Statistical Discrimination in Two-sided Matching Markets: Experimental and Theoretical Evidence*

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Abstract

This paper explores statistical discrimination within two-sided matching markets, focusing on the entrepreneurial financing market. Through an experiment involving US startup founders, we identify statistical discrimination against female investors, whose signals are also perceived as less informative than those of male investors. This discrimination is predominantly driven by male founders and disproportionately affects *high-quality* female investors. We then develop a novel search-and-matching model with endogenous information aggregation and belief formation. The model explains how statistical discrimination can arise *endogenously* within two-sided matching markets, leading to the observed glass ceiling distributional effect and perpetuating a low female participation rate in equilibrium.

Keywords: Discrimination, Two-sided Matching, Experiment, Entrepreneurship
JEL Classification: C78, C93, D83, G24, J16, J71, L26

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1 Introduction

Studying statistical discrimination in two-sided matching markets is crucial, given that various important markets, such as labor markets, college admissions, and housing rental markets, 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 through evaluators' beliefs about their productivity(Craig and Fryer, 2017). This paper aims to explore the nature and distinct characteristics of discrimination within such markets, offering crucial insights into when and how such discrimination emerges and its effects on two-sided matching market participants.

We focus on statistical gender discrimination in the entrepreneurial financing market in this paper 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 statistical gender discrimination exists on both the investor and startup sides. Prior research also documents the persistently low female participation in this market (Gompers and Wang, 2017).[2] While gender discrimination on the investor side has been widely studied (Ewens, 2022), such discrimination among startup founders remains under-explored. Considering founders' significant bargaining power (Ewens, Gorbenko and Korteweg, 2022), understanding discrimination on the capital demand side is crucial for explaining the generation process of such discrimination in two-sided markets.

To fill this gap in the literature, we begin by conducting an experiment with US startup founders to explore the potential presence of statistical gender discrimination among founders. Leveraging the experimental findings in this study and prior literature, we further develop a search-and-matching model that explains the conditions under which statistical discrimination can endogenously arise in a two-sided matching market. The model further explains why low female participation rates could persist in two-sided markets, such as the entrepreneurial financing market (Gompers and Wang, 2017), and why statistical discrimination disproportionately affects high-quality females, as shown in the experiment.

In total, 141 US startup founders who are seeking funding participated in our study through two waves of recruitment and collectively evaluated 2,820 randomly generated in-

[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 as no significant findings were observed.

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

vestor profiles.[3] Following the design in Kessler, Low and Sullivan (2019), participating founders evaluate 20 hypothetical investor profiles with randomly assigned first names highly indicative of their gender and last names highly indicative of their race.[4] We compile a comprehensive global venture capital (VC) and angel investor database and develop a matching algorithm to offer personalized investor recommendation services for participating founders based on their profile evaluations. This algorithm generates a list of matched *real* investors for each founder. While founders are aware that the investor profiles are hypothetical, they are incentivized to provide truthful evaluations due to a matching incentive: the more honest their evaluations are, the more effective and beneficial the generated investor list will be. In addition to expressing interest in contacting investors, participating founders also evaluate perceived investor quality, investment likelihood, and the informativeness of each investor profile.

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

Our experiment first identifies the presence of gender discrimination against female investors among US startup founders. When comparing female investor profiles to similar male investor profiles, startup founders rate female investors, 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 investors' entrepreneurial experience on the ratings, which is considered one of the

[3]In our experiment, the term "investors" encompasses both venture capitalists (VCs) and angel investors.

[4]Given that the US entrepreneurial financing market is dominated by whites and Asians, last names in the experiment indicate whether investors are Asian or white.

most crucial human capital characteristics of VC investors (Bottazzi, Da Rin and Hellmann, 2008; Gompers and Mukharlyamov, 2022). However, we do not observe any significant racial discrimination against Asian investors.

Secondly, the experiment further indicates that founders' discrimination behaviors are closely related to belief-driven mechanisms. Consistent with statistical discrimination, founders perceive female investors to be 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 also view female investor profiles as 5.25 p.p. less informative compared to similar male investor profiles. This finding provides crucial empirical validation for information-based discrimination theories (Che, Kim and Zhong, 2019), suggesting that signals from underrepresented groups (i.e., the minority group) are perceived as noisier than those from the majority group. As illustrated in our model, these beliefs can arise endogenously within a two-sided matching context, even when different groups possess identical quality distributions and evaluators utilize identical rating technologies.

Thirdly, we document that this statistical gender discrimination is primarily driven by male founders. On average, male founders assign significantly lower contact interest ratings to female investors, a difference of 4.84 percentage points (p.p.) compared to male investors, which is statistically significant at the 1% level. Similarly, male founders also hold more-negative beliefs about female investors' value added to their profitability and investment intentions in their startups compared to their perceptions of similar male investors. However, compared to male founders, female founders exhibit a significantly higher propensity to engage with female investors and hold more positive beliefs about their value added and investment intentions.

Lastly, we further discover a distributional effect wherein statistical discrimination disproportionately hurts *high-quality* female investors, a phenomenon we refer to as the "glass ceiling" in this paper. Using other orthogonally randomized investor characteristics as proxies for investor quality, we find that founders assign 3.71 p.p. lower contact interest ratings to high-quality female investors compared to similar high-quality male investors. Similarly, negative perceptions about female investors also predominantly impact those of high quality. However, when evaluating low-quality investors, founders do not discriminate against female investors and might even rate them slightly more positively. Consistent with the glass ceiling phenomenon, we also observe that while implicit gender discrimination might influence founders' fundraising behaviors, such implicit discrimination particularly hurts female investors in *senior* positions.[5]

To explain our stark empirical findings, we develop a novel search-and-matching model with endogenous information aggregation. In a matching market, founders search for investors, and a successful match provides an informative, albeit imperfect, rating of the VC's quality.[6] The model features a seemingly level playing field for investors from different identity groups: investors from different groups have identical quality distribution and access to the same rating technology. However, the opportunity to be evaluated is determined endogenously by the matching frequency of each group by founders, leading to an information feedback loop: a more frequently matched group has ratings that are perceived to be 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 a discriminatory equilibrium: the information from the ratings eventually corrects founders' initial biases, resulting in a unique non-discriminatory equilibrium.

The crucial insight from our model is that the feedback loop combined with homophily in the two-sided 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, the resulting statistical discrimination against the minority group features a distributional effect: the rational belief arising from the ratings "discriminates" against high ratings from the minority group (i.e., glass ceiling), as the failure to match caused by homophily disproportionately hurts the minority group with high ratings.[7]

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

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

[6] While startup founders do not formally rate VCs in the real world, the rating can be interpreted as the accumulated public information about the investors in our application of the investor-founder market. This terminology follows the discrimination theory literature (Che et al., 2019).

[7] Consistent with our experimental findings from the distributional analysis, the model also predicts that such discrimination may favor low ratings from the minority group, a phenomenon known as the "glass basement".

technology is used. However, the search-and-matching process endogenously leads to different informational quality of ratings across groups, with the ratings received by the majority groups being perceived as more reliable and accurate. This feature enables us to endogenize the key channel of belief formation in our paper. Traditional models of statistical discrimination, in comparison, take the asymmetric beliefs as an assumption, due to either intrinsic quality differences (exogenous differences in Phelps (1972) and endogenous differences in Arrow (1974); Coate and Loury (1993); Craig and Fryer (2017)) or heterogeneous observable information about different groups (Phelps (1972)). However, in our framework, we demonstrate that even with identical intrinsic quality and identical observable signals across different groups, homophily in matching and imbalanced representation among groups are sufficient to endogenously generate statistical discrimination.

The paper's contribution is both empirical and theoretical. First of all, we add to the empirical discrimination literature in several ways. Beyond detecting statistical gender discrimination in an under-explored context (i.e., founders seek funding from investors), we uncover several key empirical insights relevant to discrimination theories. Firstly, we reveal that evaluators (i.e., founders) perceive signals from minority groups (i.e., female investors) as less informative compared to majority groups (i.e., male investors), empirically confirming an important assumption in information-based 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 distributional effect. This phenomenon is difficult to explain with most statistical discrimination theories (Bohren, Imas and Rosenberg, 2019), as sending high-quality signals might also hurt minority groups in a matching context.[8] 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). 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.[9] Overall, these empirical findings offer crucial insights for devel-

[8]A similar phenomenon is also observed in Zhang (2020), where VCs' implicit gender discrimination disproportionately affects *high-quality* female startup founders.

[9]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

oping theories to explain the emergence and characteristics of statistical discrimination in two-sided matching markets.

Additionally, the paper contributes to the literature on gender gaps in the labor market. Prior research has documented that multiple factors might lead to such gender gaps, including network connections (Agarwal, Qian, Reeb and Sing, 2016), market search behaviors (Cortés, Pan, Pilossoph, Reuben and Zafar, 2023), preferences for specific workplace attributes (Flory, Leibbrandt and List, 2015; Wiswall and Zafar, 2018), self-evaluations and self-promotion (Exley and Kessler, 2022), career aspirations (Azmat and Ferrer, 2017), and credit attribution (Sarsons, Gërxhani, Reuben and Schram, 2021). In this paper, we focus on the gender gap in the US entrepreneurial financing market. We aim to explain the persistent lack of women in the VC industry by considering the two-sided matching nature of this market and imperfect evaluations of agents' quality.[10] Given that women's participation rate is a matching equilibrium outcome and investors' discrimination behaviors have been well studied on the capital supply side (Ewens and Townsend, 2020; Guzman and Kacperczyk, 2019; Hebert, 2023; Zhang, 2020), we first investigate the characteristics and nature of founders' gender discrimination, which directly influences female investors' deal flows. Taking these experimental results as building blocks, we further provide a theoretical framework that sheds light on how statistical discrimination may endogenously emerge in a matching context and lead to lower participation rates among female investors in long-run equilibria.

Lastly, this paper contributes to the theoretical literature on discrimination behaviors. Classical discrimination theories attribute statistical discrimination to either coordination failure and the resulting heterogeneity in agents' qualities (Arrow, 1971,7,9; Coate and Loury, 1993) or the heterogeneity in the observable information about different agents with the same quality (Aigner and Cain, 1977; Phelps, 1972). Unlike these models, our model endogenizes the information aggregation process about agents' true quality via a channel of informative but imperfect ratings in a two-sided matching market. The informational quality of ratings is determined by the endogenous matching frequency of a specific agent group being

more discussion of this concept, see Ebrahimian and Zhang (2024).

[10] Gompers and Wang (2017) noted that the participation rate of women as investors in the high-impact entrepreneurial financing market has consistently been low and has lagged behind their participation rates in other highly skilled occupations. Multiple potential explanations exist. For example, women are documented to be more risk-averse and less likely to participate in risky entrepreneurial activities (Croson and Gneezy, 2009; Wiswall and Zafar, 2018). Furthermore, female investors may receive less support from informal mentoring systems within VC firms (Gompers, Mukharlyamov, Weisburst and Xuan, 2014).

considered for collaboration opportunities. 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 matching context. Beyond the matching between startup founders and investors, our model can be broadly applied to other two-sided markets in economics. Closely related to our approach, two concurrent papers Echenique and Li (2023) and Bardhi, Guo and Strulovici (2023) also explore the endogenous information aggregation channel of statistical discrimination. However, they rely on very different mechanisms from our paper, making their frameworks less applicable to a two-sided market. Specifically, Echenique and Li (2023) attribute discriminatory signal quality to the strategically inattentive behavior of employers stemming from coordination failures in worker investment. Bardhi et al. (2023), on the other hand, rely on asymmetric (albeit close) prior beliefs and attribute inequality to the magnification of early-career discrimination via on-the-job learning.

The remainder of 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. Section 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 incentivized resume rating (IRR) experiment. Beyond identifying potential statistical discrimination by US startup founders against female or Asian investors during their fundraising, the experiment also aims to uncover underlying mechanisms 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 and angel 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. During the recruitment process, some founders of these commercial firms contacted the research team to inquire whether this project would compete with their businesses. These interactions reinforce our confidence that the experimental setting closely mirrors real-world conditions.

Recruitment and Sample Selection. In total, we recruited 141 US startup founders for the experiment. The founders provided 2,820 investor evaluations through two waves of recruitment. During the first wave (i.e., Wave 1) in February–March 2021, we recruited 45 founders. The second wave (i.e., Wave 2) of 96 founders were recruited between January and March of 2024. Details of the recruitment process are available in Online Appendix Section A. All startup founders participating in the same recruitment wave received identical recruitment information and were allotted abundant time to complete the survey.[11]

The overall response rate was approximately 5%. Table 1 summarizes background information on the 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 investors, with 48.23% in information technology, 19.86% in the consumer sector, and 13.48% in healthcare.

We note that standard commercial databases typically track completed deals and *funded* startups. However, we are interested in *all* startups seeking VC or angel funding, including those that may be ultimately rejected by these investors. Hence, comparing our recruited sample with VC-backed startups is not meaningful. To shed light on potential sample selection issues during recruitment, Table 1 also reports available background information on startups listed on Crunchbase. We note that startups listed on Crunchbase tend to be IT related, mature and large companies, and male-led, suggesting that they might also not be representative of the broader spectrum of all startups seeking VC or angel 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 researchers at present.

[Insert Table 1 here]

[11] For an example recruitment email, please see Online Appendix Figure A1. For the instruction poster, please see Online Appendix Figure A2.

Upon receiving the recruitment information 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 investor profiles. Notably, the experiment instructs the founders to *assume that all hypothetical investors they evaluate would invest in their startup's industry and funding stage*. While the founders understand these profiles are hypothetical, they also know that by providing honest evaluations, they can help the matching algorithm generate more accurate investor recommendations for them.

Investor Profile Creation and Variation. To generate hypothetical investor profiles, we simultaneously and independently randomize individual-level and fund-level investor characteristics. Similar to Kessler et al. (2019), the experiment dynamically populates each investor characteristic from a pool of options, and the matching tool combines these randomly selected characteristics together to create an investor profile. Each profile uses descriptions verified as gender-neutral by ChatGPT-4. For more details, see Online Appendix Section A.2. The randomization process of investor characteristics is described in Online Appendix Table A1, and an example investor profile is provided in Online Appendix Figure A3.

Names Indicating Gender and Race. Following Fryer Jr and Levitt (2004), Bertrand and Mullainathan (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).[12] Each assigned name is prominently displayed at the beginning of the profile and mentioned multiple times in evaluation questions to increase its salience, along with ample use of gender pronouns in the description. For the list of investor names, please see Online Appendix Table A2.

[12]Given that Asian investors are the largest minority group in the US VC and angel landscape and contribute significantly to the US entrepreneurial community, this study 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 American investors or Hispanic investors, as these groups share similar last-name patterns with white Americans.

Evaluation Questions. To evaluate each investor 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 A4. Participating founders face the same questions in the same order in each investor profile they are presented with. Before launching this experiment, we sought feedback from industry practitioners, particularly startup founders, to ensure clarity in our evaluation questions and investor profiles.

The first mechanism-based question, Q_1, is a quality evaluation question that assesses an investor's potential to improve a startup's profitability. The second, Q_2, is an availability rating question that captures the matching channel. Participants are asked to evaluate the likelihood of each investor showing interest in their startups. The third, Q_5, is an informativeness question that tests whether each investor profile provides enough information for founders to make their evaluations. Results related to Q_5 provide crucial insights for our theoretical framework.

The first decision-based question, Q_3, is about fundraising. Founders indicate how much of their overall fundraising goal they intend to try to raise from each investor. Another crucial decision-based question, Q_4, concerns contact interest, gauging the likelihood that founders will initiate contact with each investor. The contact interest rating is important in an IRR experiment, as it is a pivotal metric for conducting distributional effect analysis, as demonstrated in Kessler et al. (2019). Moreover, research employing similar IRR experiments on the investor 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 investor profiles, each startup founder will receive the contact information of the 10 most-matched real VC or angel investors, recommended by our matching algorithm based on a large comprehensive global VC and angel 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. We further collect startup founders' *individual-level* demographic information and explore 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, and educational level as well as 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 researcher background. Hence, even if some participants have discriminatory beliefs, various factors may obscure evidence of discrimination and lead subjects to engage in overly pro-social behaviors. Below, we share three key lessons learned from practical experience regarding the effective detection of discrimination in this type of experiment.

Consent Form — On a consent form, researchers typically disclose their names and affiliations. During recruitment, we indeed observed increased traffic to the 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 that the researchers are interested in detecting discrimination.

Candidate Characteristics — Overloading candidate profiles with numerous characteristics might also make it harder to detect discrimination. Excessively detailed profiles often dilute participants' attention to candidates' gender and race, impeding discrimination detection.[13] Additionally, overly rich information also hinders the detection of belief-driven discrimination, which generally stems from limited candidate information. Thus, maintaining an appropriate number of candidate characteristics is vital for effective discrimination detection.

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, placing all such questions

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

after the formal profile evaluation section is crucial. Additionally, researchers may consider prohibiting subjects from altering their evaluation results after entering the background information section.

3 Results

In this section, we explore statistical discrimination among US startup founders during fundraising. All the main results remain robust when focusing on the evaluations of Crunchbase-listed founders recruited in the second wave. To provide crucial empirical support for our theoretical framework, we further examine the underlying mechanisms of discrimination and delve into its corresponding distributional effects.

3.1 Detection of Gender Discrimination

Table 2 tests how investors' gender and race influence founders' evaluations in the experiment. The dependent variable in Columns (1)–(4) is, respectively, the perceived investor quality (i.e., Q_1 quality 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 investor (i.e., Q_4 contact interest ratings). We regress each dependent variable on the gender and race dummies as well as other orthogonally randomized investor characteristics in the experiment. All the regressions include subject-fixed effects, which account for the possibility that different founders have different rating levels. Standard errors in parentheses are clustered within each founder.

Column (5) of Table 2 shows that gender discrimination against female investors exists among startup founders. However, we do not detect significant racial discrimination against Asian investors. On average, startup founders assign 3.46 p.p. lower contact interest ratings to female investors compared to similar male investors. 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 investors' 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" are insignificant across all columns, we do not detect any racial discrimination against Asian investors.

[Insert Table 2 here]

As documented by Camerer and Hogarth (1999), participants tend to exhibit more pro-social behaviors when they are being observed or when incentives are weak, largely due to social image concerns. Therefore, it is unlikely that the magnitude of the gender discrimination we detect in our study is overestimated. Additionally, since founders were instructed to assume that all the evaluated investors would be interested in their industries and stages, they are comparing similar male and female investors *within* the same industry. Thus, the observed gender discrimination cannot be attributed to founders' perceptions that female investors often do not work in their startups' industries or stages.

3.2 Statistical Discrimination and Informativeness of Profiles

Statistical Discrimination. Columns (1) and (2) of Table 2 further demonstrate that the gender discrimination we detect is primarily influenced by statistical discrimination, which involves belief-driven mechanisms such as concerns about female investors' quality and investment likelihood. On average, founders assign female investors 3.17 p.p. lower quality ratings and 3.20 p.p. lower availability ratings compared to similar male investors. These results indicate that founders perceive female investors to be less likely to enhance their profitability or show investment interest in their startups. In Section 5, we further discuss whether founders' beliefs are accurate or inaccurate.

Informativeness of Investor Profiles. An important empirical finding in Table 2 is that founders deem female investors' profiles to be less informative compared to similar male investors' profiles, as demonstrated in Column (3). On average, founders assign 5.25 p.p. lower informativeness ratings to female investors compared to similar male investors, which is statistically significant at the 1% level. This effect corresponds to a 7.8% decrease compared to the average informativeness rating level. Notably, this observation confirms a crucial prediction in our model and assumptions used in other discrimination theories, such as Morgan and Várdy (2009). That is, interpreting signals or ratings from the minority group is often more challenging for evaluators compared to those from the majority group.

3.3 Gender Homophily

Table 3 tests gender and racial homophily, examining whether the influence of investors' gender and race on founders' evaluations varies depending on the founder's gender and race.[14] "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.

The results in Table 3 reveal that male founders predominantly drive statistical gender discrimination against female investors. Based on Column (5), on average, male founders assign female investors contact interest ratings that are 4.84 percentage points lower than those assigned to similar male investors, with statistical significance at the 1% level. However, the coefficient for "Female Investor × Female Founder" is significantly positive and equal to 5.97 p.p., suggesting that female founders rate female investors more positively than male founders do. Additionally, the results in Columns (1) and (2) demonstrate that founders' aggregate-level negative perceptions of female investors 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 investors' value added and investment likelihood than male founders do.

In Online Appendix Section B, we further demonstrate that while implicit gender discrimination exists, it also primarily exists among male startup founders. Therefore, both evidence in Table 3 and results in Online Appendix Section B empirically support the existence of gender homophily. However, we find no evidence of a significant racial homophily phenomenon.

3.4 Glass Ceiling: Discrimination Against High-Quality Females

In this subsection, we provide empirical evidence supporting a "glass ceiling" distributional effect, where statistical discrimination disproportionately affects high-quality minority groups, particularly in the context of gender discrimination. Although this finding may seem counter-intuitive based on traditional statistical discrimination theories, our developed model can explain how this glass ceiling phenomenon might arise as an equilibrium outcome within

[14] 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 investors, white founders prefer white investors).

a two-sided matching framework.

Our first piece of evidence is provided by Table 4, which examines whether the effects of investors' gender and race differ among high- versus low-quality investors. To proxy for each investor's quality, we assume that investor quality is an unknown linear single index of other orthogonally randomized investor characteristics that are uncorrelated with investors' gender and race.[15] 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. Results are similar when using the total sum of other orthogonally randomized appealing investor characteristics as the quality proxy. By design, these investor characteristics are independent of investors' gender and race. Hence, the estimate is consistent, and we do not have omitted variable bias issues 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.

The results in Column (5) of Table 4 reveal that the degree of gender discrimination varies depending on investor quality. Specifically, the coefficient for "Female Investor $\times$ High-Quality Investor" is -6.24 p.p., which is statistically significant at the 5% level. This result suggests that startup founders assign 3.71 p.p. lower contact interest ratings to high-quality female investors compared to similar high-quality male investors. The magnitude of this gender discrimination is approximately 50.82% (calculated as 3.71 divided by 7.30) of the effect of investors' entrepreneurial experience. Results in Columns (1) and (2) similarly indicate that founders' negative perceptions of female investors' value added on profitability and investment likelihood mainly affect high-quality female investors. These observations support a glass ceiling distributional effect. However, the coefficient for "Female Investor" is 2.53 p.p. with statistical significance at the 10% level, suggesting a weak "glass basement" phenomenon: when evaluating low-quality investors, founders exhibit no gender discrimination against female investors and even slightly favor them.

To confirm the presence of this distributional effect, we further extend our analysis using the quantile regressions shown in Table 5. We assume that the quantile function of $Q4$ (i.e., contact interest ratings) for each investor profile j varies based on the investor's gender and race. All regressions control for startup founders' rating levels, measured by the "leave-one-

[15] These investor characteristics include "Top School," "Graduate Degree," "Senior Investor," "Angel Investor," "Large Fund," "Entrepreneurial Experience," "ESG Fund," and "Years of Investment Experience."

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. Results are similar when using Q_1 (i.e., quality rating) as the dependent variable in these regressions.

Specifically, in Column (10) of Table 5, the coefficient for "Female Investor" is -3.35 p.p., indicating that when investors' contact interest ratings are high (i.e., ranked within the top 5% among female investors), they receive 3.35 p.p. lower contact interest ratings compared to 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 investors possess equally appealing characteristics as their male counterparts, they are less likely to receive high Q_4 ratings. However, the coefficient for "Female Investor" is 8.17 p.p. in Column (1), which is positive and statistically significant at the 5% level. This finding suggests that when evaluating low-quality investors, founders slightly favor female investors.

Additionally, in Online Appendix Table B3, we find that founders mainly exhibit implicit gender discrimination when evaluating senior investors. However, this implicit gender discrimination is less pronounced when they evaluate junior investors. This outcome aligns with previous findings that high-quality female investors are more affected by founders' negative perceptions about women. Finally, as in previous analyses, we do not find significant discrimination against Asian investors.

3.5 Discussion of Other Sources of Discrimination

The focus of this paper is on how *statistical* discrimination may arise endogenously in a two-sided matching market, leading to distinctive features of participants' discriminatory behaviors in matching equilibrium and the persistent low participation rate of female investors. Hence, our experiment primarily identifies belief-driven discrimination. However, it is possible that taste-driven discrimination may also coexist, although it alone cannot explain the observed distributional effects. Identifying other potential sources of discrimination, while important, is outside the scope of our study and is left for future research.

4 Theoretical Framework

In this section, we develop a theoretical model of statistical discrimination to explain our stark experimental findings in the previous section, including the endogenous formation of founders' beliefs, the observed distributional effect, and the persistently low participation rate of women in the VC industry. Specifically, the model 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 drives discriminatory beliefs?

Our model considers a frictional search-and-matching market in which startup founders search for unknown types of investors.

Investors. There is a unit mass of investors in the market. Investors are indexed by three characteristics: *type*, *group*, and *rating*.

- *Type*: An investor's type represents *unobservable* payoff-relevant information about the investor. Type is denoted by $i \in \{H, L\}$ (high-quality and low-quality, respectively). The type of an investor is exogenous and stochastic: each type turns into the other type at rate $\delta > 0$. As a result, $Pr(i = H) = Pr(i = L) = \frac{1}{2}$.

- *Group*: An investor's group represents the *observable* payoff-irrelevant identity, such as her gender identity. Group is denoted by $\ell \in \{1, 2\}$. The group of an investor is exogenous and persistent.

- *Rating*: The rating of an investor is an *observable* signal about the investor's type. Rating is denoted by $j \in \{G, B\}$ (good and bad rating, respectively). The ratings are stochastic and endogenously determined by the matching process we introduce later. The rating is a novel mechanism we introduce to the canonical search-and-matching framework. While the type of investors is unobservable, the observable ratings provide crucial information that guides the market. Importantly, as will be clear later, the informativeness of the ratings is endogenously determined by the search-and-matching process, leading to the endogenous formation of possibly discriminatory beliefs upon observing the rating of an investor. In our application of the investor-founder market, the rating can be interpreted as the public profile of the investors.[16]

We denote the mass of investors with type i, rating j, and group ℓ by P_{ij}^{ℓ}, satisfying $\sum_{i,j,\ell} P_{ij}^{\ell} = 1$. Let $P^{\ell} := \sum_{i,j} P_{ij}^{\ell}$ denote the mass of investors of group ℓ. Each pair of observable investor characteristics (j, ℓ) indexes a *submarket* of investors.

Startup Founders. There is a total mass $Q > 0$ of startup founders in the market. Founders are indexed by exogenous and persistent *group* identity $\iota \in \{1, 2\}$. They actively search for investors based on the observable rating and group. We denote the measure of founders with group ι that search for investors in submarket (j, ℓ) by $Q_j^{\ell\iota}$, satisfying $\sum_{j,\ell,\iota} Q_j^{\ell\iota} = Q$. Let $Q^{\iota} := \sum_{j,\ell} Q_j^{\ell\iota}$ denote the mass of startup founders of group ι. Throughout the paper, we maintain the following assumption about the population of investors and founders:

Assumption 1 (Under-representation)**.** $P^1 = P^2 = \frac{1}{2}$, $Q^1 > Q^2$.

We assume that the investor groups are the same size, but group 1 founders outnumber group 2 founders. The equal investor group size is just a normalization, and the model prediction hinges on $\frac{Q^1}{P^1} > \frac{Q^2}{P^2}$, i.e., compared to type 1, type 2 is relatively more under-represented among founders.

Matching. We adopt the canonical search-and-matching framework to model an interaction between investors and founders. For each submarket (j, ℓ), let $\lambda_j^{\ell} := \frac{\sum_{\iota} Q_j^{\ell\iota}}{\sum_i P_{ij}^{\ell}}$ denote the ratio of founders to investors in the submarket. For each founder-to-investor ratio λ, we let $\psi(\lambda)$ denote investors' matching rate and $\phi(\lambda)$ denote founders' matching rate, i.e., in every unit of time, each investor gets matched with probability $\psi(\lambda)$ and each founder gets matched with probability $\phi(\lambda)$, respectively. 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

[16]In other applications of the model, the rating can be customer reviews of Uber drivers, the track record of athletes, etc.

function and, therefore, satisfies various natural and desirable properties.[17] Parameter k is the "output elasticity" of investors in the matching function, i.e., the relative efficiency of the investor population in generating matches. 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 $\phi''(\lambda) > 0$. Most of our results require only these standard properties of the matching function and, therefore, can easily be generalized beyond our parametric case.

When a match is successfully formed, utility is realized via investment and ratings are updated as follows.

- *Investment*: Once an investor and a startup founder meet, they transact instantaneously and go back to the market. The transaction yields surplus $v_H(v_L)$ if the investor's type is $H(L)$, where $v_H > v_L \geq 0$. After the transaction, the founder pays a surplus transfer p to the investor.

- *Ratings*: Following a successful match, with probability $\alpha \in (0, 1]$, a B-rated investor with type H receives a G rating, and a G-rated investor with type L receives a B rating. An investor with the correct rating always keeps the same rating after a transaction. With the remaining probability $1 - \alpha$, the investor's rating remains unchanged. Note that due to the changing environment (or changing type), a correct rating in the previous period may turn inaccurate in the next period. The stochasticity of ratings makes their informativeness dependent on the endogenous "popularity" of the identity of the investor: a more frequently matched group enjoys a more accurate rating.

The search-and-matching framework is illustrated by Figure 1, where blue and red represent the two groups. Darker (lighter) colors represent high- (low-) quality types, respectively. The "star" represents a good rating. The arrows represent the stochastic transition of investor types and ratings. We introduce an exogenous disruption to match formation into the framework. When we discuss the case with such a disruption, we impose Assumption 2.

Assumption 2 (Investor Homophily). *The founder's matching rate is* $[\phi(\lambda) - \kappa 1_{l\neq\iota}]^+$*, for* $\kappa \geq 0$.

[17] Given the measure of investors and startup founders being P and Q, $Q^k P^{1-k}$ matched pairs are generated per unit of time.

Assumption 2 states a friction that a successful match breaks at an exogenous rate of κ per startup founder (leading to no investment afterward) if the founder is from a different group than the investor. Assumption 2 is referred as "investor homophily" in this paper but should be interpreted more broadly. Essentially, this differential matching rate may stem from exogenous factors, such as an investor's homophily preferences or varying meeting frequencies due to network overlaps. For example, male investors more frequently encounter male founders at shared social activities, and female investors similarly meet female founders more frequently. This assumption aligns with the well-documented gender-homophily phenomenon among investors, as shown in Raina (2021) and Zhang (2020).

Belief and Search Decision. The key endogenous variables we track throughout the analysis are the *beliefs* of founders about an investor's unobservable true type. Note that the type transition rate is δ for both types, implying that there must be an equal mass of H- and L-type investors for each group in the stationary distribution. Hence, the prior belief of type H is $\frac{1}{2}$ for both groups of investors. Let $\mu_j^\ell \in [0, 1]$ denote the Bayesian posterior belief that investors from submarket (j, ℓ) are of type H. Then, Bayes' rule implies

$$\mu_j^\ell = \frac{P_{Hj}^\ell}{P_{Hj}^\ell + P_{Lj}^\ell}.$$

Evidently, if the two groups of agents are treated differently (i.e., $P_{Hj}^1 \neq P_{Hj}^2$), the inference a founder makes about an investor with a given rating depends nontrivially on the investor's group identity ℓ. Then, we can derive the group ι founders' expected utility from searching in market (j, ℓ) given the founder-to-investor ratio λ_j^ℓ and belief μ_j^ℓ:

$$\left[\phi(\lambda_j^\ell) - \kappa 1_{\ell \neq \iota}\right]^+ (\mu_j^\ell v_H + (1 - \mu_j^\ell) v_L - p).$$

Each founder will search in the market that provides the highest expected utility. Note that the founders in our model are fully rational and Bayesian, i.e., their behaviors are "unbiased" based on their available data. Nevertheless, we will show that founders may exhibit statistical discrimination due to the endogenously asymmetric data quality about the two investor groups.

Solution Concept. We consider a steady state of the economy in terms of the distribution of types, ratings, and group identity $\{P^{\ell}_{ij}, Q^{\ell\iota}_{j}\}^{\ell,\iota=1,2}_{i=H,L,j=G,B}$. We say the tuple constitutes an equilibrium if it satisfies the following condition:

- **Stationarity**:

$$\begin{aligned} P^{\ell}_{HG}\delta =& P^{\ell}_{LG}\delta + P^{\ell}_{HB}(\lambda^{\ell}_{B})^{k}\alpha, \\ P^{\ell}_{LG}(\delta + (\lambda^{\ell}_{G})^{k}\alpha) =& P^{\ell}_{HG}\delta, \\ P^{\ell}_{HB}(\delta + (\lambda^{\ell}_{B})^{k}\alpha) =& P^{\ell}_{LB}\delta, \\ P^{\ell}_{LB}\delta =& P^{\ell}_{HB}\delta + P^{\ell}_{LG}(\lambda^{\ell}_{G})^{k}\alpha, \end{aligned} \tag{1}$$

  where $\lambda^{\ell}_{j} = \frac{\sum_{\iota} Q^{\ell\iota}_{j}}{\sum_{i} P^{\ell}_{ij}}$. Intuitively, stationarity represents a stationary equilibrium setting where the size of each submarket in Figure 1 is stable.

- **Optimality**:

$$\left[\left(\lambda^{\ell}_{j}\right)^{k-1} - \kappa 1_{\ell\neq\iota}\right]^{+}\left(\mu^{\ell}_{j}v_{H} + (1-\mu^{\ell}_{j})v_{L} - p\right),$$

  where $\mu^{\ell}_{j} = \frac{P^{\ell}_{Hj}}{P^{\ell}_{Hj}+P^{\ell}_{Lj}}$ is the same among all j, ℓ for each ι, when $Q^{\ell\iota}_{j} > 0$.

4.1 Equilibrium Without Investor Homophily

If investor homophily (i.e., Assumption 2) does not exist, a founder's group becomes irrelevant for payoffs and $\kappa = 0$. Hence, the model reduces to the one-sided model studied in Che et al. (2019). As is noted in Che et al. (2019), under no homophily, since the founder's group is irrelevant, there always exists a color-blind equilibrium where group 1 and group 2 are completely symmetric, i.e., $\mu^1_j = \mu^2_j$ and $\lambda^1_j = \lambda^2_j$. Formally, we call such a steady-state equilibrium a *non-discriminatory* equilibrium. A main result of Che et al. (2019) is the complete characterization of when such an equilibrium is unique.

Proposition 1. *If $(v_H + v_L)/2 \leq p$, then it is the unique non-discriminatory equilibrium outcome that founders do not search for investors, regardless of their ratings (i.e., $\lambda_G = \lambda_B = 0$). Conversely, if $(v_H + v_L)/2 > p$, then there always exists one non-discriminatory* *equilibrium in which $\lambda_G > \lambda_B > 0$. Such an equilibrium is unique if and only if*

$$k \leq \frac{1 + \sqrt{1 - \frac{v_H - v_L}{2(v_H - p)}}}{2} \ \underline{or}\ \frac{\alpha}{\delta} \in (\underline{\beta}, \bar{\beta}),$$

for some $\underline{\beta} < \bar{\beta}$.

In the statement of Proposition 1, we omit the superscript ℓ from λ_j^ℓ as the group identity is irrelevant. Recall that k is the output elasticity of founders in the matching function. α (δ) is the rate at which the rating corrects (deteriorates); hence, $\frac{\alpha}{\delta}$ represents the quality of the rating technology: the higher $\frac{\alpha}{\delta}$ is, the more likely the ratings are correct (conditional on a successful match). Proposition 1 states that without homophily, the unique equilibrium is non-discriminatory if investors are relatively more important in generating successful matches or the rating technology is of an intermediate quality.

The implication of Proposition 1 is that under low k or moderate $\frac{\alpha}{\delta}$, the market self-corrects all biases of the founders through information aggregation. For any starting (possibly asymmetric) composition of the market, over time the ratings become sufficiently informative about the investor's true type. As a result, the market correctly anticipates that investors from the two groups are identical. While an interesting question is why even better rating quality destabilizes the market and creates discrimination, in the current paper, we focus on the case that equilibrium is uniquely non-discriminatory without homophily.[18]

4.2 Equilibrium with Investor Homophily

In this section, we focus on the case where $(v_H + v_L)/2 > p$ and $k \leq \frac{1+\sqrt{1-\frac{v_H - v_L}{2(v_H - p)}}}{2}$. Per Proposition 1, the unique equilibrium is non-discriminatory without homophily. We return to the case $\kappa > 0$, i.e., investor homophily exists and Assumption 2 holds.

Belief Formation. The stationarity equations (1) imply that

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

[18]Detailed discussion of the extreme rating quality case in a one-sided market is provided in Che et al. (2019).

Equation (2) delineates the endogenous formation of beliefs in the market. Importantly, the market for G-rated investors and that for B-rated investors operate asymmetrically. The Bayesian posterior belief in a G-rated market increases in λ, the founder-to-investor ratio. Meanwhile, the Bayesian posterior belief in a B-rated market decreases in λ. This divergence is intuitive as a higher founder-to-investor ratio means more frequent transactions for investors in the submarket, leading to Blackwell *more informative* ratings.[19] However, more informative ratings mean G-ratings are perceived as even better whereas B-ratings are perceived to be even worse. As a result of Equation (2), group ι founders' expected payoffs from submarket (j, ℓ) are determined as functions of λ_j^ℓ:

$$u_j^{\ell\iota}(\lambda_j^\ell) := [\phi(\lambda_j^\ell) - \kappa 1_{\ell \neq \iota}]^+ (\mu_j(\lambda_j^\ell) v_H + (1 - \mu_j(\lambda_j^\ell)) v_L - p).$$

Key Observation. Consider the within-group expected payoff from searching for rating j. Note that per the expressions of $u_j^{\ell\iota}$, once κ is dropped, the expected payoff is solely defined by the founder-to-investor ratio in the submarket:

$$u_j(\lambda_j) := \phi(\lambda_j)(\mu_j(\lambda_j) v_H + (1 - \mu_j(\lambda_j)) v_L - p).$$

Both $u_G(\cdot)$ and $u_B(\cdot)$ are strictly decreasing in λ. Since $\kappa > 0$, it implies that if $\mu_G^\ell > \mu_B^\ell$,

$$\begin{aligned}
\left[u_G^{11}(\lambda_G^1) - u_B^{11}(\lambda_B^1)\right] - \left[u_G^{12}(\lambda_G^1) - u_B^{12}(\lambda_B^1)\right] &= \kappa(\mu_G^1 - \mu_B^1)(v_H - v_L) > 0; \\
\left[u_G^{22}(\lambda_G^2) - u_B^{22}(\lambda_B^2)\right] - \left[u_G^{21}(\lambda_G^2) - u_B^{21}(\lambda_B^2)\right] &= \kappa(\mu_G^2 - \mu_B^2)(v_H - v_L) > 0.
\end{aligned}$$

Put into words, for any given investor group ℓ, only one founder group may be indifferent when searching for both G- and B-rated investors. Moreover, if a founder searches for investors of a *different* group identity, the founder always favors those with B ratings. Based on this payoff order, we say an equilibrium is *regular* if either group of founders enters the market following the order of

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

[19] Throughout the analysis, we adopt the Blackwell order (Blackwell, 1951) to compare rating informativeness. Note that the posteriors μ_G and μ_B get more dispersed as λ increases, which is equivalent to the ratings getting Blackwell more informative (Green and Stokey, 2022).

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

Theorem 1. *Three types of regular equilibria exist under homophily, characterized by the investor types being actively searched for by each group of founders (i.e., Cases 1, 2, and 3):*

1. *Submarkets:* $\overbrace{G1 - - - - B1 - -}^{\textit{Group 1 founders search for}}\underbrace{- - B2 - - - - G2}_{\textit{Group 2 founders search for}}.$

2. *Submarkets:* $\mathrlap{\overbrace{}^{\textit{Group 1 founders search for}}}G1 - - - - B1 - -\underbrace{- - B2 - - - - G2}_{\textit{Group 2 founders search for}}.$

3. *Submarkets:* $\overbrace{G1 - - - - B1 - - - - B2 - - \underbrace{- - G2}_{\textit{Group 2 founders search for}}}^{\textit{Group 1 founders search for}}.$

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

Proof. See Online Appendix appendix C. □

Theorem 1 states that there are three types of regular equilibria. The first type is symmetric, where founders only search within their own group. In the second type of equilibrium, group 1 founders search for both their own group and B-rated group 2 investors. Meanwhile, group 2 founders only search within group. In the third type of equilibrium, group 1 founders search for all investors, while group 2 founders only search for G-rated group 2 investors. Moreover, Theorem 1 implies that the equilibrium belief of investor quality is higher for group 1 investors among those with good ratings and lower for group 1 investors among those with bad ratings. This belief immediately implies that $\lambda_j^2 < \lambda_j^1$.

4.3 Theoretical Explanations

When Does Discrimination Arise? Our results (Proposition 1 and Theorem 1) suggest that when investors are relatively more important in generating matches ($k \leq \frac{1+\sqrt{1-\frac{v_H - v_L}{2(v_H - p)}}}{2}$), discrimination arises if and only if investor homophily exists.

Because our model characterizes 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 founders. Also, the literature provides empirical evidence that investors exhibit gender-based homophily (Raina, 2021; Zhang, 2020).

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

1. *Men are never discriminated against by men.* In all three types of equilibria, men are always searched for by men independent of their quality ratings., which means that men do not discriminate against men.

2. *Women are discriminated against when they are significantly under-represented.* In Case 1 and Case 2, women are discriminated against by men because men do not search for all the women. In Case 3, women do not search for all the women. Only when Q^1 is roughly equal to Q^2 and the male and the female investor market can absorb each gender's founders is there no discrimination. Of course, empirical evidence suggests that this scenario usually does not exist in practice.

3. *Men discriminate against highly rated women.* When women are sufficiently under-represented among founders, we find that the direction of discrimination follows a consistent pattern. Given that $\mu_G^2 < \mu_G^1$ in all cases, women in a G-rated market are always discriminated against.

   For example, in Case 2, when there are enough male founders searching on the market, female founders actively search for female investors of all rating types. However, male founders only reach out to low-rated female investors. Consequently, highly rated female investors are under-sampled. The key intuition for this phenomenon can be seen when comparing the cross-group and within-group expected search payoffs. When $\ell \neq \iota$,

$$u_j(\lambda) - u_j^{\ell\iota}(\lambda) = \kappa \cdot (\mu_j(\lambda)v_H + (1-\mu_j(\lambda))v_L - p). \tag{3}$$

The payoff gap is κ scaled by the potential gain from matching. Therefore, the failure to match caused by homophily is more severe in a market with a lower matching rate ϕ and higher average quality μ. Since G-rated women have higher average quality than B-rated women, homophily hurts G-rated females more from the male founders' perspective.

Theorem 1 also predicts the equilibrium Bayesian posterior belief of founders' quality in regular equilibria. Remember that in all cases $\mu_G^2 < \mu_G^1$ and $\mu_B^2 > \mu_B^1$. Thus, female founders with good ratings are always perceived to be inferior to male founders with the same rating—a glass ceiling effect. Meanwhile, female founders with bad ratings are always perceived to be superior to male founders with the same rating—a glass basement effect. These two effects combined resemble the anecdotal evidence that women are often favored in entry-level jobs but find it significantly harder to climb the career ladder.

Since belief is monotonic in the founder-to-investor ratio λ, this immediately implies that λ is lower for both highly-rated female investors and poorly-rated female investors relatively to male investors with similar ratings. Note that the matching probability of investors increases in λ, which predicts a lower female participation rate as investors in equilibrium, i.e., a smaller proportion of women being matched among all female investors for each rating comparing to similar male investors.[20]

What Drives Discriminatory Beliefs? Note that in our model, different groups have identical distributions of quality and identical rating technologies, enabling us to endogenize the "statistics" that lead to statistical discrimination. The key mechanism that drives the theoretical results is the endogenous formation of the founders' beliefs, which can be

[20]A lower rating-specific participation rate also implies a lower overall participation rate for female investors.

illustrated by the founder's payoff function (4):

$$u_j^{\ell\iota}(\lambda_j^\ell) = \underbrace{[\phi(\lambda_j^\ell) - \kappa 1_{\ell\neq\iota}]^+}_{\substack{\text{(Adjusted)}\\ \text{Matching rate}}}(\underbrace{\mu_j^\ell(\lambda_j^\ell)}_{\text{Belief}}(v_H - v_L) + v_L - p). \tag{4}$$

As we have discussed, following Equation (2), the belief μ_j^ℓ depends asymmetrically on the "congestion" parameter λ_j^ℓ for the good ratings versus the bad ratings: the more popular investor group (with higher λ) gets sampled more often; hence, the rating informativeness of the popular group is higher (i.e., the signal involves less noise), leading to higher posterior beliefs from a good rating but lower posterior beliefs from a bad rating. This result provides a foundation for the key asymmetric signal quality assumption made in Phelpsian models of statistical discrimination.

Notably, the beliefs convert to the founders' 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 investors with different ratings: since male founders find it more costly to search for lower-rated female investors than similar male investors, the required return has to be higher. This means, from the analysis in the previous paragraph, that female investors should necessarily be less popular in order to make low ratings more attractive. However, this under-sampling of female investors hurts the highly rated ones. The ratings received by female investors are endogenously noisier compared to those received by male investors; hence, a high rating received by female investors leads to lower perceived quality than male investors.

5 Discussion

Policy Implications. The theoretical framework in section 4 has several important policy implications for mitigating statistical discrimination when gender homophily is present.

- *Color-blind search*: The most straightforward and drastic way to tackle statistical discrimination in a two-sided matching market is to eliminate the identity-dependent search behavior among startup founders. For example, by sanitizing investors' public profiles (such as CVs) and removing gender-identifiable information, startup founders are compelled to search all groups of investors uniformly, leading to a stable, non-discriminatory equilibrium.

- *Affirmative action*: Affirmative action can be an effective tool to support female investors, who are often disadvantaged in our framework. However, its effect may vary depending on the exact form of the policy. For example, affirmative action can be quota-based (requiring more women to be hired) or benefit-based (providing additional transaction benefits for women). Both approaches can improve female investors' *overall* standing but may exaggerate the glass ceiling effect, where highly rated women still face discrimination. The *rating gap* that drives discrimination against highly rated women would remain, as eq. (3) differs between G ratings and B ratings. Effective affirmative action should be opportunity-based, which increases the matching probability with female investors so that the homophily effect κ can be canceled out. Importantly, such a policy would disproportionately benefit highly rated women, helping to break the glass ceiling.

- *Better rating technology*: Intriguingly, as implied by Proposition 1, improving the informativeness of the rating technology does not always debias the discriminatory beliefs. In fact, it can sometimes backfire. When $\frac{\alpha}{\delta}$ is sufficiently high, a stable equilibrium can remain discriminatory even without homophily. Such a scenario occurs because a highly accurate rating technology can strengthen the feedback loop: investors with poor but accurate ratings can receive no further opportunities to work with startup founders and improve their ratings.

- *Objective evaluation criteria*: As shown in the model, evaluators' negative beliefs about minority groups can arise endogenously in a matching market. To address this statistical discrimination, it is crucial to adopt objective evaluation measures that minimize reliance on subjective beliefs or expectations.

Experimental Setting. In our 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 investors and subsequently impacting investor financial performance. If relevant data or field experiment opportunities are available, future research could also explore other scenarios where startup founders receive multiple offers from different investors.

Result Applicability. While this study focuses on the entrepreneurial financing market, our empirical and theoretical insights extend to the broader context of women's underrepresentation in other two-sided matching scenarios. For instance, research shows that women hold small percentages of board positions and 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, information-based discrimination might play an important role.

Accurate Beliefs or Not? According to the model, even if the minority and majority groups have the same distribution of unobservable quality or ability, evaluators can still form different beliefs about their productivity. Therefore, these different beliefs are inherently *inaccurate*. However, they might appear accurate based on ex-post observations of minority groups' performance. For example, Gompers et al. (2014) document that female venture capitalists are associated with worse financial performance compared to their male counterparts, which might make founders' discriminatory beliefs seem justified.

However, the worse performance of women documented in the literature could be self-fulfilling as female investors' financial performance is influenced by both their intrinsic ability and how founders treat them. If founders avoid collaborating with female investors due to discriminatory beliefs, female investors will struggle to attract high-quality deals from men-led startups, leading to worse portfolio performance. Thus, the perceived accuracy of these beliefs can be misleading, as it fails to account for the biased treatment that female investors receive.

6 Conclusion

This paper delves into statistical discrimination within a two-sided matching market, providing insights into its distinct features, emergence, and impact on participants. We primarily focus on statistical 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 founders' gender discrimination against female investors. Startup founders are invited to evaluate multiple randomly generated investor profiles in order to receive personalized investor recommendations based on their revealed collaboration preferences.

Our experiment shows that statistical discrimination against female investors exists among US startup founders. Founders often perceive female investors as less helpful in enhancing startup profitability and less likely to invest in their startups compared to similar male investors. Notably, founders also view female investor profiles as less informative, consistent with information-based discrimination theories. Additionally, we find that such statistical gender discrimination is primarily driven by male founders and disproportionately affects high-quality female investors, leading to a glass ceiling distributional effect. However, we do not find any racial discrimination against Asian investors in our experiment.

To explain the experimental findings and the low participation rate of women in the entrepreneurial financing market, 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 group representation are sufficient to generate statistical discrimination, leading to an equilibrium where women, as the underrepresented group, experience lower matching rates than men. The model also explains why statistical discrimination primarily affects high-quality female investors in the two-sided matching equilibrium.

Researchers can replicate our experiments across different countries and timeframes. In addition to examining the presence and features of discrimination in other two-sided matching markets, researchers can build on our study by developing more sophisticated experimental systems to explore equilibrium outcomes when discrimination exists among multiple market players. 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 investor profile evaluations. Among these subjects, 45 founders participated in the Wave 1 experiment, and 96 participated in the Wave 2 experiment. Panel A reports founder-level background information. Panel B reports 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 were collected only during the Wave 2 experiment. Founders can choose multiple sectors and only one stage option that best fits 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 Experience	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 and Wave 2 experiments. 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 Column (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. "Top School," "Graduate Degree," "Senior Investor," "Angel Investor," "Larger Fund," "Entrepreneurial Experience," and "ESG Fund" are all indicator variables that are equal to one for startup founders who graduated from US top schools (defined in Online Appendix Table A5), hold graduate degrees, hold senior positions (refer to Table A3), are angel investors, have a larger amount of AUM and dry powder (defined in Online Appendix Table A7), possess entrepreneurial experience, and care about positive environmental, social, and governance (ESG) impact. "Years of Investment Experience" 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 × Female Founder	5.24**	3.63*	5.89**	1.70	5.97**
	(2.26)	(2.00)	(2.12)	(1.56)	(2.27)
Asian Investor	-1.57*	-1.37*	0.11	-0.42	-0.86
	(0.94)	(0.71)	(0.71)	(0.61)	(0.86)
Asian Investor × Asian Founder	2.28	3.22*	1.13	1.91	3.29
	(2.47)	(1.93)	(1.33)	(1.21)	(2.11)
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 impacts of investors' genders and races on founders' evaluations also vary depending on startup founders' gender and race. The sample includes 2,820 profile evaluations from the Wave 1 and Wave 2 experiments. 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 Column (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 and low-quality investor profiles. The sample includes 2,820 profile evaluations from the Wave 1 and Wave 2 experiments. 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 Column (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 "Top School," "Graduate Degree," "Senior Investor," "Angel Investor," "Larger Fund," "Entrepreneurial Experience," "ESG Fund," and "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 5: Quantile-Regression Estimates for Startup Founders' Discrimination (Distributional Effect)

	5th [1]	15th [2]	25th [3]	35th [4]	45th [5]	55th [6]	65th [7]	75th [8]	85th [9]	95th [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. $*p < 0.10, **p < 0.05, ***p < 0.01$

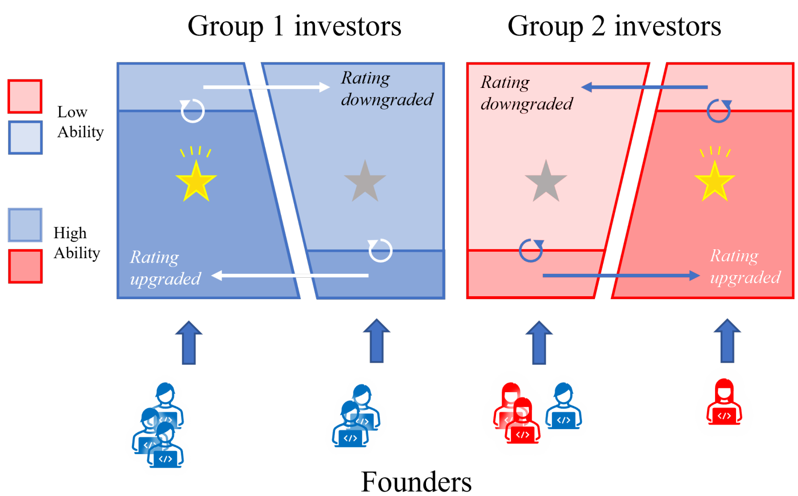


Figure 1: Ratings-guided Matching Market

Online Appendix

A Experimental Design and Implementation

A.1 Recruitment and Sample Selection

The recruitment process was implemented in two waves. Wave 1 ran from February to March 2021 via Qualtrics, a third-party recruitment company that enables outreach to US startup founders and small business owners. To recruit startup founders in Wave 1, this company sent recruitment emails with the survey link. After completing the 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 venture capital (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.[21] Similar to Kessler et al. (2019), the consent form emphasizes the matching purpose of our "investor–startup" matching tool without mentioning the research purpose of testing discrimination.[22]

Participants in Wave 1 receive monetary compensation, which 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 to mitigate the impact of noisy participants in the experiment. In total, 45 valid founders' evaluations are collected through Wave 1, and the response rate of Wave 1 is about 6.5%.

a. Use attention check questions. We insert one attention check question and several other

[21] 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.

[22] 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.

background questions requiring participants to manually enter the answer. If participants fail the attention check question, the Qualtrics system will terminate their evaluation and inform them that they are unqualified for this study. If participants type in irrelevant answers, their responses are also removed from our formal data analysis.[23]

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 have almost no variations for Q_1 (i.e., profitability evaluation) or Q_4 (i.e., likelihood of contacting the investor), we 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 receiving investment), 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.[24]

If participants' evaluation results have almost no variation 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 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 enter their industry background, amount of funding needed, or general comments about the study, any answers containing gibberish lead to removal of subjects' evaluations.

[23]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.

[24]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.

e. Other subsidiary criteria. In addition to the criteria mentioned above, we also take the following subsidiary criteria into consideration when identifying noisy participants: (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; and (iv) the list of low-quality responses identified by the Qualtrics team based on their designed "data scrub" algorithms.

Note that these methods cannot fully eliminate all noise, which biases our discovered results towards null results. However, these noise reduction techniques generally work well in improving experimental power and detecting invalid responses in practice.

To increase the sample size of the experiment, we conducted a second wave of recruitment between January 2024 and March 2024 after collecting contact information for startups listed on Crunchbase. Unlike in Wave 1, we sent recruitment emails directly to these startups (see Figure A1) without providing any monetary compensation. While many emails listed on Crunchbase are 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 Wave 2.[25]

A.2 Profile Creation and Investor Characteristics Randomization

We make the following efforts to improve the realism of the generated investor profiles. First, we try to mimic the real-world distribution of most displayed characteristics . Specifically, we use investors' information collected by Pitchbook to generate our randomization parameters. Second, the wording used to describe investors' work experiences and their funds' investment philosophies is extracted from real-world investors' experiences and funds' descriptions posted online. Lastly, our profile is essentially a combination of investors' publicly available information, which follows the Crunchbase format. 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

[25] 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 for the whole experiment (both Waves 1 and 2) is roughly 5%.

profiles tries to mimic these platforms rather than their resumes, displaying key points of investors' characteristics.[26]

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 assets under management (AUM) and dry powder. We do not include important investor characteristics that 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 remaining 30% of profiles to angel investors. Among the 70% that are institutional investor 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 are randomly assigned to senior positions with titles like "Partner," "Investment Director," "Co-founding Partner," etc.

Entrepreneurial Experience. Prior research shows that investors' entrepreneurial experience is done of the most important human capital characteristics of investors (Dimov and Shepherd, 2005; Zarutskie, 2010). This information is also generally available on investors' LinkedIn profiles or their biographies posted on personal websites. To increase the realism of hypothetical investors' experience, we extract real investors' entrepreneurial experience posted on Pitchbook, and remove relative information indicating the investor's gender, race, or interested industries and stages. A detailed description of the entrepreneurial experiences we use is provided in Online Appendix Table A4. As judged by Chatgpt 4.0, the provided investor description is gender neutral.[27]

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

[27] We provide the following task for Chatgpt 4.0 to judge whether the investor description is gender neutral. "Scoring Guidance for Analyzing Gender Neutrality in Writing:

Score 0: Indicates that the writing style is gender-neutral, showing no inclination toward male or female styles.

Scores from -10 to 0: These scores indicate a male writing style, with -10 being strongly male. The closer

Educational Background. Educational background is another important human capital characteristic. We independently randomize both investors' degrees (bachelor degree vs. graduate degree) and graduated schools (top university vs, common university).[28] All the selected schools have been verified to have alumni who are working in the US VC industry or working as angels based on Google search. A detailed school list is provided in the Online Appendix Table A5.

Years of Experience and Total Number of Deals. Investors with more work experience are also 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 the total number of involved deals to indicate their work 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 in which 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 benefits. However, identifying impact funds and accurately estimating their distribution is still difficult. Different data sources and classification methods often provide different results. Based on 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

the score is to -10, the more the style leans toward males.

Scores from 0 to +10: These scores suggest a female writing style, with +10 being strongly female. The closer the score is to +10, the more the style leans toward females.

Context: The sentences you will score are descriptions of early-stage investors. Keep in mind that both male and female investors can have experiences such as entrepreneurial endeavors or working in venture capital. This means both genders might share similar attributes and roles traditionally seen in investor profiles.

Task: Based on the scale provided, please assign a score to each sentence reflecting its gender-specific writing style, considering the shared capabilities and roles of both genders in the venture capital industry."

[28]Graduate degrees include MBA, JD, master's, and PhD. Bachelor's degrees include BA and BS. Top universities include Ivy League colleges, California Institute of Technology, Duke University, MIT, Northwestern University, Stanford University, University of California Berkeley, and University of Chicago. Common universities are defined as other universities that also foster venture capitalists or angel investors but are not in our list of top universities.

randomly assign half of the hypothetical investors into impact funds and the other half into profit-driven funds, which helps to maximize the experimental power.

Fund Size. We use AUM (assets under management) and dry powder to indicate the size of the VC firm or angel group that each investor works for.[29] The Pitchbook platform and other standard databases contain this information, and it is summarized in the annual National Venture Capital Association Yearbook. The distribution used in the randomization process mimics the fund size distribution of early-stage VC or angel firms recorded in the Pitchbook database.

Investor Matching Algorithm. Following Kessler et al. (2019), the machine learning–based matching algorithm uses ridge regressions to provide each founder with the contact information (e.g., email, telephone number) and other publicly available details (including job title, company, etc.) of the matched investors. To ensure the quality of the recommendations, we manually review the recommended investors, addressing any issues that the algorithm may overlook (e.g., whether the investor has previously invested in competitors of the startup). In the main experiment, participants received their recommendation lists within two months.[30] Similar to Kessler et al. (2019), the algorithm does not use demographic information about gender and race to avoid gender discrimination in the recommendation process.

Specifically, we first selected a subset of investors for each participant whose preferred industry and stage match the participant's background. We then ran individual ridge regressions for the participants' responses to each of the five evaluation questions onto the corresponding investor characteristics (i.e., matching variables). This step provided us with five sets of slope coefficients for each participant. We then plugged in the estimates to form out-of-sample forecasts for each participant using profiles of the real investors who are in the selected subset in the first step. Then, for each participant, We obtained five predicted scores corresponding to the five questions in the experiment for each real investor in the subset.

[29] "Dry powder" refers to cash reserves kept on hand by a VC firm or individual angel 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.

[30] In Wave 1, participating founders received investor lists via a shared Dropbox folder whose link was provided at the end of the experiment. To protect confidentiality, each recommendation list is encrypted with a unique password that is automatically generated by the Qualtrics system, with access granted only to the corresponding participant. In Wave 2, we sent each recommendation list to participants' email addresses.

Aggregating the scores by taking simple averages, we recommended the top 10 investors with the highest scores to the participant.

Algorithm 1: Matching Algorithm

for *each participant* **do**
  Find the subset of real investors that match industry and stage;
  for *each evaluation question* **do**
    Evaluation question $\xrightarrow{\text{ridge}}$ matching variables. ▷ (Penalty coefficient obtained by pooled cross-validation);
    Compute fitted value using the matching variables of the real investors in the subset.
  end
  Aggregate the 5 scores by simple average and obtain the top 10 investor profiles.
end

We adopted ridge regression because each participant only evaluated 20 profiles, and the number of matching variable is relatively large (8) in comparison. We followed Kessler et al. (2019) in pooling all the participants together and using cross-validation to find the optimal penalty coefficient for each question. Specifically, for each question, we randomly selected two-thirds of the pooled data and ran five-fold cross-validation[31] to obtain the best penalty coefficient for this question and this subset of data. We repeated this process 1,000 times, took the average of the 1,000 best penalty coefficients, and treated it as the optimal penalty for this question. Algorithm 1 summarizes these steps.

[31] k-fold cross-validation refers to the following procedure. Begin by randomly dividing the data into k groups. For each group, treat it as the test data set and use the remaining $(k-1)$ groups to fit the model for all candidate penalty coefficients. Then form out-of-sample predictions using the test data set and obtain the mean squared error (MSE). Repeat this procedure for all the groups, and take the average of the MSE for each candidate penalty coefficient. The best penalty coefficient is the one yielding the smallest average MSE.

Table A1: Randomization of Investor Profile Components

Profile Component	Randomization Description	Analysis Variable
Investor's Individual-level Characteristics		
First and Last Names	Randomly drawn from a list of 50 names with randomly assigned races and genders. For detailed names, please see Online Appendix Table A2. Race and gender are randomly drawn, with 40% Asian and 60% White, and 40% Female and 60% Male.	White Female (24%), Asian Female (16%), White Male (36%), Asian Male (24%)
Position/Titles	Randomly drawn with 35% VC Junior, 35% VC Senior, and 30% Angel Investor. Within each category, we uniformly draw a detailed position according to Online Appendix Table A3.	Junior VC (35%), Senior VC (35%), Angel Investors (30%)
Entrepreneurial Experience	Randomly 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	Randomly drawn with 50% bachelor's degree (BA/BS) and 50% graduate degrees (JD/MBA/Master/PhD). The detailed list of degrees is in Online Appendix Table A5.	Graduate Degree (10/20)
College	Randomly drawn with 50% top universities and 50% common universities. For a detailed list of universities, please see Online Appendix Table A5.	Top University (10/20)
Investment Experience		
Years of Investment Experience	Within each investor's type and seniority, years of investment experience is randomized based on Online Appendix Table A6.	Years of Investment Experience
Investor's Fund-level Characteristics		
Fund Size	Within each investor type (i.e., VC or angel), the fund size measured by AUM and dry powder is randomly drawn based on the distribution shown in Online Appendix Table A7. To facilitate entrepreneurs' understanding of the relative size of each fund, we add one of the following descriptions in the profile: "relatively large VC fund," "relatively small VC fund," "relatively large angel group," or "relatively small angel group."	Large Fund (10/20)
Investment Philosophy	Randomly drawn with 50% profit-driven funds and 50% impact funds. No extra description is used to elaborate the meaning of impact funds and profit-driven funds.	Impact Fund (10/20)

Notes. This table provides details about the randomization of components in an investor profile. 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 as 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

Asian Female	White Female	Asian Male	White Male
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 investor 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/herself earlier on in his/her career, cofounding 2 successful startups. Currently, he/she 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/she 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/she later co-founded his/her own startup and became an early-stage investor.
4. When (Investor Name) was a student at college, he/she co-founded a startup during him/her undergraduate years. he/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/she was starting to ruminate on the idea of founding a company and co-founded a startup with his/her classmate after graduation.
7. Prior to joining the current position, (Investor Name) co-founded and sold a startup with utilizing his/her strategic, commercial and leadership skills.
8. An entrepreneur at heart, during his/her undergraduate years, (Investor Name) co-founded a startup and raised VC money. Later he/she decided to become an investor, helping more startups to grow.
9. (Investor Name) launched a startup project with his/her classmates at college before joining the current position. After selling his/her company, he/she 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/she 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/she was also a startup founder.
14. Previously, (Investor Name) founded a startup and a studio. Prior to that, he/she 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/she 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/she 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/she is helping other startups develop innovative products and attract more investors.
20. (Investor Name) has diversified experience in various industries. he/she 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/she 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/her investment experience spans a wide range of industries.
3. (Investor Name) performed in various executive roles and began him/her career as a product development engineer. he/she has experience in operations, budgeting, and strategic planning.
4. Previously, (Investor Name) worked in a consulting company and started his/her career in a global investment bank. his/her 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/she moved to a venture capital firm, focusing on early-stage startup investment.
8. (Investor Name) started his/her 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/her 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/her 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/she 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. he/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/she 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/she joined the job, identifying additional opportunities for financial vehicles to further expand the investment.
17. (Investor Name) started his/her career as an investment analyst in a leading private equity investment firm. he/she held various operations and business development roles for the portfolio companies.
18. (Investor Name) began his/her 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/she 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)

Undergraduate Programs(BA/BS)	Graduate Programs
Panel A. Top Schools	
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
	PhD, Stanford University
University of Chicago	MBA, University of Chicago (Booth)
Panel B. Common Schools	
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	PhD, University of Nebraska
CUNY-Hunter College	JD, 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: Uniformly distributed on the set of integers from 12 to 30	35%
Junior Position	Years of experience: Uniformly distributed on the set of integers from 1 to 6	35%
Angel Investors	Years of experience: Low: Uniformly distributed on the set of integers from 1 to 6. High: Uniformly distributed on the set of integers from 12 to 30	30%

Notes. This table presents details about 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; Uniformly drawn from $[20, 50]$ to second decimal place	50%
Small Fund	Description: Relatively small angel fund; Uniformly drawn from $[1, 10]$ to second decimal place	50%

Notes. To introduce more variation within larger and smaller funds, we also randomize the assets 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 US investors' 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.

[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]

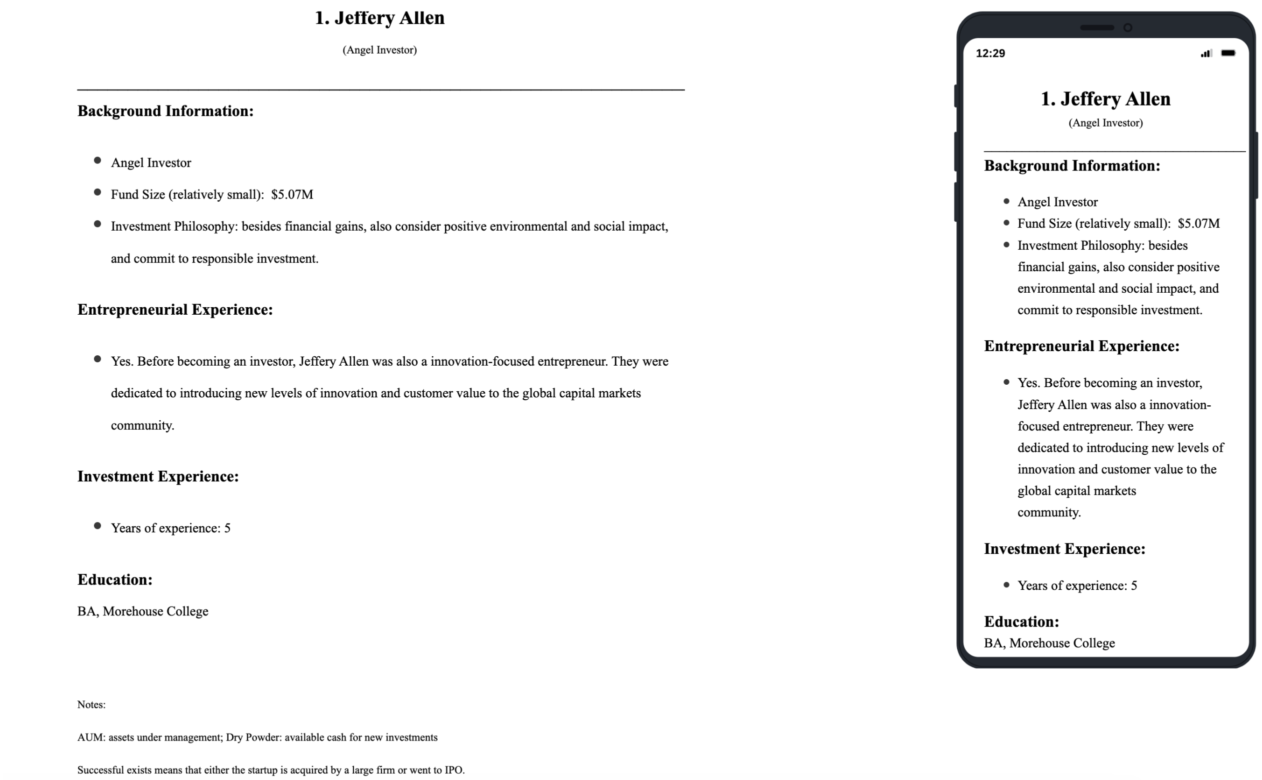
We greatly appreciate your time and look forward to your valuable contribution to our study.

Sincerely,
[redacted]

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

Figure A1: Recruitment Email

Figure A2: 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.

12:29
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Investment Experience:
Years of experience: 5
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Figure A3: Sample Investor Profile

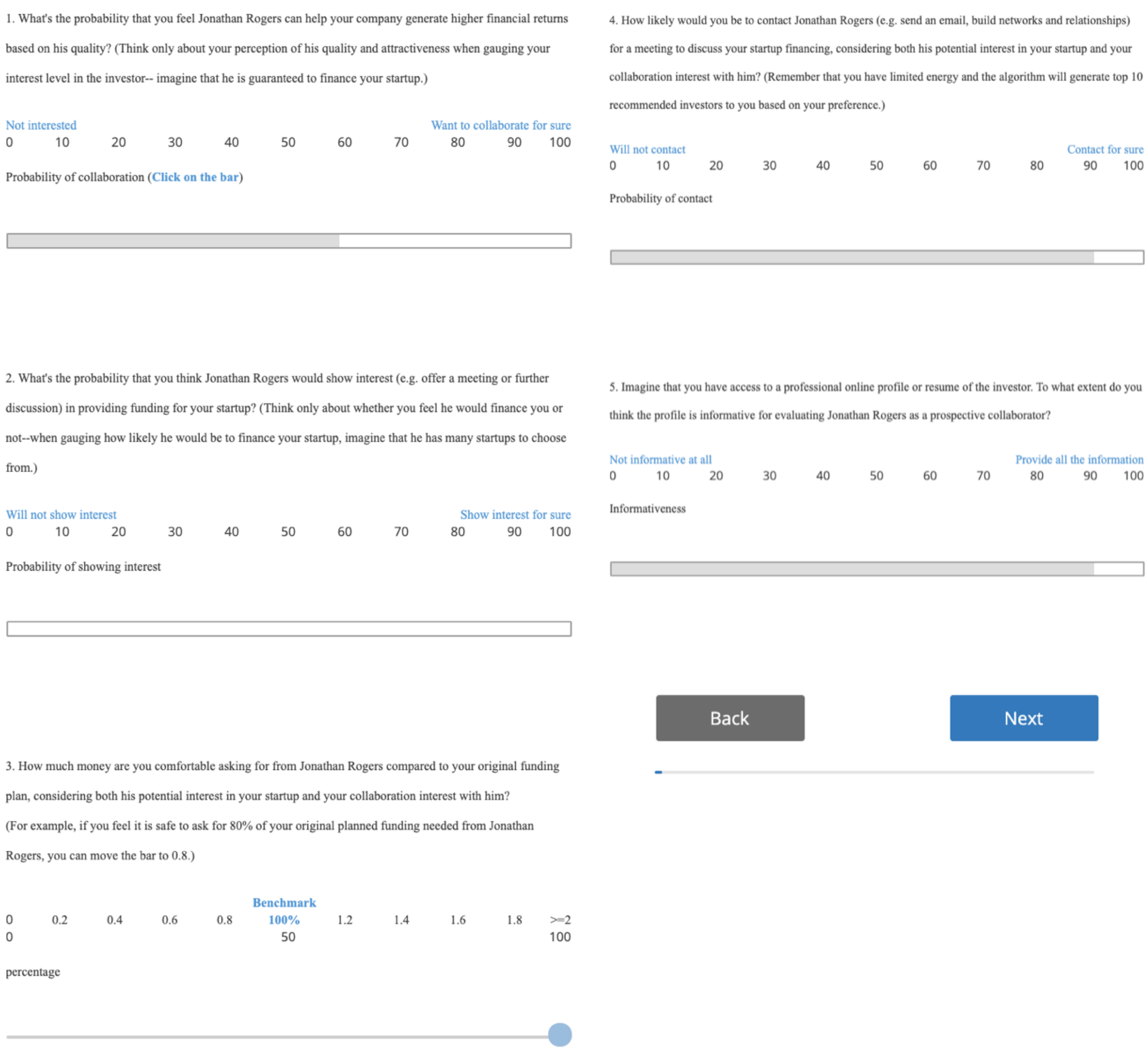

Figure A4: Sample Evaluation Questions

B Complementary Results: Implicit Discrimination

Given that startup founders' fundraising process is often stressful and entails subjective and ambiguous evaluations of different collaboration opportunities, implicit discrimination might play a role in this process.[32] In this section, we further investigate the existence of implicit discrimination.

Following Kessler et al. (2019) and Zhang (2020), Table B1 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. 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 also pre-registered this method on the AEA RCT Registry. Column (1) shows that, on average, founders spent 21.96 fewer seconds 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. 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), (5), and (6) of Table B1, the coefficients for "Female Investor" are insignificant. However, the coefficients for the interaction term "Female Investor $\times$ Second Half of Study" are significantly negative except for Column (5). 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 B1 finds that implicit gender discrimination influences founders' fundraising decisions. However, we do not find any evidence of implicit racial discrimination against Asian investors.

Figure B2 provides additional empirical evidence supporting the presence of implicit gender discrimination. It examines whether the impact of investors' gender on founders' evaluations becomes more negative as the profile evaluations progress to the end of the study.

[32] 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.

As shown in this figure, founders' ratings of female investors gradually decline compared to their ratings of male investors as they evaluate more profiles. This trend is consistent with the presence of implicit gender discrimination. Considering that real-world fundraising environments are more stressful and cognitively demanding than experimental settings, the detected gender discrimination is likely to have an even greater impact on founders' fundraising processes in real life. Conversely, as depicted in Figure B4, we observe no such patterns regarding racial discrimination.

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 increasingly act on their discriminatory tendencies against female investors. However, this explanation is unlikely in our experimental setting. Given the simplicity and intuitiveness of our evaluation interface, founders can easily understand the evaluation task after completing a few profiles. As shown in Figure B1, the evaluation time of founders does not sharply decrease after the first four profiles and only slightly decreases at the very end of the study. However, as shown in Figure B2, the decline in founders' ratings of female investors continues and is more pronounced in the last few profile evaluations. These findings suggest that factors beyond the learning story are at play. Moreover, even if the learning story were dominant, it would simply indicate a more severe situation where founders explicitly discriminate against women.

Another alternative interpretation is the "balance the profile" hypothesis. Since startup founders are often busy and hard to recruit, we intentionally set the gender distribution of investors to 40% female and 60% male. This adjustment helps create sufficient variation in the experiment with a limited number of participants by allowing for a slightly higher fraction of female investors compared to the real world, where female investors account for about 20% as mentioned in the NVCA-Deloitte Human Capital Survey Report.

This adjustment may have two potential effects. Firstly, it might risk priming subjects to our experimental objectives, making it more difficult to uncover evidence of gender discrimination. Secondly, suppose subjects perceive an over-representation of female investors 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.

To rule out the profile-balancing hypothesis, 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 Table B2. We find that evaluating more female investors' profiles in the first half of the study is not associated with more positive attitudes toward female investors in the second half of the study. This goes against the profile-balancing hypothesis. Moreover, according to this hypothesis, we should also observe similar data patterns for the evaluation results of Asian investors. However, both Table B1 and Figure B4 show that investors' race does not influence entrepreneurs' evaluations. These results show that the profile-balancing hypothesis is not the major driver of our findings of implicit discrimination.

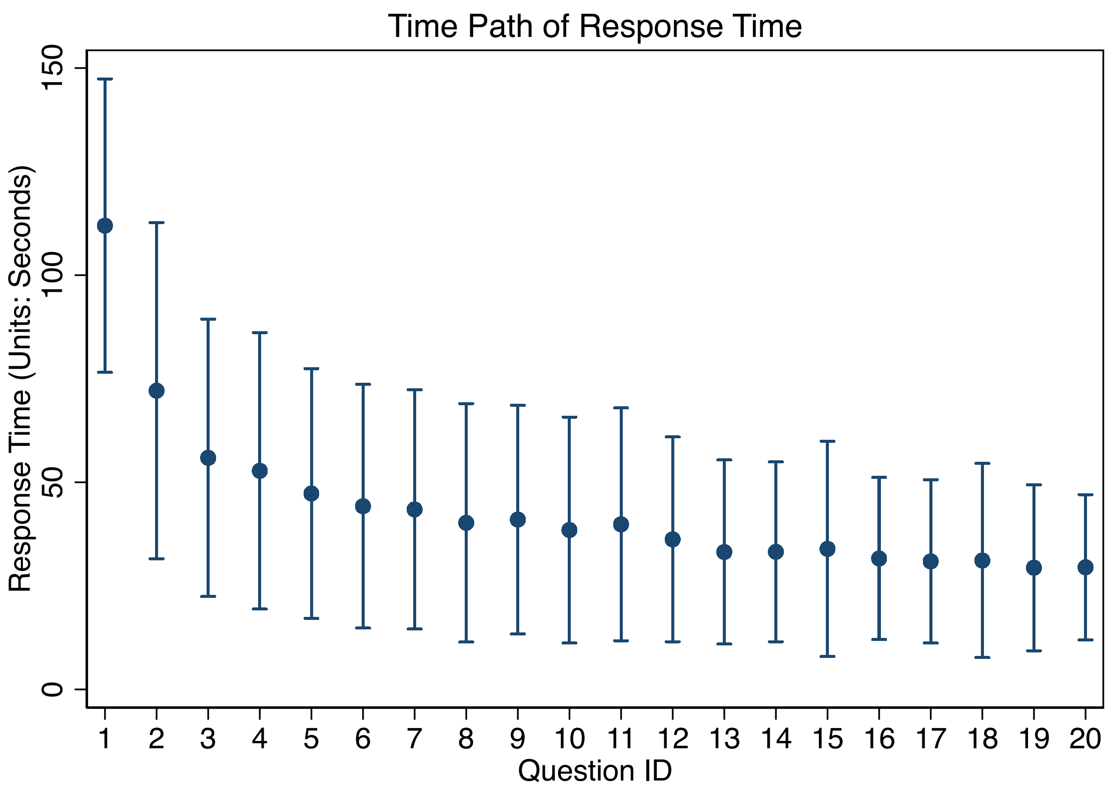

Figure B1: Time Path of Response Time

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.

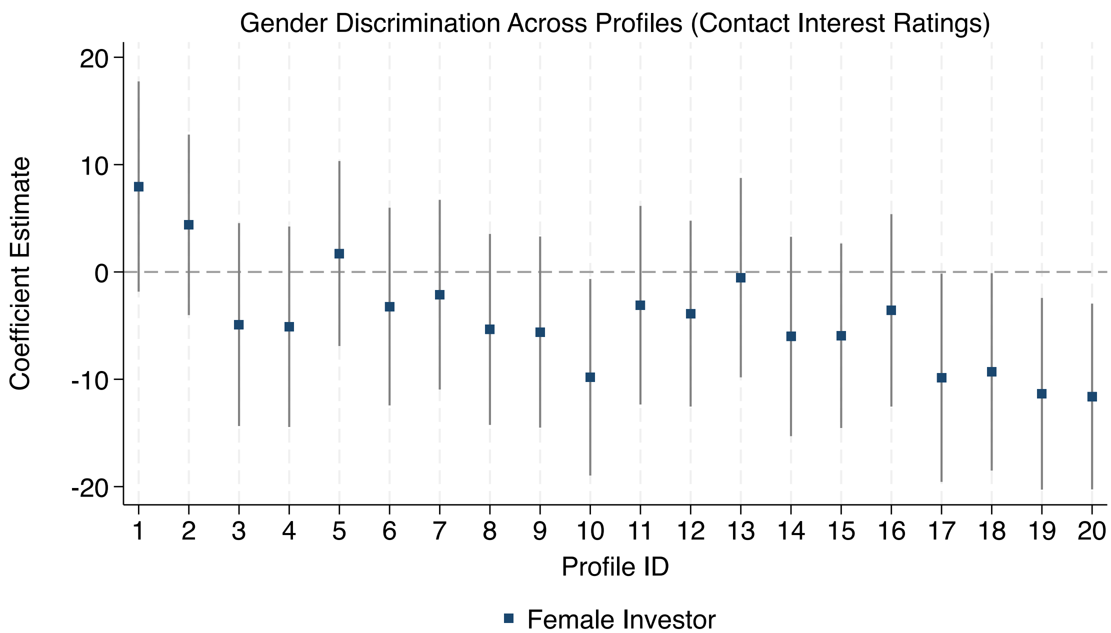

Figure B2: Gender Discrimination Across Profiles (Contact Interest Ratings)

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 lines are the coefficients 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 intervals. These represent the magnitude of gender discrimination as measured by startup founders' contact interest ratings (i.e., Q_4).

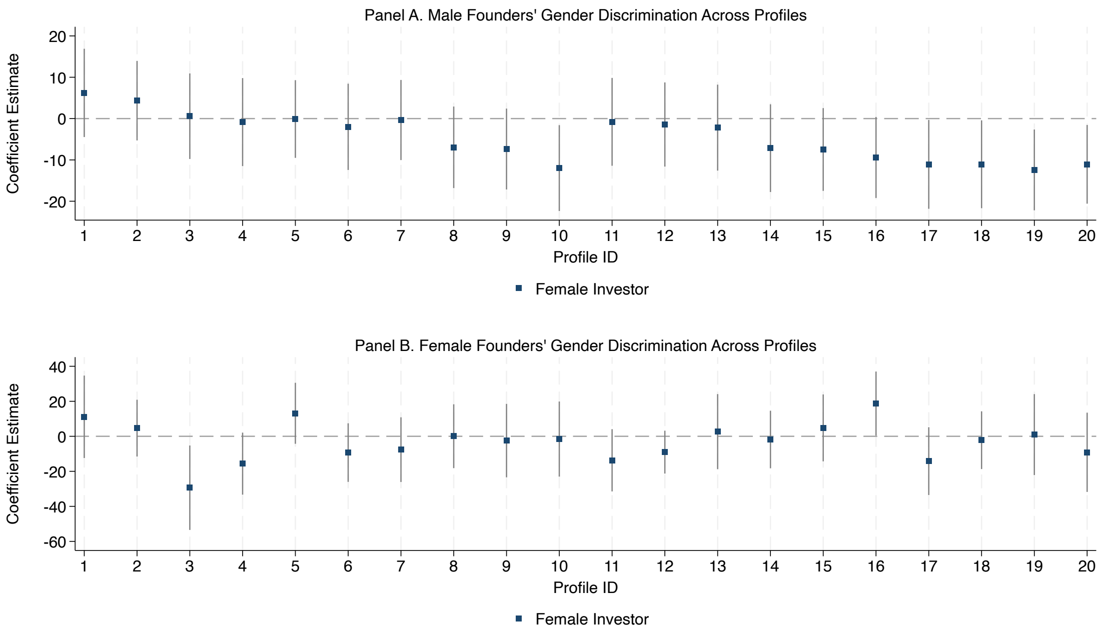

Figure B3: Gender Discrimination Across Profiles (Male Founders vs. Female Founders)

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 lines are the coefficients 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 intervals. These represent the magnitude of gender discrimination as measured by startup founders' contact interest ratings (i.e., Q_4).

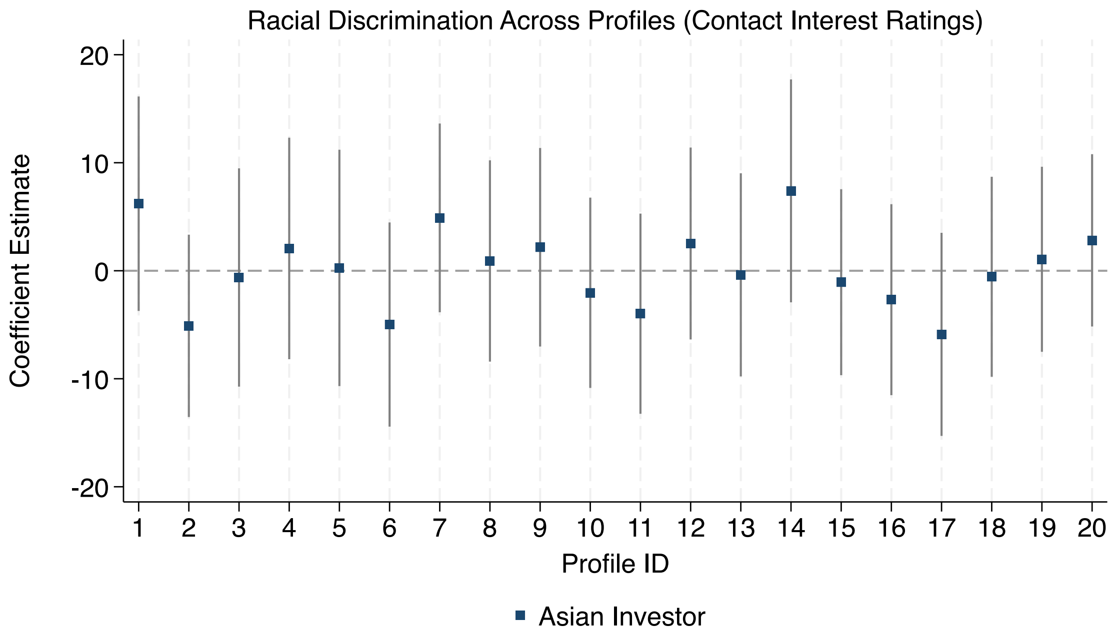

Figure B4: Racial Discrimination Across Profiles (Contact Interest Ratings)

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 lines are the coefficients 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 intervals. These represent the magnitude of racial discrimination as measured by startup founders' contact interest ratings (i.e., Q_4).

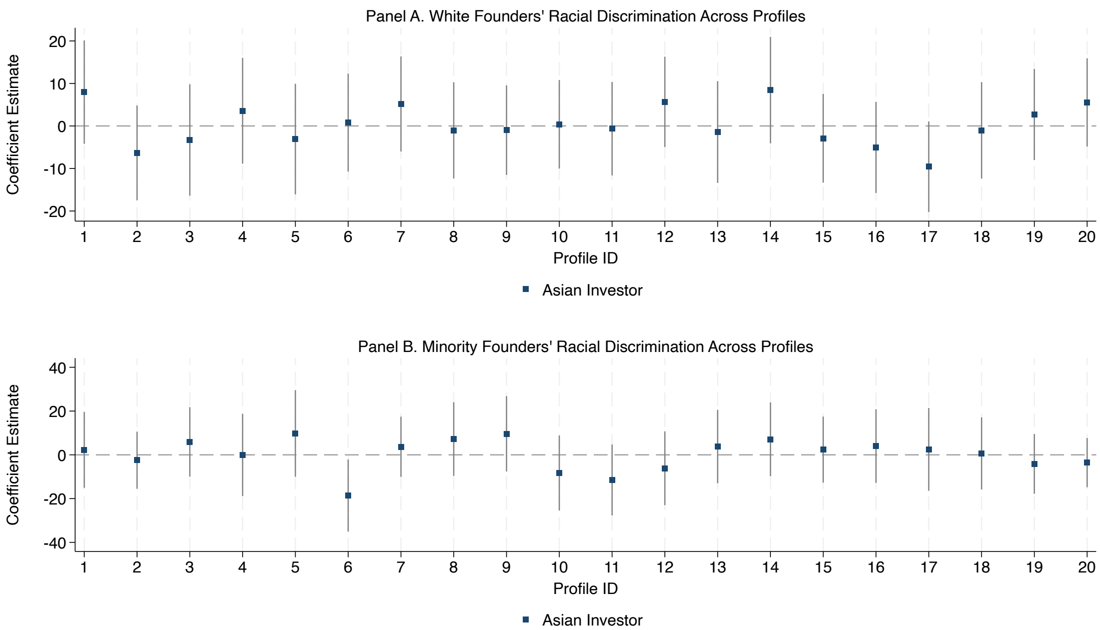

Figure B5: Racial Discrimination Across Profiles (White Founders vs. Minority Founders)

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 lines are the coefficients 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 intervals. These represent the magnitude of racial discrimination as measured by startup founders' contact interest ratings (i.e., Q_4).

Table B1: 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 × Second Half of Study		-6.51***	-4.88***	-2.65**	-0.98	-4.15**
		(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 × Second Half of Study		-1.80	-1.59	-1.03	0.93	-0.80
		(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 Column (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 from 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. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table B2: Profiles in the First Half and Evaluations in the Second Half

	Profitability (1)	Availability (2)	Informativeness (3)	Funding (4)	Contact (5)
Panel A. Gender					
Fraction of Female Investors in the First Half	2.09	8.57	5.49	10.86	-1.31
	(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 Investors in the First Half	12.48	7.55	18.48*	1.54	3.91
	(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

Notes. This table tests whether startup founders' evaluations of the female or Asian investors 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 Investors in the First Half" and "Fraction of Asian Investors in the First Half" represent the fraction of female investors and Asian investors in the first half profiles, respectively. These cross-sectional regressions use robust standard errors.

Table B3: Implicit Discrimination Based on the 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 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 B1. 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 Proof for Theorem 1

Proof. Firstly, we enumerate all possibilities for regular equilibria. Define $\widehat{Q}_G(Q), \widehat{Q}_B(Q)$ as the mass of startup founders in markets G, B, respectively, in the identity-blind equilibrium when the total mass of founders and investors are Q and $\frac{1}{2}$. Define $\widehat{u}(Q)$ as the utility from entering either market in the (identity-blind) equilibrium when the total mass of founders and investors are Q and $\frac{1}{2}$. 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 founders 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 both founder groups in the two markets.

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

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

  The left-hand side is strictly higher than group 2 founders' payoff from market $B1$ due to $\kappa > 0$. The right-hand side is group 2 founders' payoff from market $G2/B2$. This means group 2 founders have no incentive to enter market $B1$. Therefore, this case is not possible.

- *Case 1*: Group 1 founders only enter markets $G1$ and $B1$. This scenario immediately implies that group 2 founders do 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 founders enter $B1$ with strictly positive mass. Then, group 2 founders' 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 founders have no incentive to enter market $B1$; hence, this case is not possible. Therefore, the only possibility is that group 2 founders only enter $G2, B2$.

- *Case 2*: Group 1 founders enter all markets. This scenario 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 founders enter only $G2$.

- *Case 3*: Group 1 founders enter markets $G1, B1$, and $G2$. Like in case 2, group 2 founders do not enter $B1$. Group 1 founders being indifferent between $G1$ and $G2$ also implies that group 2 founders strictly prefer $G2$. Therefore, group 2 founders enter 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 because 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.

□