in the second half of study		0.32	0.28	0.83	0.95	0.37
Subject FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean of Dependent Variables	45.20	66.15	58.43	69.43	50.97	66.94
Observations	987	987	987	987	987	987
R-squared	0.53	0.55	0.67	0.72	0.72	0.58
Panel B: Junior Investors						
Second Half of Study	-23.80***	3.11	0.63	1.15	-1.61	2.06
	(2.10)	(2.13)	(1.90)	(1.74)	(1.80)	(2.30)
Female Investor	0.92	1.78	1.39	-5.67***	0.63	0.78
	(2.11)	(1.66)	(1.59)	(1.45)	(1.44)	(1.79)
Female Investor × Second Half of Study		-6.19**	-2.72	-0.51	-1.07	-3.34
		(2.28)	(2.27)	(1.84)	(2.10)	(2.51)
Asian Investor	1.80	0.28	-0.70	-0.27	-0.40	2.55
	(2.04)	(1.96)	(1.59)	(1.41)	(1.61)	(2.22)
Asian Investor × Second Half of Study		0.09	1.38	1.21	2.01	-0.06
		(2.98)	(2.48)	(2.33)	(2.60)	(3.17)
p-value of Female Investor in the second half of study		0.13	0.70	0.02	0.81	0.40
p-value of Asian Investor in the second half of study		0.94	0.85	0.67	0.41	0.39
Subject FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean of Dependent Variables	44.16	51.59	50.57	64.83	48.27	53.14
Observations	987	987	987	987	987	987
R-squared	0.44	0.62	0.68	0.73	0.70	0.63

Notes. This table tests whether startup founders' implicit discrimination affects senior investors and junior investors differently. Panel A focuses on evaluations of senior VC investors. Panel B focuses on evaluations of junior VC investors. Evaluations of angel investor profiles are excluded from the sample. Definitions of independent and dependent variables are the same as those in Table 6. All the regressions add subject fixed effect. R-squared is indicated for each OLS regression. Standard errors in parentheses are clustered within each experimental subject. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

C Omitted proofs

C.1 Proof for Theorem 1

Proof. Firstly, we enumerate all possibilities for regular equilibria. Define $\widehat{Q}_G(Q), \widehat{Q}_B(Q)$ the mass of E in markets G, B respectively in the (identity blind) equilibrium when the total mass of E and VC are Q and $\frac{1}{2}$ and $p = p_0$. Define $\widehat{u}(Q)$ the utility from entering either market in the (identity blind) equilibrium when the total mass of E and VC are Q and $\frac{1}{2}$ and $p = p_0$. Then, $\widehat{u}(Q)$ is a strictly decreasing function.

The key observation is that whenever a group ι searches in both $G\ell$ and $B\ell$ markets for $\iota = \ell$, the equilibrium total mass of E in each market is determined by $\widehat{Q}_G(Q)$ and $\widehat{Q}_B(Q)$. The equilibrium payoff is determined by $\widehat{u}(Q)$, where Q is the total mass of <u>both</u> E groups in the two markets.

- *Case 1*: Group 1 E only enters market $G1$. This requires the mass of group 2 E in market $B1$ at least equal to $\widehat{Q}_G^{-1}(Q_1) - Q_1$. However, this implies

  $$\widehat{u}(Q_G^{11} + Q_B^{12}) < \widehat{u}(Q_G^{22} + Q_B^{22})$$

  LHS is strictly higher than group 2 E's payoff from market $B1$ due to $\kappa > 0$. RHS is group 2 E's payoff from market $G2/B2$. This means group 2 E has no incentive to enter market $B1$. Therefore, this case is not possible.

- *Case 2*: Group 1 E only enters markets $G1$ and $B1$. This immediately implies that group 2 E does not enter $G1$:

  $$0 = u_G^{11}(\lambda_G^1) - u_B^{11}(\lambda_B^1) > u_G^{12}(\lambda_G^1) - u_B^{12}(\lambda_B^1)$$

  Suppose group 2 E enters $B1$ with strictly positive mass. Then, group 2 E's payoff from $B1$ is strictly lower than

  $$\widehat{u}(Q_1 + Q_G^{12}) < \widehat{u}(Q_2 - Q_G^{12}).$$

  This means group 2 E has no incentive to enter market $B1$; hence, this case is not possible. Therefore, the only possibility is that group 2 E only enters $G2, B2$.

- *Case 3*: Group 1 E enters all markets. This implies

$$u_G^{22}(\lambda_G^2) - u_B^{22}(\lambda_B^2) > u_G^{21}(\lambda_G^2) - u_B^{21}(\lambda_B^2) = 0$$

  This immediately implies that group 2 E enters only $G2$.

- *Case 4*: Group 1 E enters markets $G1, B1$ and $G2$. Like case 2, group 2 E does not enter $B1$. Group 1 E being indifferent between $G1$ and $G2$ also implies that group 2 E strictly prefers $G2$. Therefore, group 2 E enters either only $G2$ or both $G2$ and $B2$.

Next, we prove $\mu_G^2 < \mu_G^1$ and $\mu_B^2 > \mu_B^1$.

- *Case 1*: In this case, the utility from group 2 markets is higher than the utility from group 1 markets (note that since matching only forms within groups, there is no loss from homophily) since $\hat{u}$ is strictly decreasing and $Q_1 > Q_2$. This means $u_G(\lambda_G^1) < u_G(\lambda_G^2)$ and $u_B(\lambda_B^1) < u_B(\lambda_B^2)$. This implies $\lambda_G^1 > \lambda_B^1$; $\lambda_G^2 > \lambda_B^2$ since u_G, u_B are strictly decreasing. Then, $\mu_G(\lambda_G^1) > \mu_G(\lambda_G^2)$; $\mu_B(\lambda_B^1) < \mu_B(\lambda_B^2)$.

- *Case 2*: In this case, $u_B^{11}(\lambda_G^1) = u_B^{12}(\lambda_G^2) \implies \lambda_B^1 > \lambda_B^2$. This implies $Q_1 > Q_2$. The rest follows from the analysis for Case 1.

- *Case 3*: In this case, $u_B^{11}(\lambda_B^1) = u_B^{12}(\lambda_B^2) \implies \lambda_B^1 > \lambda_B^2$. $u_G^{11}(\lambda_G^1) = u_G^{12}(\lambda_G^2) \implies \lambda_G^1 > \lambda_G^2$. The rest follows from the analysis for Case 1.

□