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

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**Abstract**

To explain the unique persistent gender gap in the US entrepreneurial community, this paper conducts an experiment with real US startup founders. Results show that male entrepreneurs have implicit gender discrimination against female investors due to statistical discrimination. The discrimination is more salient among high-quality and senior investors, suggesting the existence of a glass ceiling for women. However, Asian investors do not suffer from a similar level of discrimination. We further provide a theoretical framework to explain several novel findings in recent experiments and demonstrate how two-sided gender discrimination perpetuates a persistently low female participation rate in entrepreneurial financing settings.

**Keywords:** Discrimination, Matching, Field Experiments, Venture Capital, Entrepreneurship

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# 1 Introduction

Entrepreneurial activities are crucial to the development and innovation of the economy. However, it has been well documented that women's participation rate in high-growth entrepreneurial activities has been consistently lower than other high-skilled occupations in previous decades (Gompers and Wang, 2017). Multiple potential explanations have been proposed. For instance, on the startup side, women are documented as more risk-averse and less likely to participate in risky entrepreneurial activities (Croson and Gneezy, 2009). On the investor side, multiple papers discovered the empirical evidence that venture capitalists (VC) have implicit gender bias against female entrepreneurs (Ewens and Townsend, 2020; Zhang, 2020).[1]. These explanations generally ignore the two-sided matching nature of the entrepreneurial financing process. Hence, none of these by themselves can fully explain the uniqueness of the persistent gender gap in entrepreneurship compared to other occupations where gender discrimination also exists (Egan, Matvos and Seru, 2017; Sarsons, 2017) but women's participation steadily increases.[2] To explain the persistence of the gender gap in entrepreneurship, which is essentially a matching equilibrium outcome, we first investigate startups' fund-seeking behaviors with a startup-side incentivized resume rating (IRR) experiment. Combined with experimental results from a symmetric investor-side IRR experiment proving the existence of implicit bias against female founders among venture capitalists (Zhang, 2020), this paper completes an experimental system discovering implicit gender bias on both the investor side and startup side.[3] Taking these experimental results as building blocks, we provide a theoretical framework explaining that when gender discrimination exists on both sides of a two-sided matching market, how women can become trapped into a long-lasting "low participation rate" equilibrium outcome.

Identifying discrimination and its nature in the entrepreneurial financing setting is empirically challenging. Standard databases mainly record the completed deals. The data that only captures matching equilibrium outcomes are usually not enough to empirically separate the investors' investment decisions and startups' fund-seeking behaviors. Even after researchers access proprietary data describing how investors select startups and how startups search for investors Ewens and Townsend (2020); Hsu (2004), it is hard to judge whether differential treatments towards female and male candidates stem from discrimination or other private information only obtained by decision-makers and unobservable to researchers. Furthermore, in this high-skilled labor market, commonly used experimental methods, such as correspondence tests, might generate results that only apply to low-stake situations (Zhang, 2020). These empirical difficulties motivate us to exploit the IRR experimental method to investigate discrimination issues in startups' fundraising setting.[4]

[1] Other relevant papers studying gender discrimination in the US venture capital industry include Guzman and Kacperczyk (2019) and Hebert (2020).

[2] Similarly, although venture capitalists are also documented to have implicit bias against Asian founders (Zhang, 2020), participation of Asians still improves for the previous two decades.

[3] An experimental system is a framework within which individual experiments are conducted. It usually contains series of experiments which complements each other. The concept is widely used in biology, and "the choice of an appropriate experimental system is often seen as critical for a scientist's long-term success." For more discussions of this concept, please see Zhang and Zhong (2020).

[4] IRR experiment belongs to one of the burgeoning lab-in-the-field experimental methods and proves to be powerful in addressing

Since Zhang (2020) has thoroughly examined investor-side gender discrimination issues, this paper complements that work by testing whether startup founders discriminate against female investors. To implement the startup-side IRR experiment, we collaborated with a third-party company that helped us to recruit real U.S. startup founders to evaluate 20 randomly generated investor profiles. In addition to the randomization of the investors' gender and race information, which is indicated by their first and last names, the experiment also dynamically and orthogonally randomizes multiple other investor characteristics to introduce more quality variations in each profile. Startup founders know these investor profiles are hypothetical, but they are willing to provide truthful evaluations to get algorithm generated investor recommendation lists. To increase the sample size and mitigate the sample selection bias, we also provide each participant with $47 as monetary compensation in addition to the "matching incentive" that provides matched investors' contact information.

The experimental results provide the following findings. First, although we do not find evidence about group-level *explicit* discrimination, *implicit* gender discrimination against female investors does exist when experimental subjects become fatigued or rushed. On average, startup founders spend 19 seconds less on evaluating each investor profile displayed in the second half of the study compared to time spent in the first half of the study. During the same time, their evaluations of female investors also significantly decline compared to the evaluations of similar male investors. In the second half of the study, female investors are considered to be 4.7 p.p. less likely to help startups to succeed and 2.5 p.p. less likely to have investment intentions. This belief-driven implicit gender discrimination is mainly caused by male entrepreneurs. Although female entrepreneurs generally provide more positive ratings to female investors, the result is not statistically significant. However, we do find weak evidence that female entrepreneurs feel comfortable raising more funding from female investors.

Second, we find evidence of a glass ceiling for female investors in the US venture capital industry. Results of multiple quantile regressions show that implicit gender discrimination is most severe for more attractive investors. For the bottom 10th quantile investors in terms of attractiveness, which is measured by investors' contact interest ratings, female investors only receive 1 p.p. less contact interest ratings compared to male investors and the result is not statistically significant. However, the magnitude and significance of implicit gender discrimination gradually increase with investors' attractiveness. For the 90th quantile investors in terms of attractiveness, the magnitude of implicit gender discrimination has increased to -7 p.p., which is statistically significant at the 1% level. We also find that compared to junior venture capitalists, senior female venture capitalists suffer more from implicit gender discrimination. Although junior female investors are considered to be 2.96 p.p. less helpful compared to similar junior male investors, the magnitude of this gender gap is 4.35 p.p. for senior investors. Results suggest that women face more discriminatory barriers when they rise to senior positions.

preference related questions. In the entrepreneurial finance literature, papers that have applied this method in testing venture capitalists' investment strategies include Zhang (2020), Zhang (2021), Zhang and Zhong (2020), and Colonnelli, Li and Liu (2022).

Third, the magnitude of discovered implicit gender discrimination also varies with market conditions and startups' internal thresholds. A distributional analysis shows that implicit gender discrimination mainly exists when startups' internal thresholds are above 50% contact interest ratings. The magnitude of discrimination is the largest when the internal threshold is around 70% contact interest ratings. This indicates that female investors also face more difficulties in attracting high-quality deal flows when the capital supply is abundant on the market and investors need to compete for better deals. However, when startups become less picky about who they collaborate with, their internal thresholds are lower. In this situation, startups can even slightly prefer to contact female investors.

Fourth, despite the existence of implicit gender discrimination, we do not find any evidence of racial discrimination against Asian investors among US entrepreneurs. The experiment was implemented in 03/2021 when widespread anti-Asian violence surged in the US.[5] As the largest minority group contributing to the US entrepreneurial community, Asian Americans play a crucial role in promoting the innovation and development of the economy. Based on our experimental results, this anti-Asian atmosphere seems not to have influenced startups' attitudes towards Asian investors in the US entrepreneurial financing setting.

To explain the empirical findings discovered in this paper and Zhang (2020), we propose a novel theoretical model of "two-sided statistical discrimination." The model adapts the statistical discrimination theory from Che, Kim and Zhong (2020) by introducing homophily based on investor/founder identities. The main result of the theoretical model is the following: when startups' searches of potential investors are based on the observed identities of investors and investors exhibit homophily, there is a unique persistent (stable) discriminatory equilibrium, even though there is no intrinsic difference between the quality of investors with different identities. The theoretical model also predicts the "discrimination reversion" phenomenon discovered in this paper: if one interprets the identity as gender, then female investors with *high* ratings are discriminated *more* than female investors with *low* ratings by *male entrepreneurs*.

The key theoretical novelty of our model is that it is based on "statistical discrimination," where the difference between different identity groups is just the "perceived attractiveness" based on an informative rating instead of the actual quality. Traditional models of discrimination are based on the intrinsic quality difference of agents (exogenous difference in Phelps (1972) and endogenous difference in Arrow et al. (1973) and Coate and Loury (1993)). In the same spirit, Craig, Fryer et al. (2017) studies two-sided discrimination based on endogenous investment choices. However, their model cannot explain the "discrimination reversion" phenomenon discovered in this paper and Zhang (2020).

This paper makes the following contributions. First, we provide novel experimental causal evidence on the existence and nature of implicit gender discrimination against female venture capitalists. Combined with Zhang (2020), we provide the empirical foundation that gender discrimination can exist on both sides of a two-sided matching market. Moreover, the discovered phenomenon that more attractive and senior female investors suffer more from implicit gender discrimination also proves the existence of a glass ceiling for female investors in the US financial industry.

[5] See "Anti-Asian hate crimes surged in early 2021, study says".

While Hegde, Ljungqvist and Raj (2021) uses a comprehensive database to identify the glass ceiling for minorities in the US, we complement their work by documenting the existence of a glass ceiling for women. Hence, the paper directly contributes to the empirical literature studying discrimination.

Second, our experimental results also provide another explanation for female venture capitalists' worst performance compared to their male colleagues as documented by Gompers, Mukharlyamov, Weisburst and Xuan (2014a). According to Gompers et al. (2014a), this gender gap in performance is mainly driven by the lack of formal feedback mechanisms because female investors benefit less from the experience and skill of their colleagues within their firms. Our paper finds that the lower success rates of female venture capital investors' investments can also be caused by their difficulties in attracting high-quality deal flows. Based on Sørensen (2007), sorting is almost twice as important as a direct influence to explain VC firms' portfolio companies' outcomes. If female investors cannot get high-quality deals at the beginning due to entrepreneurs' implicit gender discrimination, then their investment outcomes are naturally worse than their male colleagues' investment outcomes. Hence, this paper contributes to the gender literature that studies the gender gap in work performance.

Third, the experimental results also shed light on startup founders' fund-seeking behaviors in the entrepreneurial financing process by showing how the investor's gender affects startups' fundraising decisions. Hsu (2004) shows that startups highly value investor reputation, and offers made by venture capitalists (VC) with a high reputation are more likely to be accepted. Sørensen (2007) finds that more experienced venture capitalists can attract higher quality companies. Zhang and Zhong (2020) prove that multiple investor human capital characteristics and VC firm organizational capital characteristics causally influence startups' fundraising plans and intentions to contact the investor. Following this literature, this paper shows that a venture capitalist's gender is another factor influencing startups' decisions. Hence, the paper also contributes to the entrepreneurial finance literature eliciting startup founders' preferences on investors.

Methodologically, this paper follows the recent trend of applying lab-in-the-field experiments to study finance-related questions. Since Kessler, Low and Sullivan (2019) create the IRR experimental paradigm as a preference elicitation technique, several papers have applied this methodology to study entrepreneurial finance related questions. For example, Zhang (2020) combines an IRR experiment and a correspondence test with real US venture capitalists to study whether early-stage investors discriminate against female and Asian startup founders. Later, Zhang (2021) use the same methodology to study venture capitalists' preferences on startups' ESG characteristics in the US private equity market. Zhang and Zhong (2020) implements an experimental system to investigate the matching process of US startups and venture capitalists. Similarly, Colonnelli et al. (2022) uses the IRR experiment in China to study the role of government participation in the Chinese venture capital industry.

Theoretically, this paper contributes directly to the theoretical literature explaining discrimination behaviors. Classical models of discrimination assume that agents have intrinsic quality differences. (Coate and Loury, 1993;

Phelps, 1972). Craig et al. (2017) extend these models to a two-sided matching labor market to investigate the effect of several anti-discrimination policies. Unlike these models, our model tells an information story where different identity groups only differ in the "perceived attractiveness/quality" instead of actual quality. This helps to explain the persistent gender gap in entrepreneurship and the finding in recent experiments that discrimination mainly hurts candidates receiving higher evaluation ratings.

This paper is organized as follows. Section 2 presents the experimental design of the startup-side IRR experiment. Section 3 identifies the existence and nature of implicit gender discrimination by analyzing the effect of the investor's gender and race on startup founders' evaluation results. Section 4 develops a theoretical framework that explains the persistent gender gap in high-growth entrepreneurship and other novel experimental findings based on our experimental evidence. Section 5 concludes.

# 2 Experimental Design

In this experimental setting, we build a data-driven investor-founder matching tool, following the recent trend of exploiting machine learning algorithms to recommend matched venture capitalists for startup founders. Multiple companies have provided similar commercial matching services through collecting basic background information of both startup founders and investors.[6] These matching tools are generally designed to reduce the frictions during entrepreneurs' fund-seeking process by facilitating entrepreneurs to search their "dream" investors. Therefore, our experiment tries to mimic this real world setting as much as possible.

To directly test the nature of founders' preferences about investors' gender and race, this experiment mainly exploits an incentivized resume rating experiment with real US startup founders. Through evaluating multiple randomly generated hypothetical investor profiles, startup founders can obtain an investor list containing their dream investors' demographic and contact information. This list is generated by a matching algorithm based on our collected comprehensive global venture capitalist database.[7] Although entrepreneurs know that all the investor profiles are hypothetical, truthfully revealing their preferences helps our algorithm to generate a better matched investor recommendation list.

## 2.1 Recruitment Process and Sample Selection

The experiment was implemented during 02/2021-03/2021. In total, we obtain evaluation results of 1020 investor profiles from 51 startup founders. In our formal analysis, we only use 860 "valid" evaluation results from 43 startup founders which pass our "noise reduction techniques". However, the results are still robust when the sample includes all the experimental subjects, which are reported in the Appendix.

[6]These companies include dealroom.co, VC Match, the Community Fund, VCWiz, etc.
[7]For details of this global investor database, please see the data section of Zhang (2020).

To recruit a representative sample of real US startup founders who fit our research purposes, we collaborate with a third-party recruitment company which targets real US small business owners. We further add two filter questions and several screeners to recruit founders satisfying the following three criteria: 1) being a startup founder or business owner who plans to raise funding for her company from the venture capital industry, 2) understanding the designed incentive and agreeing that the more truthfully they reveal their preferences, the more benefits they can obtain from the study, 3) pass several carefully designed attention checks based on participants' evaluation time and Bot Detection algorithms designed by Qualtrics system. If participants fail any of these criteria, Qualtrics will automatically terminate the experiment process and inform experimental participants that they are no longer qualified for this study. Unqualified participants do not have the second chance of joining the study. Similar to the classical IRR experimental design (Kessler et al., 2019), we inform experimental participants of the research purposes as required by Columbia IRB and Stanford IRB, but emphasize the matching purpose of this created "investor-entrepreneur" matching tool.

The recruitment method through this third-party company has the following pros and cons. On the one hand, it is an efficient way to recruit startup founders who are in the stage of searching for investors and plan to raise funding for their businesses.[8] Also, the company's network provides a more representative subject pool. Moreover, as the company does not allow researchers to collect any identifiable information of experimental participants, this mitigates the Hawthorne effect caused by the social image concern. On the other hand, recruiting founders through the third-party company is costly. In this project, we pay $47 for each completed questionnaire, which is used to provide monetary compensation to each experimental subject according to the company's business model. This mandatory monetary compensation also brings extra noises, requiring researchers to use extra survey techniques of reducing noises. Also, not being able to collect participants' identifiable information limits the potential to merge the experimental data with other administrative databases. We also tried multiple alternative recruitment methods, such as collaborating with incubators through researchers' network or sending cold-call recruitment emails to entrepreneurs in the pilot study. The currently used recruitment method is the only feasible method to recruit enough representative experimental subjects who fit our research purposes. For the pros and cons of alternative recruitment methods, please see Online Appendix.

The response rate of our study is roughly 6% based on the background data of Qualtrics. Table 1 summarizes the background information of recruited startup founders. Panels A and B describe the sector distribution and stage distribution of participants' startups, separately. Panel C reports the background information of the recruited founders and their startup teams. Panel D provides the startup's missions, indicating whether they are purely profit-driven or aim to increase the diversity of the community. Based on Table 1, there are roughly 48.8% of entrepreneurs recruited in Wave 1 who are working in the IT industry. The startups of 74.4% entrepreneurs are still in the early stage. 30.2%

[8]Standard ways of collecting startup founders' contact information online usually identify established entrepreneurs who have successfully raised money with a relatively mature business. These startup founders have already built connections with the VC industry and are more likely to approach investors through their own network.

of recruited entrepreneurs are female.

## 2.2 Structure of the Matching Tool

To elicit startup founders' preferences for various venture capitalists, we have designed a matching tool using Qualtrics (i.e., "Nano-Search Financing Tool"), which randomly generates hypothetical investor profiles for startup founders to evaluate.[9] After potential experimental subjects receive the recruitment email from the third-party company, they need to open the inserted survey link, read the consent form to decide whether to enter the designed matching tool and participate in this experiment. The tool consists of the following parts.

#### Part A: Evaluation Section (IRR Experiment to Detect Belief-driven Preferences)

Before the evaluation section starts, startup founders need to provide us with some non-sensitive background information of their startups, including the amount of money they aim to raise. This is a standard procedure for other investor recommendation services on the market. As these background questions are very standard, they do not prime experimental participants for our research purposes of testing socially sensitive preferences, such as gender or racial discrimination. Participants also need to assume that all investors to be evaluated by them are active investors, investing in the industry (industries) and stage(s) of their interest. After reading the relevant guidance and passing an attention check question, they will enter the formal investor evaluation section.

In the evaluation process, startup founders need to evaluate 20 randomly generated venture capitalists' profiles. Although participants know that these investor profiles are hypothetical, truthfully revealing their preferences towards these investors enables the matching algorithm to generate better-matched investor recommendations. Essentially, this part follows an IRR experimental paradigm designed to directly identify belief-driven preferences.

**A.1 Investor Profile Creation and Variation**

To generate VC investors' hypothetical profiles, we randomize multiple investors' individual-level characteristics and fund-level characteristics simultaneously and independently across profiles. Each characteristic is dynamically populated from a pool of options, and the matching tool combines these randomly selected characteristics together to create an investor profile.[10] Profile templates are built-in HTML for display in a web browser and populated dynamically in Qualtrics using Javascript. The detailed randomization process is described in Table 2.

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

[9] The "Nano-Search Financing Tool" created in Zhang (2020) recommends *matched startups* to investors while our "Nano-Search Financing Tool" recommends *matched investors"* to startup founders.

[10] This randomization process is similar to that used by a factorial experimental design.

online. We remove relative information indicating the investor's interested industries and stages. Lastly, our profile is essentially a combination of investors' publicly available information rather than their resumes. Different from the job seeking process, investors rarely post their resumes online. Instead, startup founders do their due diligence on investors by collecting information from multiple online platforms, such as LinkedIn, personal websites, Crunchbase, AngelList, Pitchbook, etc. Therefore, the format of our investor profiles tries to mimic these platforms, displaying key points of investors' characteristics.[11]

All investor profiles contain three sections in the following order: i) individual-level characteristics, including first name, last name, title/position, investment experience, educational background, and previous entrepreneurial experience or other working experience. ii) fund-level sensitive characteristics, including the fund's investment philosophy and type (i.e., profit-driven funds or impact funds). iii) fund-level nonsensitive characteristics, including the fund's size measured by AUM (i.e., asset under management) and dry powder. We do not include important investor characteristics which are not publicly accessible online or available on mainstream startup fundraising platforms as such information is usually not used by typical investor recommendation algorithms on the market. (For a sample investor profile, see Figure 6).

***Names Indicating Gender and Race.*** — We generate a list of commonly used first names highly indicative of investors' gender (Male or Female), and investors' last names highly indicative of race (Asian or White) following Fryer Jr and Levitt (2004) and Gornall and Strebulaev (2020).[12] Each assigned name is displayed at the beginning of the profile and also mentioned multiple times in the evaluation questions to increase its salience. To make sure that U.S. startup founders can correctly associate these names with investors' gender and race identities, we hire 107 Mturks located in the U.S. to manually associate each potential candidate name with different gender and race categories. Only those highly indicative names are selected. (For the full list of selected names and detailed name selection procedures, please see Online Appendix.) Moreover, we use gender pronouns (i.e., she/her/his/him/he) in both the evaluation questions and the description of each investor's entrepreneurial/work experiences.

***i) Individual-level Human Capital Characteristics***

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

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

[12] Given that white and Asian investors dominate the U.S. venture capital industry, we only focus on these two ethnic groups in this study. Also, since Asian Americans and white Americans follow similar first name naming patterns but distinct last name naming patterns, using last names to indicate race is a valid way. However, this method might cause some problems when studying racial bias against African Americans or Hispanic Americans. Many African Americans share similar last names with white Americans. However, unique first names used by some African Americans can indicate other background information, such as family background, etc.

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

***Educational Background.*** — Educational background is another human capital characteristic which is correlated with investors' investment strategies. We independently randomize both investors' degrees (bachelor degree vs graduate degree) and graduated schools (top university vs common university).[13] All selected schools have been verified to have alumni who are working in the US venture capital industry based on Google search. Detailed randomization process and school lists are provided in the Online Appendix.

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

***ii) Fund-level Sensitive Characteristics***

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

***iii) Fund-level Nonsensitive Characteristics***

***Fund Size.*** — We use AUM (i.e., "asset under management") and dry powder to indicate the size of the VC

[13]Graduate degrees include MBA, JD, master, and PhD. Bachelor 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, University of Chicago. Common universities are defined as other universities which also foster real startup founders and venture capitalists.

firm that each investor works for.[14] This information exists on the Pitchbook platform and is summarized by annual National Venture Capital Association (NVCA) Yearbook. The information about fund size exists on the Pitchbook Platform and other standard databases. The distribution used in the randomization process mimics the fund size distribution of early-stage VC firms recorded by Pitchbook database.

In this paper, our research question mainly focuses on gender and race discrimination issues in entrepreneurs' fund-seeking process. The purpose of simultaneously and orthogonally randomizing other investor and fund characteristics is to introduce quality variations in the experiment and examine potential useful interaction effects between gender and other characteristics. The introduced quality variations are crucial to test the nature of discrimination and to investigate both gender's distributional effect and heterogeneous effect across the investor's attractiveness.[15]

**A.2 Evaluation Questions** A key design feature, which enables IRR experiment to directly identify detailed nature of discrimination, is its carefully designed, discrimination theory-based evaluation questions. For each investor profile, we ask startup founders to answer three mechanism questions and two decision questions (see Appendix Figure 7 for an example of designed evaluation questions).

**Mechanism Questions** Three mechanism questions are designed to test the following three standards, belief-driven sub-mechanisms explaining why investors' gender and race might affect startup founders' willingness to collaborate. The first sub-mechanism is that subjects might use investors' group membership as a signal of their quality (i.e., ability to help startups to achieve higher financial returns). To test this mechanism, startup founders need to evaluate the quality of each hypothetical investor (i.e., $Q_1$). The second sub-mechanism (i.e., "availability") is that investors' gender and race might be suggestive of their intention of investing in certain types of startups. Similar to the marriage market, an entrepreneurial financing process is often considered as a two-sided matching process. Hence, the likelihood of successfully raising funding from an investor theoretically also affects startup founders' fundraising behaviors given the high search cost. To test this channel, subjects need to evaluate the likelihood that each investor would show interest in their own startups (i.e., "$Q_2$"). The third sub-mechanism is that founders' beliefs of the variance of minority investors and majority investors (i.e., "higher moment beliefs") theoretically also affect their decisions (Heckman, 1998; Neumark, 2012) in a situation with information asymmetry.

$Q_1$ **(First Moment: Quality Evaluation)** 1. What's the probability that you feel [investor name] can help your company generate higher financial returns based on [his/her] quality? (Think only about your perception of [his/her] quality and attractiveness when gauging your interest level in the investor– imagine that [he/she] is guaranteed to finance your startup.)

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

[15]We realize that the impact of other investor-level and fund-level characteristics on entrepreneurs' fund-raising decisions is an important but under-explored question in the entrepreneurial finance literature. Therefore, we provide relevant results in a separate paper Zhang and Zhong (2020).

0-10%-20%-30%-40%-50%-60%-70%-80%-90%-100%

$Q_2$ **(Strategic Mechanism: Availability)** 2. What's the probability that you think [investor name] would show interest (e.g. offer a meeting or further discussion) in providing funding for your startup? (Think only about whether you feel [he/she] would finance you or not–when gauging how likely [he/she] would be to finance your startup, imagine that [he/she] has many startups to choose from.)

Probability of showing interest

(Will not show interest) 0-10%-20%-30%-40%-50%-60%-70%-80%-90%-100% (Show interest for sure)

$Q_5$ **(Second Moment: Informativeness & Variance)** 5. Imagine that you have access to a professional online profile or resume of the investor. To what extent do you think the profile is informative for evaluating [investor name] as a prospective collaborator?[16]

Informativeness

(Not informative at all) 0-10%-20%-30%-40%-50%-60%-70%-80%-90%-100% (Provide all the information)

**Decision Questions** We design two decision questions that capture the following important dimensions of startups' fundraising decisions. The first decision question (i.e., $Q_3$) asks startup founders about their proposed funding plan for each investor (i.e., internal margin). $Q_3$ is designed to elicit the *relative* funding amount compared to the founder's original fundraising plan rather than the absolute amount of funding. This design creates a standardized question that accommodates startups with different amounts of targeted funding. The second decision question (i.e., $Q_4$) is about their likelihood of contacting each investor (i.e., external margin).

$Q_3$ **(Intensive Margin: Fundraising Plan)** 3. How much money are you comfortable asking for from [investor name] compared to your original funding plan, considering both [his/her] potential interest in your startup and your collaboration interest with [him/her]? (For example, if you feel it is safe to ask for 80% of your original planned funding needed from [investor name], you can move the bar to 80%.)

Percentage 0-20%-40%-60%-80%-100%-120%-140%-160%-180%->=200%

One unit of $Q_3$ stands for 2% relative amount of funding to be raised from this investor. For example, if some entrepreneurs' evaluation results of $Q_3$ are equal to 50, it means that they are comfortable asking for the amount of funding in their original funding plan. However, if the evaluation results of $Q_3$ are equal to 25, it means that they only want to raise $2\% \times 25 = 50\%$ of the amount of funding required to support their businesses.

$Q_4$ **(Extensive Margin: Likelihood of Contact)** 4. How likely would you be to contact [investor name] (e.g. send an email, build networks and relationships) for a meeting to discuss your startup financing, considering

[16] This evaluation question comes from the complementary survey used in Bartoš, Bauer, Chytilová and Matějka (2016).

both [his/her] potential interest in your startup and your evaluation of [his/her] ability to help your startup succeed? (Remember that you have limited energy and the algorithm will generate top 10 recommended investors to you based on your preference.)

Probability of Contact

(Will not contact) 0-10%-20%-30%-40%-50%-60%-70%-80%-90%-100% (Contact for sure)

**A.3 Incentive** In the most general form of incentivized resume rating experiment, the incentive structure should guarantee that the more truthful and accurate experimental subjects' evaluation results are, the more value and benefits these subjects can receive from their participation. The most mainstream incentive structure used is the "matching incentive". In a two-sided matching market, such as the marriage market, entrepreneurial finance process, and the job-seeking process, researchers can use data-driven methods and subjects' revealed preferences to help them identify the most matched collaborators or provide certain consulting services (see Kessler et al. (2019), Low (2014), Zhang (2020)). In our experimental setting, we choose to provide this standard "matching incentive" to all experimental participants.

Specifically, after evaluating 20 hypothetical investor profiles, each startup founder will receive 10 profiles of real venture capital investors' information recommended by the matching algorithm. This recommendation service relies on the availability of a large comprehensive global venture capital investor database collected in Zhang (2020). Startup founders generally need to purchase licenses to get access to this information on Pitchbook. Hence, we provide valuable benefits to experimental participants. At the same time, this incentive also makes truthful evaluations to maximize subjects' benefits. Details of the matching algorithm are provided in the Online Appendix.

This incentive has its own advantages and limitations. The most important merit is its powerful ability to incentivize all the evaluation questions on the individual level. Also, participants attracted by this incentive on average spend 7 more seconds on evaluating each question. However, the cost of this incentive is the sample selection bias during the recruitment process. Based on its design, attracted subjects are more likely to be founders who lack connections with the VC industry or subjects who love to help with research projects. In this project, since researchers must provide experimental participants with monetary compensation as required by Qualtrics, this monetary compensation helps to mitigate this sample selection bias caused by pure "matching incentive" and to recruit a more representative sample.

**A.4 Reduce Noise** Providing monetary compensation will inevitably lead to more noisy outcomes as some participants attracted by this monetary compensation may not value the "matching incentive". For these noisy participants, their optimal strategy is to complete the tool as quickly as possible and get paid. To filter out such noisy participants, we exploit the following noise reduction techniques used by survey studies:

*a. Enough Evaluation Time.* We only include evaluation results from participants who satisfy the following criteria based on evaluation time: 1) spend at least 12 minutes on this study. 2) spend at least 60 seconds on evaluating the first profile.

*b. Reasonable Rating Variations.* If participants' evaluation results almost have no variations for $Q_1$ (i.e., quality evaluation) or $Q_4$ (i.e., likelihood of contacting the investor), we also remove their responses in our formal data analysis. We create the following three measures for each subject $i$ to detect such situations using their evaluation ratings $Y_{ij}^k$ for the $k^{th}$ question of $j^{th}$ profile: i) sample variance of $Q_1$ (i.e., $Var_i(Q_1)$), $\frac{1}{20-1}\sum_{j=1}^{j=20}(Y_{ij}^k - \frac{1}{20}\sum_{k=1}^{k=20} Y_{ij}^k)^2$ where $k=1$. ii) sample variance of $Q_4$ (i.e., $Var_i(Q_4)$), $\frac{1}{20-1}\sum_{j=1}^{j=20}(Y_{ij}^k - \frac{1}{20}\sum_{k=1}^{k=20} Y_{ij}^k)^2$ where $k=4$. iii) sum of sample variance of $Q_1$ and sample variance of $Q_4$ (i.e., $Var_i(Q_1) + Var_i(Q_4)$). If any of the three measures for subject $i$ falls below the $5th$ percentiles of the corresponding measures in the full sample, evaluation results of subject $i$ will be removed. We do not apply this criteria to $Q_2$ (i.e., likelihood of being invested), $Q_3$ (i.e., funding to raise), or $Q_5$ (i.e., informativeness) because it is reasonable that participants give the same evaluation to these questions.[17]

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

*c. Other Subsidiary Criteria.* In addition to the criteria mentioned above, we also take the following subsidiary criteria into consideration when identifying "noisy participants". These criteria include i) a reasonable amount of required funding; ii) time spent on evaluating profiles (i.e., "Timing - Last Click", "Timing - Page Submit", "Duration (in seconds)"); iii) distribution of rating variations; iv) the list of low-quality responses identified by Qualtrics team based on their designed "data scrub" algorithms.[18]

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

**Part B: Background Questions**

To check the representativeness of our recruited startup founders and test potential alternative stories, we ask several background questions about subjects' gender, race, entrepreneurial experience, educational level, startup team composition, and the goal of their startups. This pre-determined demographic information also helps us to test heterogeneous effects and provide the portrait of entrepreneurs whose decisions are affected by investors' gender and race.

[17] 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.

[18] Unreasonable amount of required funding includes extreme values, such as "25" or "8799977776555566432". "Timing - Last Click" measures duration between enter the profile and lastly click the profile. "Timing - Page Submit" measures time spent on each profile until subjects submit their evaluation results of the profile. "Duration (in seconds)" measures total time spent on this study. Definitions of other used variables are provided in the Online Appendix.

# 3 Results

This experiment recruits 51 real US startup founders, and 43 of them provide 860 "valid" evaluation results that survive our noise filtering process. The rate of noisy/careless evaluations is roughly 14%, confirming the importance of using "noise reduction techniques" for our recruitment method. We report experimental results of valid "responses" in the formal analysis part and experimental results of the full sample in the Appendix. Since we do not find any group-level explicit discrimination against female investors and Asian investors when combining all the profiles together (see Online Appendix Table E1), we start directly from investigating implicit gender discrimination.

"Implicit discrimination" refers to the attitudes or stereotypes that affect evaluators' decisions in an unconscious manner. Bertrand, Chugh and Mullainathan (2005) provides a good summary of how implicit attitudes influence people's behaviors in meaningful ways. For example, Correll, Park, Judd and Wittenbrink (2002) show that subjects were quicker at deciding not to shoot a white target compared to a similar black target. This difference was considered as implicit bias and it was not related to subjects' explicit racial prejudice. Under conditions of ambiguity, more cognitive load and inattentiveness to task, even controllable behaviors can be prone to implicit attitudes.

Entrepreneurs' fundraising settings satisfy several conditions where implicit discrimination can significantly affect startups' fund-seeking decisions. First, startup founders are often under more pressure and need to handle other administrative work, hence the setting satisfies the situation of "more cognitive load". Second, deciding which investor to approach usually involves considerable ambiguity since there are no clear standards of evaluating the attractiveness of each potential investor. Therefore, it also satisfies the condition of "ambiguity". Considering that the level of fatigue introduced in this experiment is not huge, any detected "implicit discrimination" against women and minorities can play a more important role in affecting startups' fund-seeking decisions in the real world.

## 3.1 Belief-driven Implicit Discrimination Against Female Investors

Testing implicit discrimination using the IRR experimental design has been used in Kessler et al. (2019) and Zhang (2020). The rationale behind this method is the fact that implicit discrimination is more likely to show up and influence people's behaviors when they feel rushed or fatigued (Bertrand et al., 2005). After making experimental subjects fatigued with the first half of profile evaluation tasks, researchers can test implicit discrimination by comparing experimental subjects' ratings of the second half of the study with their ratings of the first half of the study. If subjects' ratings of female investors significantly decline compared to their ratings of male investors as they evaluate more and more profiles, this is potentially a strong signal of implicit discrimination.

Table 3 tests whether startup founders have any implicit gender and racial discrimination against female investors and Asian investors. Panel A (B) reports regression results of implicit gender (racial) discrimination. "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. "Second Half of Study" is an indicator variable for investor profiles displayed among the last ten investor resumes viewed by an experimental subject. In column (1), the dependent variable is a startup founder's response time, which is defined as the number of seconds before each page submission, winsorized at the 95th percentile (40.77 seconds on average). Columns (2)-(6) show the evaluation results of the investor's quality, availability, the relative amount of funding to be raised from the investor, contact interest ratings, and the perceived informativeness of each investor profile, separately. The "p-value of Female Investor (or Asian Investor) in the second half of study" provides the p-value of the coefficient of "Female Investor" (or "Asian Investor") when we only include the evaluation results in the second half of the study. All the regressions add subject fixed effect. R-squared is indicated for each OLS regression. Standard errors in parentheses are clustered within each experimental subject.

Panel A of Table 3 shows that our recruited startup founders have group-level belief-driven implicit discrimination against female investors. Column (1) shows that experimental subjects spend 18.15 seconds less on evaluating profiles in the second half of the study compared to the time spent on profiles in the first half of the study. The result is statistically significant at the 1% level, indicating that subjects are more rushed/fatigued in the second half of the study.[19] Column (2) of Panel A shows that although female investors receive 5.04 p.p. higher quality evaluations (i.e., $Q_1$) in the first half of the study, their quality ratings decline dramatically by 10.41 p.p. compared to the quality ratings received by male investors in the second half of the study. The coefficient of the interaction term between "Female Investor" and "Second Half of Study" is significantly negative at the 1% level, indicating that experimental subjects implicitly feel female investors are less likely to help their startups to generate higher financial returns compared to male investors.

Similarly, Column (2) of Panel A shows that although subjects generally believe female investors are 2.87 p.p. more likely to invest in their startups, this rating of "availability" sharply declines by 6.26 p.p. in the second half of the study for female investors compared to male investors. This indicates that on the group level, startup founders also implicitly assume that female investors are less likely to invest in their companies. As shown in Zhang and Zhong (2020), startup founders' beliefs of the investor's "availability" (i.e., willingness to invest in their startups) are significantly correlated with their fund-seeking behaviors and willingness to contact the investor. However, Column (6) shows that the perceived informativeness of each investor's profile is not significantly different between female investors' profiles and male investors' profiles. This is not surprising as each investor profile follows the same structure, providing information of the same types of investor characteristics.

In terms of startup founders' decisions, Column (5) of Panel A shows that although subjects on average give 4.81 p.p. higher contact interest ratings to female investors, this rating also declines significantly by 6.76 p.p. in the second

[19]Table E12 in the Online Appendix documents the distribution of experimental subjects' evaluation time across investor profiles. There is a clear pattern that recruited startup founders spend less time on evaluating profiles displayed in the latter part of the study, confirming that attention is costly in our experimental setting.

half of the study. The coefficient of the interaction term between "Female Investor" and "Second Half of Study" is significantly negative at the 5% level, suggesting that subjects are implicitly less willing to contact female investors compared to male investors. Similarly, Column (4) of Panel A shows that although subjects are comfortable to raise 5.38 p.p. more funding from female investors, the result gets reversed in the second half of the study as the relative amount of funding to be raised declines by 10.56 p.p. All of these results confirm subjects' partiality towards male investors when they are rushed according to their indicated decisions on approaching the investor and their adjusted fundraising plans.

Despite the evidence of implicit gender discrimination, Panel B of Table 3 shows that there is no evidence about implicit racial discrimination against Asian investors. In Columns (2) - (6), none of the coefficients, especially the coefficients of the interaction terms between "Asian Investor" and "Second Half of Study", are significantly different from zero. This indicates that the information about an investor's race does not enter the subjects' evaluation decisions in our experimental setting. In the Appendix, we also report regression results testing the existence of racial discrimination in different subgroups of experimental subjects and across the attractiveness and quality of investors. However, we do not find any racial discrimination evidence in all of those tests. Therefore, the formal analysis part of this paper mainly focuses on gender discrimination in the fund-seeking process of US startups.

Figure 1 demonstrates the evolution of subjects' gender discrimination across investor profiles as the experiment progresses to the end. The horizontal line describes the order of each investor profile displayed to the experimental subjects (i.e., the $i^{th}$ displayed investor profile). The vertical line is the coefficient of "Female Investor" of the following regressions: $Q_4 = \beta \text{Female Investor} + \epsilon$ for all subjects' evaluation results of the $i^{th}$ displayed investor profiles. This indicates the magnitude of gender discrimination as measured by entrepreneurs' contact interest ratings (i.e., $Q_4$). Panel A uses all subjects' evaluation results and Panel B uses only male entrepreneurs' evaluation results.

Panel A of Figure 1 clearly shows that after the short break inserted after the $10^{th}$ profile, subjects' attitudes towards female investors gradually become worse, especially after they evaluate the $15^{th}$ investor profile. This pattern is even more significant and salient for male entrepreneurs as demonstrated in Panel B. Male entrepreneurs' contact interest ratings of female investors are significantly lower than their ratings of male investors for the $17^{th}$ and $19^{th}$ investor profiles. This is consistent with the findings of Subsection 3.4, showing that implicit gender discrimination mainly exists among male entrepreneurs rather than female entrepreneurs.

***Robustness Check.***— One of the concerns is that the observed "fatigue effect" is caused by subjects' intention to "balance the profile" instead of the "implicit gender discrimination". To increase the experimental power, we deliberately randomize investor's gender following the distribution: Female Investor: Male Investor = 40% : 60% rather than the real world distribution (i.e., Female Investor: Male Investor ≈ 20% : 80% ). The higher proportion of women used in our randomization process can cause two problems. First, it might prime subjects of our experimental purposes, making it harder to discover evidence about gender discrimination. Second, if subjects realize that they contact "too many" female investors in the first half of the study compared to the real world distribution, they might want to "balance the profile" and deliberately contact more male investors.

To rule out this alternative interpretation of our experimental result, we empirically test whether subjects evaluating more female investors in the *first* half of the study give lower ratings to female investors in the *second* half of the study. Results are reported in Table E2 of the Appendix. We find that evaluating one more female investor's profile among the first ten profiles is insignificantly associated with more positive attitudes towards female investors in the second half of the study. This goes against the "balance the profile" hypothesis. Moreover, according to the "balance the profile" hypothesis, we should also observe similar data patterns for evaluation results of Asian investors. However, both Table 3 and Figure E1 in the Appendix show that investor's race does not influence entrepreneurs' evaluation results. Similarly, this "fatigue effect" phenomenon does not exist for the other nonsensitive investor characteristics. All of these results make us confident to conclude that "balance the profile" hypothesis is not the driver of our "implicit discrimination" findings.

***Alternative Interpretation.***— Another alternative interpretation of the experimental results is a "learning" story. As subjects are more familiar with the profile evaluation process, they discriminate more against female investors. This situation is even more serious because subjects might be aware that they are discriminating against women and still choose to do so. Then the evidence demonstrating the "implicit gender discrimination" becomes evidence showing the "explicit gender discrimination".

***Rational Beliefs or Not.*** — We find that entrepreneurs generally implicitly assume that female venture capitalists are less likely to assist their startups in succeeding compared to male venture capitalists. Is this belief rational or not? As documented in Gompers, Mukharlyamov, Weisburst and Xuan (2014b), female venture capitalists are indeed associated with lower performance compared to their male colleges. Moreover, Barber, Jiang, Morse, Puri, Tookes and Werner (2021b) documents that the productivity of women are more negatively influenced by the Pandemic compared to men. Hence, the belief of female investors' lower ability seems to be consistent with previous empirical findings. However, this correlation can also be a self-fulfilling phenomenon. As it is harder for female investors to attract high-quality deal flows, the performance of their portfolio companies naturally becomes worse. Our theoretical framework developed in Section 4 will demonstrate how the gender discrimination arises as an equilibrium outcome in a two-sided matching market.

### 3.2 Heterogeneous Effect Based on Entrepreneurs' Gender

Table 4 tests gender homophily by checking whether female entrepreneurs and male entrepreneurs have different fund-seeking patterns. Panel A tests whether male founders have implicit gender discrimination. Panel B tests whether female founders have implicit gender discrimination. "Female Investor" is a dummy variable that is equal to one if the investor has a female first name, and zero otherwise. Columns (1)-(5) show the investor quality evaluation, founders' beliefs in the investor's availability, relative amount of funding asked, contact interest ratings, and the informativeness of each investor profile, separately. The "p-value of Female Investor in the second half of study" provides the p-value of the coefficient of "Female Investor" when we only include the evaluation results in the second half of the study. All the regressions add subject fixed effect. R-squared is indicated for each OLS regression. Standard errors in parentheses are clustered within each experimental subject.

Table 4 shows that it is mainly male entrepreneurs who have implicit gender discrimination against female investors. Column (1) of Panels A and B show that both male and female entrepreneurs spend significantly less time on evaluating profiles in the second half of the study. Column (2) of Panel A shows that male entrepreneurs give 5.15 p.p. higher quality ratings to female investors in the first half of the study. However, this quality ratings of female investors decrease by 12.22 p.p. in the second half of the study. When zooming into the evaluation results of the last 10 investor profiles, we find that female investors receive significantly lower quality ratings than similar male investors. The result is statistically significant at the 1% level, indicating that male entrepreneurs implicitly assume female investors to be less likely to help their startups succeed. Column (2) of Panel B shows that this implicit gender discrimination does not exist for female entrepreneurs, whose quality evaluation results are not significantly influenced by investors' gender information.

Similarly, this "fatigue effect" also exists for male entrepreneurs' availability evaluations and informativeness evaluations. In Column (2) of Panel A, the coefficient of the interaction term between "Female Investor" and "Second Half of Study" is -9.25, which is significant at the 1% level. Moreover, female investors receive 4.09 p.p. fewer availability evaluations in the second half of the study, which is significant at the 10% level. All the results indicate that compared to similar male investors, female investors are perceived to have less investment intention in male entrepreneurs' startups when subjects become rushed or fatigued. Column (5) of Panel A demonstrates similar evaluation patterns of male entrepreneurs in terms of informativeness evaluations. Although male entrepreneurs give 4.23 p.p. higher evaluations to female investors' profiles, this rating declines by 6.47 p.p. in the second half of the study. However, Columns (2) and (5) show that investors' gender information does not influence female entrepreneurs' evaluations of their investment intentions and profiles' perceived informativeness.

Columns (4) and (5) of Panel A find that male entrepreneurs' fundraising decisions are also influenced by investors' gender. In Column (5), male entrepreneurs' willingness to contact female investors is 3.33 p.p. lower than the willingness to contact male investors when they become rushed, which is significant at the 10% level. The coefficient of the interaction term of "Female Investor" and "Second Half of Study" is -9.50, which is significant at the 1% level and confirms the existence of implicit gender discrimination among male entrepreneurs. Column (4) shows that male entrepreneurs also ask for 6.5 p.p. less amount of funding from female investors compared to male investors, although the p-value of this result is only 0.115. Interestingly, Column (4) of Panel B shows that female entrepreneurs feel more comfortable to ask for roughly 5 p.p. more funding from female entrepreneurs in the second half of the study, which is significant at the 10% level. However, female entrepreneurs' likelihood of contacting the investor is still not sensitive to investors' gender information as demonstrated by those insignificant coefficients in Panel B.

To sum up, Table 4 shows that male entrepreneurs have implicit gender discrimination against female investors. However, we do not find gender homophily phenomenon among female entrepreneurs as investor's gender information generally does not influence female entrepreneurs' beliefs or willingness to contact the investor.[20] However, female entrepreneurs might feel more comfortable to raise more funding from female investors, although this result only exists in the second half of the study.

### 3.3 Glass Ceiling: Heterogeneous Effect across Investors' Attractiveness and Positions

In the previous subsections, we only test the average treatment effects of an investor's gender and race on founders' evaluation results. However, as documented in Hegde et al. (2021) and suggested by plenty of anecdotal evidence, there is a glass ceiling phenomenon in the US society where many of the discrimination phenomena concentrate at the senior positions. Hence, to test this "glass ceiling" hypothesis, we exploit multiple quantile regressions and also test whether implicit gender discrimination is more severe for senior female investors.

Table 5 reports the quantile regression results about investor's gender impact across the spectrum of the investor's attractiveness (measured by startups' contact interest ratings $Q_4$) and the investor's quality (measured by startups' quality ratings $Q_1$). The sample only includes evaluation results of profiles in the second half of the study where implicit gender discrimination exists. Dependent variables of Columns [1]–[9] in Panels A and B are the $k$th percentile ($k \in 10, 20, ..., 90$) of the distribution of the investor's perceived attractiveness (i.e., $Q_4$) and quality (i.e., $Q_1$). The dependent variable of Column [10] is the average contact interest ratings of investors in Panel A and the average perceived quality of investors in Panel B. Standard errors are clustered at the startup level and reported in the parentheses.

It should be noted that "attractiveness" and "quality" are different concepts in this paper. "Attractiveness" is a more comprehensive assessment of an investor, which is influenced by both entrepreneurs' taste-driven preferences (i.e., partiality) and belief-driven preferences. Belief-driven preferences are generally influenced by the evaluation of an investor's "quality", investment intentions, and other dimensions. Therefore, "attractiveness" is a better measurement for our purpose compared to "quality" because startups usually choose to collaborate with the most attractive investors in their eyes after assessing many other dimensions of each investor in addition to the investor's quality.

Panel A of Table 5 shows that implicit gender discrimination mainly concentrates on more attractive investors who receive higher contact interest ratings from startup founders. For the bottom 10th quantile investors in terms

[20] Homophily is the tendency of individuals to be attracted by similar others. This homophily mechanism can exist based on gender and race (i.e., female founders prefer female investors and Asian founders prefer Asian investors).

of attractiveness, the coefficient of "Female Investor" is only -1 p.p. and not statistically significant. For the 40th quantile investors, the coefficient of "Female Investor" has increased to -5 p.p. For the 90th quantile investors, the magnitude of implicit gender discrimination has increased to -7 p.p. All these coefficients are statistically significant at the 1% level. This increased significance and magnitudes of implicit gender discrimination confirm the hypothesis that attractive female investors suffer more from implicit gender discrimination compared to unattractive female investors.

Panel B of Table 5 shows that implicit gender discrimination exists for most parts of the investor quality spectrum, especially for those whose quality falls between the 20th quantile and the 80th quantile. Implicit gender discrimination is strongest for the 80th quantile investors in terms of quality. The coefficient of "Female Investor" becomes -10 p.p., which is statistically significant at the 1% level. For the 40th and 50th quantile investors, the coefficient of "Female Investor" is -9 p.p., which is also statistically significant at the 1% level. These results document the widespread existence of the belief that female investors' quality is lower than male investors.

Table 6 further checks whether the impact of investors' gender on startups' evaluation results differs between junior venture capitalists and senior venture capitalists. The sample only includes evaluation results of investor profiles assigned as institutional venture capital investors. Panels A and B test whether startup founders have implicit gender discrimination for senior VC investors and junior VC investors, separately. 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.

Results of Table 6 confirm the existence of glass ceiling for women. Panel A of Table 6 shows that the implicit gender discrimination mainly exists for senior venture capitalists. Column (2) finds that although investors on average give 7.57 p.p. higher quality evaluations to female investors, the evaluations decrease by 16.64 p.p. in the second half of the study, and the coefficient of the interaction term is significantly negative at the 1% level. The p-value of the coefficient of "Female Investor" in the second half of study is 0.093. Columns (3) - (6) show that similar data patterns also exist for startups' evaluations of the investor's other dimensions. However, this phenomenon is not salient in terms of both magnitudes and significance of gender implicit discrimination when subjects evaluate junior VC investors.

## 3.4 Distributional Effect across Startups' Contact Interest Ratings

One special feature of the IRR experimental design is the introduction of candidate quality variations and elicit evaluators' detailed contact interest ratings. This feature enables researchers to test how the direction and magnitude of discrimination vary with the evaluators' internal thresholds and various market conditions. When the capital supply is abundant (limited) on the market, startups have more (less) outside options for their fund-raising purposes and generally increase (decrease) their internal thresholds of choosing future collaboration partners. It is important to check whether startups' implicit gender discrimination becomes more severe when the VC market becomes more competitive for investors.

Figure 2 demonstrates the effect of investor's gender and race across startup founders' contact interest ratings' distribution using the profiles evaluated in the second half. Panel A provides the empirical CDF for investor's gender on startup founders' contact interest ratings (i.e. $Pr(\text{Contact Interest} \leq x|\text{Female Investor})$ and $Pr(\text{Contact Interest} \leq x|\text{Male Investor})$). Panel B provides the OLS coefficient estimates (i.e. $Pr(\text{Contact Interest} \leq x|\text{Female Investor}) - Pr(\text{Contact Interest} \leq x|\text{Male Investor})$) and the corresponding 95% confidence level. Similarly, Panel C provides the empirical CDF for investor's race. Panel D provides the OLS coefficient estimates for investor's race.

Panels A and B show that the implicit gender discrimination mainly exists when the entrepreneur's internal thresholds are higher than 50% contact interest ratings. In this market situation, startups are pickier about which investor they cooperate with, and the competition between different VC firms is more competitive. According to Panels A and B, the negative coefficients of "Female Investor" are the strongest when startups' internal thresholds are around 70% likelihood of contacting the investor. Moreover, the coefficients are mostly significantly negative at the 5% level when the internal thresholds are above 70% likelihood. Similarly, the cdf curve of male investors is always to the right of the cdf curve of female investors in this situation. All the results suggest that female investors face more difficulties in attracting deal flows in a competitive market condition. Panels C and D of Figure 2 show that Asian investors generally do not suffer much from implicit racial discrimination because the coefficients of "Asian Investor" are generally insignificantly positive across startups' contact interest ratings.

### 3.5 Lessons about Implementing Discrimination-related IRR Experiments

As IRR experiment adopts a non-deceptive experimental design, experimental subjects generally receive the consent form, which informs them of the experimental purpose and the researchers' background information. Hence, many factors can cause evidence about discrimination to disappear even though discrimination does exist in the real world setting. From this perspective, IRR experiments are more likely to capture the lower bound of discrimination, especially when monetary compensation is involved. In this subsection, we discuss several noteworthy lessons learned by us when implementing the IRR experiments to test discrimination.

***Consent Form and Risk of Priming Subjects.*** — In the consent form, researchers generally provide their own names and affiliated institutions. During the period when the IRR experiment is implemented, the traffic of researchers' websites can also increase. If some researchers post their discrimination-related research papers on their personal websites, this will significantly increase the risk of priming subjects and failing to get evidence about discrimination. Similarly, if researchers recruit subjects through their own networks, it is important to make sure that these subjects do not deliberately provide pro-social evaluations because they know the exact research purpose of detecting discrimination.

***Candidates' Characteristics.*** — Since IRR experiment can simultaneously test the causal effects of a rich set of candidate characteristics, some researchers might be inclined to add many candidate characteristics into one profile to study more research questions. However, including many characteristics can significantly dilute evaluators' attention on the candidate's gender and race information, leading to weak or no evidence about discrimination. Therefore, it is important to include an appropriate number of candidate characteristics and also make the gender and race information as salient as possible. Moreover, it is dangerous to include other gender or race related characteristics that might also be prime subjects. For example, if researchers include the fraction of women in senior management teams of a VC firm in our experiment, it can make it difficult to discover both gender and racial discrimination.

***Sample Selection Bias.*** — The most commonly used incentive structure in the IRR experiment is still the "matching incentive" created in Kessler et al. (2019). Although this incentive is powerful to incentivize most of the designed evaluation questions, it can also lead to sample selection bias that makes it harder to detect discrimination. For example, in our experimental setting, this matching incentive generally attracts startup founders without many connections in the VC industry, who are more likely to be women and minorities. If discrimination is mainly driven by those mainstream startup founders with enough connections, researchers might not capture it due to the sample selection bias in the recruitment process.

***Subjects' Background Information.*** — Some standard background questions, such as asking for subjects' gender and race, might also prime subjects with the experimental purpose of testing discrimination. This is a more serious concern if some of the background questions are directly related to subjects' attitudes about women and minorities. Therefore, it is important to put all of these questions after the formal evaluation section. If possible, researchers can also forbid subjects from adjusting their evaluation results after they enter the background information section.

# 4 Theoretical Framework

We consider a frictional search market in which entrepreneurs (E) search for venture capital investors (VC) of unknown types.

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

On the other side of the market, there is mass $Q(>0)$ of E. They search for VC based on public information about VC. Specifically, they condition their search on VC's two observable characteristics, rating $j = G, B$ and group identity $\ell = 1, 2$. Each E also belongs to either of the two groups, indexed by $\iota = 1, 2$. Let $Q_\iota$ denote the mass of each E group. Throughout the analysis, we assume $Q_1 > Q_2$.[21]

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

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

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

**Investment.** Once a VC and an E meet, they transact instantaneously and go back to the market. The transaction yields surplus $u_H(u_L)$ if the VC's type is $H(L)$, where $u_H > u_L \geq 0$. If a group $\ell$ VC transacts with a group $\iota$ E, E pays a return $p_{1_{\ell=\iota}}$ to the VC. We say that there exhibits **homophily** in the market *iff* $p_1 > p_0$.

**Ratings.** Market accumulates information about sellers through simple summary indices, called "ratings." There are two possible ratings: $G$ (as in "good") and $B$ (as in "bad"). After each transaction, the VC's rating may be updated to reveal her type. Specifically, with probability $\alpha \in (0, 1]$, a $B$-rated VC with type $H$ receives $G$ rating, and a $G$-rated VC with type $L$ receives $G$ rating. A VC with correct rating keeps the same rating after a transaction. With the remaining probability $1 - \alpha$, the VC's rating remains unchanged. Note that due to the changing environment (or changing type), a correct rating may turn inaccurate.

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

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

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

- **Stationarity**:

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

  where

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

- **Optimality**:

$$
\left(\frac{Q^{\ell 1}_{j} + Q^{\ell 2}_{j}}{P^{\ell}_{Hj} + P^{\ell}_{Lj}}\right)^{k-1} \left(\frac{P^{\ell}_{Hj}u_H + P^{\ell}_{Lj}u_L}{P^{\ell}_{Hj} + P^{\ell}_{Lj}} - p_{\ell=\iota}\right)
$$

  is maximized among all $j, \ell$ for each $r$, when $Q^{\ell\iota}_{j} > 0$.

## 4.1 Equilibrium without homophily

Since $p_0 = p_1$ in this case, we write $p_0 = p_1 = p$. Note that in this setting, E's group becomes irrelevant for payoffs. Hence, the model reduces to the one studied in Che et al. (2020).

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

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

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

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

The above equalities implies:

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

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

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

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

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

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

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

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

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

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

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

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

## 4.2 Equilibrium with homophily

In this setting, we focus on the case where $(u_H + u_L)/2 > p_1$ and $k \leq \frac{1+\sqrt{1-\frac{u_H-u_L}{2(u_H-p_1)}}}{2}$. Per Proposition 1, the gain from trade is large enough to sustain a non-trivial equilibrium and $k$ is sufficiently small to rule out discrimination without homophily. In this case, $u_G(\lambda_G)$ $(u_B(\lambda_B))$ is a strictly decreasing(increasing) function (for either $p = p_0/p_1$).

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

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

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

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

**Key observation:** Since $p_1 > p_0$, then it is straightforward that $\lambda_G^\ell > \lambda_B^\ell$ implies

$$u_G^{11}(\lambda_G^1) - u_B^{11}(\lambda_B^1) < u_G^{12}(\lambda_G^1) - u_B^{12}(\lambda_B^1);$$
$$u_G^{22}(\lambda_G^2) - u_B^{22}(\lambda_B^2) < u_G^{21}(\lambda_G^2) - u_B^{21}(\lambda_B^2).$$

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

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

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

**Theorem 1:** The exists only three types of regular equilibria under homophily:

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

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

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

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

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

  LHS is strictly higher than group 2 E's payoff from market $B1$ due to $p_1 > p$. RHS is group 2 E's payoff from market $G2/B2$. This means group 2 E has no incentive to enter market $B1$. Therefore, this case is not possible.

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

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

  Suppose group 2 E enters $G1$ with strictly positive mass. Then group 2 E's payoff from $B1$ is strictly lower than

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

  This means group 2 E has no incentive to enter market $G1$; hence, this case is not possible. Therefore, the only possibility is that group 2 E only enters $G2, B2$.

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

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

  This immediately implies that group 2 E enters only $B2$.

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

## 4.3 Discussions

**Ethnicity based discrimination** When the group's identity $\ell, \iota$ represents ethnicity, empirical evidence suggests there is no significant homophily. Our results (Proposition 1) then predict that under moderate market congestion ($k \leq \frac{1+\sqrt{1-\frac{u_H-u_L}{2(u_H-p)}}}{2}$) there does not exist any discriminatory equilibrium where group identity leads to differential opportunity for any VC types.

Since our model characterized the stationary equilibrium. We can also interpret it as a long-run prediction: even though statistical discrimination may prevail in the short-run, as long as there is not homophily, the market corrects itself through information revelation.

**Gender based discrimination** When the group identity $\ell, \iota$ represents gender, we interpret group 1 as "men" and group 2 as "women". This interpretation is consistent with the empirical findings that women are "under-represented" among entrepreneurs. Different from the ethnicity-based discrimination case, there is strong empirical evidence that entrepreneurs exhibit homophily based on gender.

Our results (Theorem 1) then predict potential statistical discrimination towards VC based on gender. We say a gender group is (not) discriminated against if whether the quality ratings of the group that are searched does (not) vary with the gender of entrepreneurs.

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

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

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

   When there are not too much male entrepreneurs, female entrepreneurs actively search for female VC of all ratings. However, male entrepreneurs only reach out to highly rated female VC. This leads to low rated female VC to be under-sampled. The key intuition for this phenomenon is that the opportunity cost of searching a different gender group is the real cost scaled by the matching probability. Therefore, homophily as a cost for male entrepreneurs is less costly in a market with lower matching rate & higher average quality. In other words, homophily "hurts" low-rated female more from male entrepreneurs' perspective. Note that there is an "informational externality" associated with searching a Low rating VC: higher frequency of transaction allows those VC with high quality but low ratings to stand out.

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

# 5 Conclusion

This paper aims to explain the unique persistent gender gap in the US entrepreneurial communities through the angle of gender discrimination on both sides of a two-sided matching market. We first implement a startup-side IRR experiment with real US startup founders to examine whether startup founders discriminate against female and Asian investors. Together with Zhang (2020), this experiment complements an experimental system that tests gender discrimination on both the startup side and the investor side. We invite US startup founders to evaluate multiple randomly generated VC and angel investor profiles, which they know to be hypothetical. Then the more truthfully founders provide their evaluation results, the more likely our matching algorithms can help them find matched investors' information from our comprehensive global venture capitalist databases.

We mainly find the following experimental results. First, US startup founders have implicit gender discrimination against female investors, who are perceived to have lower quality and fewer investment intentions. However, this result is mainly driven by male entrepreneurs rather than female entrepreneurs. Second, most of the implicit gender discrimination against women exists among those most attractive investors and senior investors, which suggests the existence of glass ceiling for women in the financial industry. Third, the implicit gender discrimination is also more likely to show up in a competitive market condition when startup founders' internal thresholds are higher and investors need to compete for great deal flows. However, we do not find any evidence about racial discrimination against Asian investors.

Built on the experimental evidence of this paper and Zhang (2020), we also develop a theoretical framework to illustrate how two-sided statistical discrimination can lead to a persistent gender gap in the US entrepreneurial community. Our model can explain several novel empirical findings in recent experiments, such as the potential "discrimination reversion" phenomenon across investors' and startups' attractiveness. Moreover, it also explains why Asians' participation rate in the high-growth entrepreneurship still increases during the previous two decades, although Asian entrepreneurs also suffer from racial discrimination by early-stage investors in the US. This theoretical framework helps to better understand the discrimination issues in any similar two-sided matching markets.

Researchers can replicate our experiments in different countries and at different times. In addition to testing the existence and nature of gender and racial discrimination in other settings, researchers can also implement more sophisticated experimental systems to understand the equilibrium outcomes when discrimination exists among multiple agents of an economic system in the future. Any innovation of experimental methods, which enables more effective detection of discrimination, is also extremely helpful.

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# Tables

Table 1: Summary Statistics of Startup Founders

Panel A: Founder Stated Interest Across Sectors

| Sector | N | Fraction (%) |
|---|---|---|
| *Standard Classification* | | |
| B2B | 22 | 51.2% |
| B2C | 13 | 30.2% |
| Healthcare | 4 | 9.3% |
| Others | 4 | 9.3% |
| | | |
| *Detailed Classification (Repeatable)* | | |
| Information technology | 21 | 48.8% |
| Consumers | 4 | 9.3% |
| Healthcare | 3 | 7.0% |
| Finance | 5 | 11.6% |
| Education | 1 | 2.3% |
| Manufacture & Construction | 5 | 11.6% |
| Others | 5 | 11.6% |
| Industry Agnostic | 1 | 2.3% |

Panel B: Founder Stated Interest Across Stages

| Stage | N | Fraction (%) |
|---|---|---|
| Seed Stage (developing products or services) | 8 | 18.6% |
| Seed Stage (mature products, no revenue) | 4 | 9.3% |
| Seed Stage (mature products, positive revenue) | 21 | 48.8% |
| Series A | 5 | 11.6% |
| Series B | 3 | 7.0% |
| Series C or later stages | 2 | 4.7% |

Panel C: Founder Stated Background Information

| | N | Fraction (%) |
|---|---|---|
| Female Founder | 12 | 27.9% |
| Minority Founder | 8 | 18.6% |
| Serial Founder | 32 | 74.4% |
| Have Female Co-founder | 38 | 88.4% |
| US Founder | 43 | 100% |

Panel D: Startup's Goal

| | N | Fraction (%) |
|---|---|---|
| Financial Gains | 35 | 81.4% |
| Promote Diversity | 27 | 62.8% |
| ESG Criteria | 17 | 39.5% |
| Destructive Innovation | 9 | 20.9% |

*Notes.*This table reports descriptive statistics for the startup founders who participated in this experiment. In total, 43 startup founders all from the U.S. provided evaluations of 860 randomly generated investor profiles. Panel A reports the sector distribution of participants' startups. In the detailed Classification method, founders can indicate their interests in multiple industries. "Others" includes HR tech, Property tech, infrastructure, etc. "Industry Agnostic" means the founder does not indicate his/her startup sectors. Panel B reports the stage distribution of the participants' startups where each founder can only choose one unique stage. Panel C reports the background information of the recruited founders and their startup teams. "Female Founder" is an indicator variable which equals one if the founder is female, and zero otherwise. "Minority Founder" is an indicator variable which equals one if the investor is Asian, Hispanic, Middle Eastern, Native American, Pacific Islander, or African Americans, and zero otherwise. "Serial Founder" is equal to one if the founder is a serial entrepreneur, and zero otherwise. "Have Female Co-founder" indicates whether the startup team has at least one female founder. "US Founder" is equal to one if the founder is located in the US based on the longitude and latitude collected by the Qualtrics System, and zero otherwise. Panel D provides the startup's missions which contain whether they aim for any financial returns, aim to promote diversity of the entrepreneurial community, care about ESG impact, or aim for destructive innovations. Each founder can choose multiple startup missions.

Table 2: Randomization of Investor Profile Components

| Profile Component | Randomization Description | Analysis Variable |
|---|---|---|
| *Investor's individual-level characteristics* | | |
| First and Last Names | Drawn from list of 50 candidate names given randomly assigned race and gender. For detailed names, please see Online Appendix. Race randomly drawn (40% Asian, 60% White), Gender randomly drawn (40% Female, 60% Male) | White Female (24%) Asian Female (16%) White Male (36%) Asian Male (24%) |
| Position/Titles | Drawn randomly following the distribution VC Junior: VC Senior: Angel=35%:35%:30%. Within each category, uniformly drawn a detailed position according to Online Appendix Table E6 | Junior VC (35%) Senior VC (35%) Angel Investors (30%) |
| Entrepreneurial Experiences | Drawn from a list of entrepreneurial experience descriptions extracted from real venture capitalists' and angel investors' biography. For detailed wording used, please see Online Appendix Table E7 and Table E8 | With Entrepreneurial Experience (10/20) |
| *Educational background* | | |
| Degree | Degree drawn randomly (50% Bachelor (BA/BS), 50% graduate school degrees (JD/MBA/Master/PhD)) For detailed list of degrees, please see Online Appendix Table E9 | Graduate Degree (10/20) |
| College | College drawn randomly (50% prestigious universities, 50% common universities). For detailed list of schools, please see Online Appendix Table E9. | Prestigious College (10/20) |
| *Investment experience* | | |
| Years of Investment Experience & Number of deals | Within each investor's type and seniority, years of investment experiences and number of deals are randomized based on Table E10 | Years of investment experiences; Number of deals |
| *Investor's fund-level characteristics* | | |
| Fund Size | Within each investor type (i.e., VC investor or angel investor), the fund size as measured by AUM and dray powder will be drawn based on the distribution shown in Table E11. To facilitate entrepreneurs to understand the relative size of each fund, we add a description of "relatively large VC fund", "relatively small VC fund" or "relatively large angel fund", "relatively small angel fund" in the profile. | Large Fund (10/20) |
| Investment Philosophy | Drawn randomly (50% profit-driven fund, 50% impact fund) No extra description is used to elaborate the meaning of impact funds and profit-driven funds. | Impact Fund (10/20) |

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

Table 3: Implicit Gender and Racial Discrimination

| Dependent Variable | Response Time (Unit: Second) (1) | Q1 Quality (2) | Q2 Availability (3) | Q3 Funding (4) | Q4 Contact (5) | Q5 Informativeness (6) |
|---|---|---|---|---|---|---|
| *Panel A: Gender* | | | | | | |
| Second Half of Study | -18.93*** | 4.28** | 3.95** | -0.06 | 4.69** | 3.69* |
| | (2.60) | (2.05) | (1.70) | (1.62) | (1.81) | (2.03) |
| Female Investor | 0.97 | 5.04** | 2.87** | 2.69* | 4.81** | 2.56 |
| | (2.00) | (1.97) | (1.68) | (1.45) | (1.95) | (1.71) |
| Female Investor × Second Half of Study | | -10.41*** | -6.26*** | -5.28** | -6.76** | -3.55 |
| | | (2.64) | (2.20) | (2.30) | (2.54) | (2.36) |
| p-value of Female Investor in the second half of study | | 0.008 | 0.077 | 0.280 | 0.164 | 0.684 |
| Subject FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Mean of Dependent Variables | 40.77 | 63.90 | 64.01 | 55.58 | 66.68 | 71.39 |
| Observations | 860 | 860 | 860 | 860 | 860 | 860 |
| R-squared | 0.41 | 0.31 | 0.35 | 0.55 | 0.34 | 0.42 |
| *Panel B: Race* | | | | | | |
| Second Half of Study | -19.06*** | 1.46 | 2.26 | -2.01 | 2.05 | 3.14 |
| | (2.63) | (2.19) | (1.93) | (1.85) | (2.10) | (2.36) |
| Asian Investor | 2.02 | 0.94 | -0.23 | -1.11 | -0.42 | -0.14 |
| | (2.28) | (1.91) | (1.78) | (1.62) | (2.14) | (2.26) |
| Asian Investor × Second Half of Study | | -2.41 | -1.35 | 0.22 | 0.52 | -1.63 |
| | | (2.96) | (2.67) | (2.81) | (3.03) | (3.09) |
| p-value of Asian Investor in the second half of study | | 0.546 | 0.412 | 0.939 | 0.953 | 0.608 |
| Subject FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Mean of Dependent Variables | 40.77 | 63.90 | 64.01 | 55.58 | 66.68 | 71.39 |
| Observations | 860 | 860 | 860 | 860 | 860 | 860 |
| R-squared | 0.41 | 0.30 | 0.35 | 0.54 | 0.33 | 0.42 |

*Notes.* This table reports regression results of how founders' response time and evaluation results respond to an investor's gender and race in the first and second half of the study. Panel A tests the implicit discrimination based on investor's gender. Panel B tests the implicit discrimination based on investor's race. "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. "Second Half of Study" is an indicator variable for investor profiles shown among the last ten investor resumes viewed by an experimental subject. In column (1), the dependent variable is startup founders' response time, which is defined as the number of seconds before each page submission, winsorized at the 95th percentile (40.77 seconds on average). Columns (2)-(6) show the quality evaluation, founders' beliefs in the investor's availability, relative amount of funding asked, contact interest ratings, and the perceived informativeness of each investor profile, separately. The "p-value of Female Investor (or Asian Investor) in the second half of study" provides the p-value of the coefficient of "Female Investor" (or "Asian Investor") when we only include the evaluation results in the second half of the study. All the regressions add subject fixed effect. R-squared is indicated for each OLS regression. Standard errors in parentheses are clustered within each experimental subject. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Table 4: Homophily Based on Founder's Gender

| Dependent Variable | Response Time (Unit: Second) (1) | Q1 Quality (2) | Q2 Availability (3) | Q3 Funding (4) | Q4 Contact (5) | Q5 Informativeness (6) |
|---|---|---|---|---|---|---|
| *Panel A: Male Founders* | | | | | | |
| Second Half of Study | -18.15*** | 3.72 | 4.57** | 0.24 | 4.52** | 4.60* |
| | (2.27) | (2.42) | (2.13) | (2.10) | (2.17) | (2.59) |
| Female Investor | -0.39 | 5.15** | 4.72*** | 3.12* | 6.49*** | 4.23** |
| | (2.23) | (2.05) | (1.69) | (1.60) | (2.07) | (1.67) |
| Female Investor × Second Half of Study | | -12.22*** | -9.25*** | -7.20** | -9.50*** | -6.47** |
| | | (3.30) | (2.48) | (2.76) | (3.05) | (2.80) |
| p-value of Female Investor in the second half of study | | 0.004 | 0.071 | 0.115 | 0.086 | 0.280 |
| Subject FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Mean of Dependent Variables | 40.64 | 62.49 | 62.98 | 52.01 | 65.99 | 70.41 |
| Observations | 620 | 620 | 620 | 620 | 620 | 620 |
| R-squared | 0.44 | 0.25 | 0.27 | 0.46 | 0.27 | 0.37 |
| *Panel B: Female Founders* | | | | | | |
| Second Half of Study | -20.79** | 5.66 | 2.34 | -0.80 | 4.98 | 1.41 |
| | (7.32) | (4.11) | (2.80) | (2.29) | (3.47) | (3.16) |
| Female Investor | 4.52 | 4.40 | -2.39 | 1.35 | -0.07 | -2.14 |
| | (4.19) | (4.72) | (3.82) | (3.32) | (4.14) | (3.99) |
| Female Investor × Second Half of Study | | -4.42 | 2.49 | 0.50 | 1.77 | 4.86 |
| | | (3.41) | (3.58) | (3.82) | (3.71) | (3.12) |
| p-value of Female Investor in the second half of study | | 0.981 | 0.954 | 0.066 | 0.505 | 0.117 |
| Subject FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Mean of Dependent Variables | 41.10 | 67.53 | 66.66 | 64.78 | 68.48 | 73.93 |
| Observations | 240 | 240 | 240 | 240 | 240 | 240 |
| R-squared | 0.34 | 0.45 | 0.56 | 0.66 | 0.53 | 0.56 |

*Notes.* This table reports regression results of how female founders and male founders respond to an investor's gender differently. Panel A tests whether male founders have implicit gender discrimination. Panel B tests whether female founders have implicit gender discrimination. "Female Investor" is a dummy variable that is equal to one if the investor has a female first name, and zero otherwise. Columns (1)-(5) show the investor quality evaluation, founders' beliefs in the investor's availability, relative amount of funding asked, contact interest ratings, and the informativeness of each investor profile, separately. The "p-value of Female Investor in the second half of study" provides the p-value of the coefficient of "Female Investor" when we only include the evaluation results in the second half of the study. All the regressions add subject fixed effect. R-squared is indicated for each OLS regression. Standard errors in parentheses are clustered within each experimental subject. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 5: Quantile-Regression Estimates for Startups' Evaluations (Gender)

Panel A. Contact Interest Ratings (i.e., $Q_4$)

| | 10th [1] | 20th [2] | 30th [3] | 40th [4] | 50th [5] | 60th [6] | 70th [7] | 80th [8] | 90th [9] | Mean [10] |
|---|---|---|---|---|---|---|---|---|---|---|
| Female Investor | -1.00 | -5.00 | -3.00 | -5.00** | -6.00*** | -5.00** | -3.00 | -5.00** | -7.00*** | -2.12 |
| | (6.87) | (3.54) | (2.73) | (2.50) | (2.20) | (2.24) | (2.06) | (2.25) | (2.03) | (1.50) |
| Quantile of Dep. Var. | 39 | 50 | 58 | 63 | 70 | 74.5 | 80 | 84 | 92 | 66.68 |
| Observations | 430 | 430 | 430 | 430 | 430 | 430 | 430 | 430 | 430 | 430 |

Panel B. Quality Ratings (i.e., $Q_1$)

| | 10th [1] | 20th [2] | 30th [3] | 40th [4] | 50th [5] | 60th [6] | 70th [7] | 80th [8] | 90th [9] | Mean [10] |
|---|---|---|---|---|---|---|---|---|---|---|
| Female Investor | -5.00 | -7.00** | -8.00*** | -9.00*** | -9.00*** | -6.00*** | -5.00** | -10.00*** | -5.00 | -5.14*** |
| | (4.78) | (3.01) | (2.89) | (2.54) | (2.17) | (2.27) | (2.47) | (3.83) | (3.83) | (1.83) |
| Quantile of Dep. Var. | 37 | 50 | 55.5 | 61 | 67 | 70 | 74 | 80 | 90 | 63.90 |
| Observations | 430 | 430 | 430 | 430 | 430 | 430 | 430 | 430 | 430 | 430 |

*Notes.* This table reports the effects of investor's gender on the quantiles and the mean of investors' attractiveness evaluations (i.e., $Q_4$) and quality evaluations (i.e., $Q_1$) of the second half of the experiment in Wave 1. In each of Columns [1]–[9], the dependent variable is the $k$th percentile ($k \in 10, 20, ..., 90$) of the distribution of the investor's perceived attractiveness measured by startups' contact interest ratings (i.e., $Q_4$) in Panel A and perceived quality measured by startups' quality ratings (i.e., $Q_1$) in Panel B; in Column [10], the dependent variable is the average startup's contact interest ratings of the second half profiles in Panel A and the average quality ratings of the the second half profiles in Panel B. Standard errors are clustered at the subject level, and reported in parentheses. $*p < 0.10, **p < 0.05, ***p < 0.01$

Table 6: Heterogeneous Effect Based on Investor's Seniority

| Dependent Variable | Response Time (Unit: Second) (1) | Q1 Quality (2) | Q2 Availability (3) | Q3 Funding (4) | Q4 Contact (5) | Q5 Informativeness (6) |
|---|---|---|---|---|---|---|
| *Panel A: Senior Investors* | | | | | | |
| Second Half of Study | -20.15*** | 8.29*** | 6.53*** | 4.15* | 9.45*** | 7.06** |
| | (2.93) | (2.83) | (2.10) | (2.35) | (2.44) | (2.74) |
| Female Investor | -0.18 | 7.57** | 4.87* | 5.42*** | 7.23** | 4.23 |
| | (3.55) | (3.19) | (2.44) | (1.85) | (2.98) | (2.79) |
| Female Investor × Second Half of Study | | -16.64*** | -12.06*** | -7.56* | -11.70** | -8.97** |
| | | (5.21) | (3.11) | (3.79) | (4.69) | (4.09) |
| p-value of Female Investor in the second half of study | | 0.093 | 0.128 | 0.791 | 0.227 | 0.343 |
| Subject FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Mean of Dependent Variables | 44.19 | 66.66 | 64.47 | 57.22 | 68.99 | 74.25 |
| Observations | 301 | 301 | 301 | 301 | 301 | 301 |
| R-squared | 0.61 | 0.42 | 0.51 | 0.67 | 0.44 | 0.50 |
| *Panel B: Junior Investors* | | | | | | |
| Second Half of Study | -20.47*** | 3.39 | 3.75 | -1.62 | 3.64 | 3.48 |
| | (3.78) | (2.80) | (2.53) | (2.68) | (3.00) | (3.17) |
| Female Investor | 0.12 | 3.91 | 2.25 | 1.71 | 2.31 | 0.31 |
| | (3.48) | (3.18) | (2.83) | (3.28) | (3.00) | (2.86) |
| Female Investor × Second Half of Study | | -8.48** | -3.11 | -3.57 | -5.42 | -1.27 |
| | | (3.52) | (3.71) | (4.17) | (4.06) | (3.88) |
| p-value of Female Investor in the second half of study | | 0.166 | 0.894 | 0.993 | 0.342 | 0.611 |
| Subject FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Mean of Dependent Variables | 39.51 | 61.25 | 61.79 | 54.70 | 64.28 | 68.82 |
| Observations | 301 | 301 | 301 | 301 | 301 | 301 |
| R-squared | 0.36 | 0.50 | 0.54 | 0.59 | 0.52 | 0.55 |

*Notes.* This table reports regression results of how senior investors' gender information and junior investors' gender information affect startups' evaluation results. Panel A tests whether startup founders have implicit gender discrimination for senior VC investors. Panel B tests whether startup founders have implicit gender discrimination for junior VC investors. "Female Investor" is a dummy variable that is equal to one if the investor has a female first name, and zero otherwise. Columns (1)-(5) show the investor quality evaluation, founders' beliefs in the investor's availability, relative amount of funding asked, contact interest ratings, and the informativeness of each investor profile, separately. The "p-value of Female Investor in the second half of study" provides the p-value of the coefficient of "Female Investor" when we only include the evaluation results in the second half of the study. All the regressions add subject fixed effect. R-squared is indicated for each OLS regression. Standard errors in parentheses are clustered within each experimental subject. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

## Figures

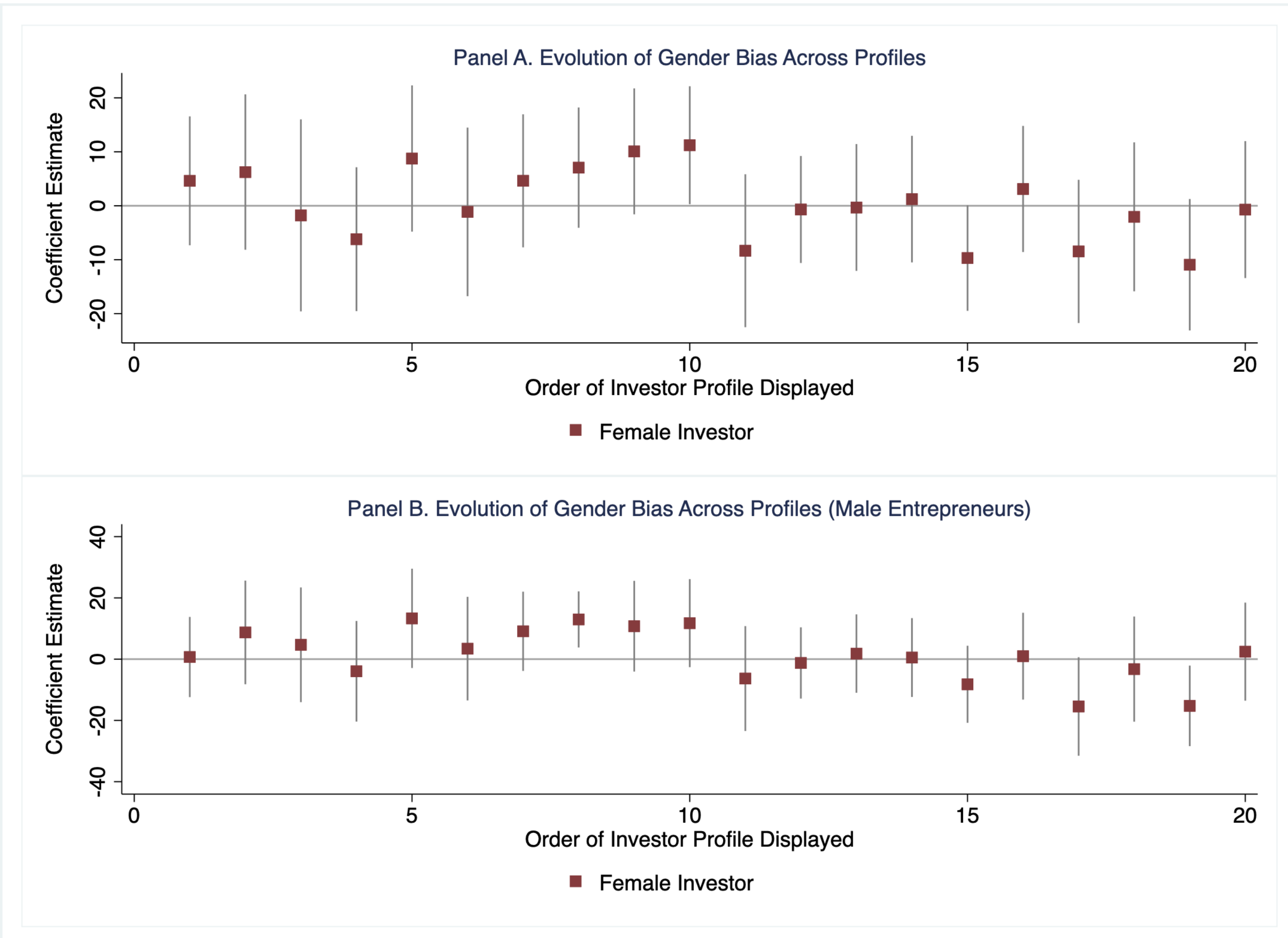



Figure 1: Evolution of Gender Discrimination

*Notes.* This figure demonstrates how the 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 $i^{th}$ displayed investor profile). The vertical line is the coefficient of "Female Investor" of the following regressions: $Q_4 = \beta$Female Investor$+\epsilon$ for all subjects' evaluation results of the $i^{th}$ displayed investor profiles. This indicates the magnitude of gender discrimination as measured by entrepreneurs' contact interest ratings (i.e., $Q_4$). Panel A uses all subjects' evaluation results and Panel B uses only male entrepreneurs' evaluation results.

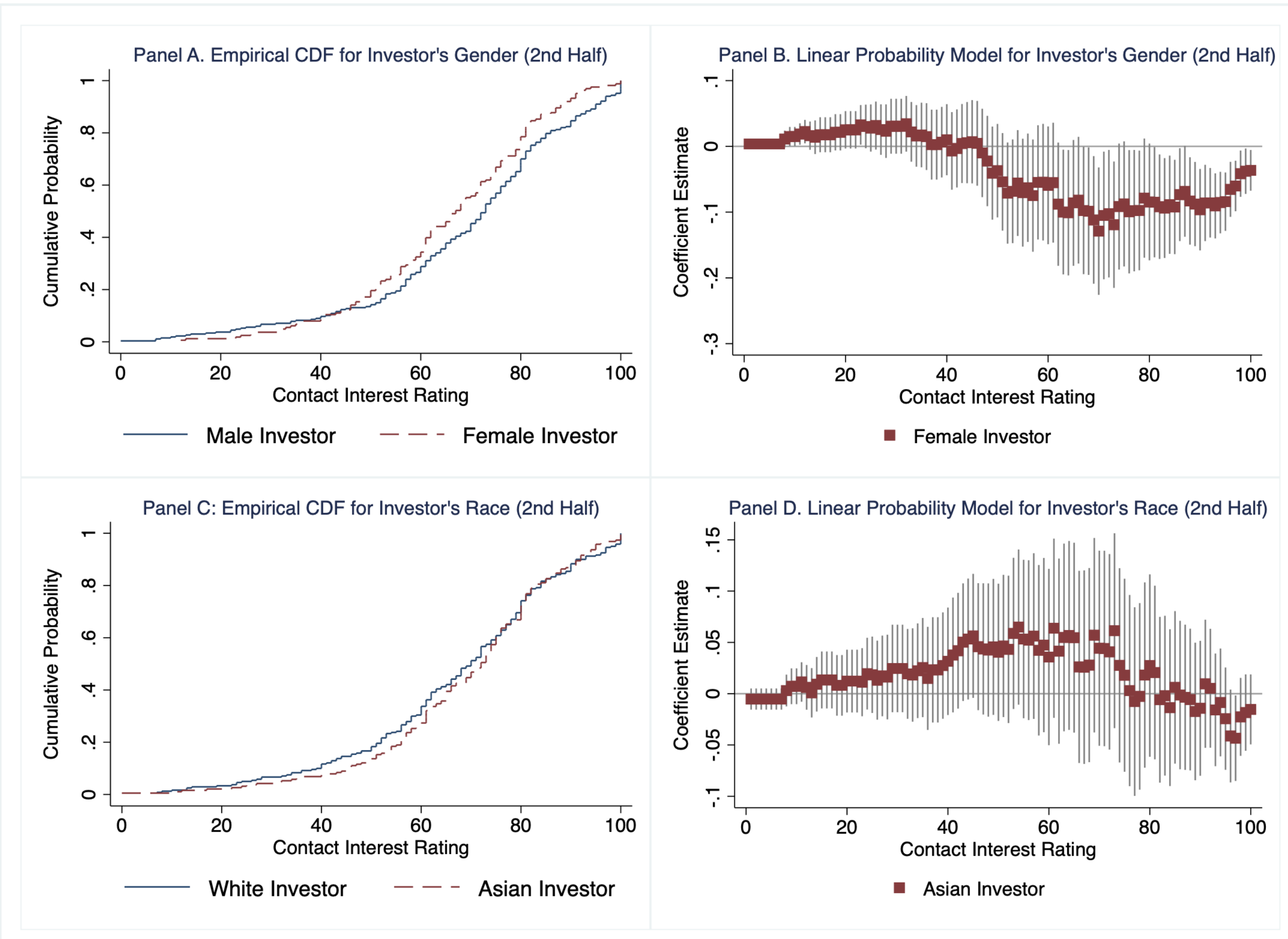



Figure 2: Effect of Investor's Gender and Race across the Contact Interest Distribution (2nd Half of Profiles)

*Notes*: This figure demonstrates the effect of investor's gender and race across startup founders' contact interest distribution using the profiles evaluated in the second half. Panel A provides the empirical CDF for investor's gender on startup founders' contact interest rating (i.e. $Pr(\text{Contact Interest} \leq x|\text{Female Investor})$ and $Pr(\text{Contact Interest} \leq x|\text{Male Investor})$). Panel B provides the OLS coefficient estimates (i.e. $Pr(\text{Contact Interest} \leq x|\text{Female Investor}) - Pr(\text{Contact Interest} \leq x|\text{Male Investor})$) and the corresponding 95% confidence level. Similarly, Panel C provides the empirical CDF for investor's race. Panel D provides the OLS coefficient estimates for investor's race.

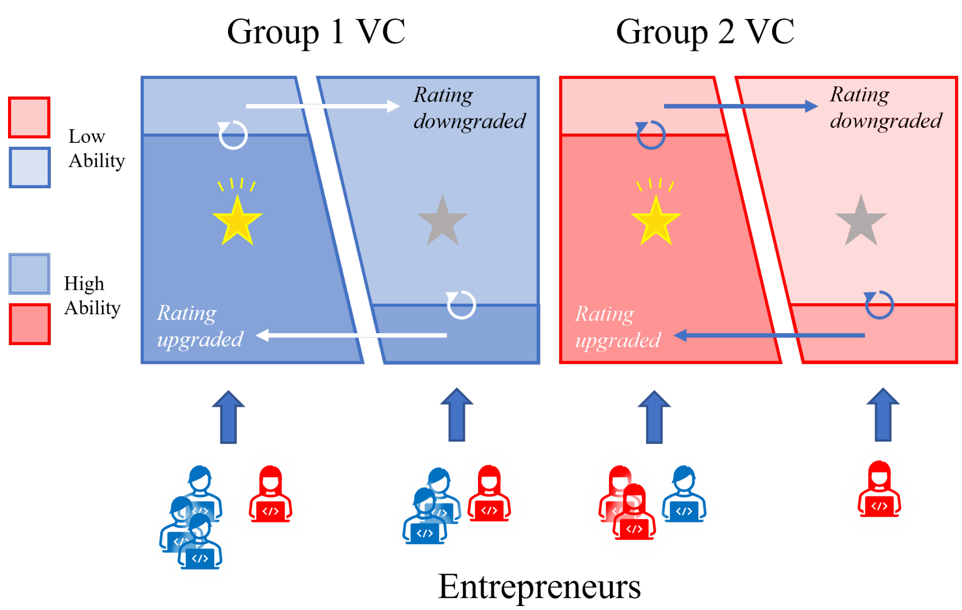



Figure 3: Ratings-guided matching market

**Title: Invitation for Trying a Startup-Investor Matching Tool from Columbia University**

Dear [Founder First Name],

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

The purpose of this research project is to understand the entrepreneurial financing process (for example, founders' preferences for future collaborative investors) and remove the frictions typically found in the fund-raising process using the matching algorithms we have developed (i.e., the "Nano-Search Financing Tool") that can match startup founders with the best potential investors from our Global Investor Database. The research project is supervised by Prof. Jack Willis and led by a Columbia Economics Ph.D. student, Ye (Iris) Zhang.

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

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

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

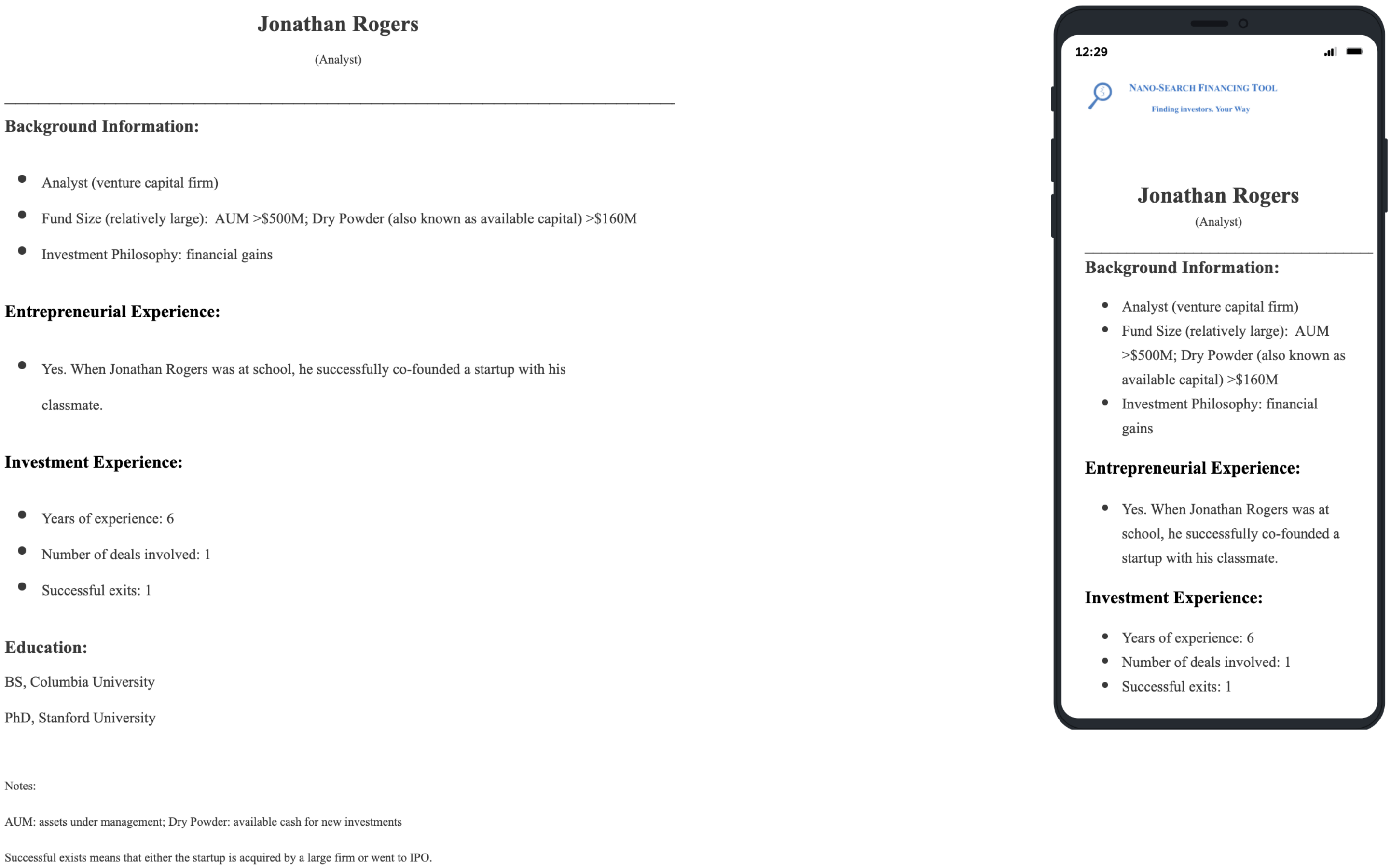
If you would like more detailed information about how the tool will enhance your startup's fund-raising process or have questions, please contact the tool developer and project investigator, Ye (Iris) Zhang (yz2865@columbia.edu).

Sincerely,

Columbia Economics Research Team

Figure 4: Recruitment Email


Figure 5: Instruction Poster



**Jonathan Rogers**

(Analyst)

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**Background Information:**

- Analyst (venture capital firm)
- Fund Size (relatively large):  AUM >$500M; Dry Powder (also known as available capital) >$160M
- Investment Philosophy: financial gains

**Entrepreneurial Experience:**

- Yes. When Jonathan Rogers was at school, he successfully co-founded a startup with his classmate.

**Investment Experience:**

- Years of experience: 6
- Number of deals involved: 1
- Successful exits: 1

**Education:**

BS, Columbia University

PhD, Stanford University

Notes:

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

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



Figure 6: Sample Investor Profile

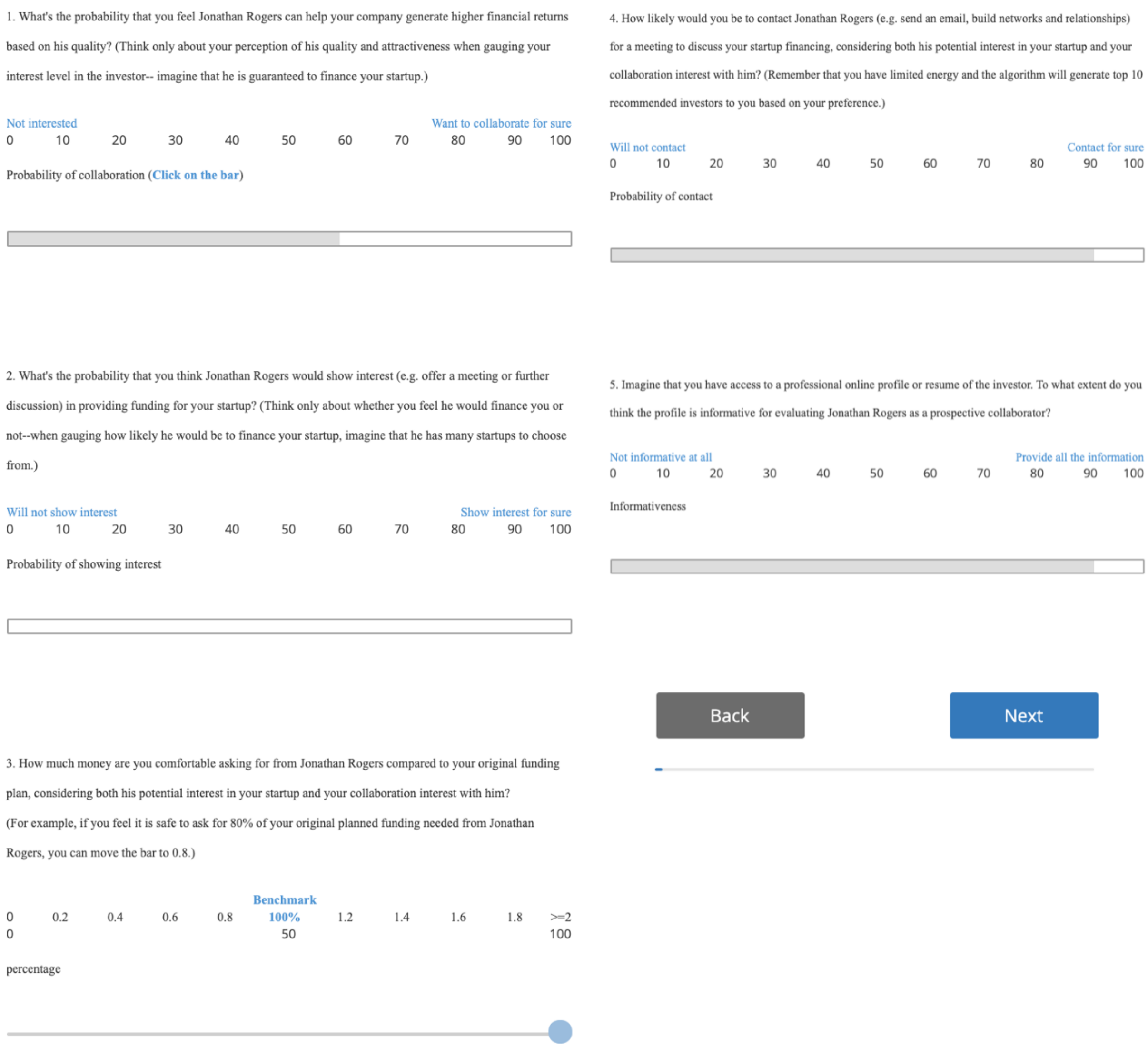


Figure 7: Sample Evaluation Questions

# Appendix

Table E1: Explicit Gender and Racial Discrimination

| Dependent Variable | Q1<br>Quality<br>(1) | Q2<br>Availability<br>(2) | Q3<br>Funding<br>(3) | Q4<br>Contact<br>(4) | Q5<br>Informativeness<br>(5) |
|---|---|---|---|---|---|
| *Panel A. Gender* | | | | | |
| Female Investor | -0.21 | -0.25 | -0.03 | 1.46 | 0.83 |
| | (1.27) | (1.13) | (0.89) | (1.12) | (1.00) |
| Subject FE | Yes | Yes | Yes | Yes | Yes |
| Mean of Dependent Variables | 63.90 | 64.01 | 55.58 | 66.68 | 71.39 |
| Profile Observations | 860 | 860 | 860 | 860 | 860 |
| R-squared | 0.29 | 0.35 | 0.54 | 0.33 | 0.41 |
| *Panel B. Race* | | | | | |
| Asian Investor | -0.27 | -0.78 | -1.16 | 0.04 | -0.78 |
| | (1.36) | (1.23) | (1.41) | (1.32) | (1.54) |
| Subject FE | Yes | Yes | Yes | Yes | Yes |
| Mean of Dependent Variables | 63.90 | 64.01 | 55.58 | 66.68 | 71.39 |
| Profile Observations | 860 | 860 | 860 | 860 | 860 |
| R-squared | 0.29 | 0.35 | 0.54 | 0.33 | 0.41 |

*Notes.* This table describes entrepreneurs' evaluation results combining total profile evaluations provided by startup founders recruited in Wave 1, including the ten profiles in the first half and the ten profiles in the second half. Panel A shows founders' evaluation results based on investors' gender. "Female Investor" is a dummy variable that is equal to one if the investor has a female first name, and zero otherwise. Panel B shows evaluation results based on investor's race. "Asian Investor" is a dummy variable that is equal to one if the investor has an Asian last name, and zero otherwise. In column (1), the dependent variable is the quality evaluation, which indicates the probability that the investor can help founders to generate higher financial returns based on the investor's quality. In column (2), the dependent variable measures how likely the founder thinks that the investor will choose their startup among many potential alternative options. In column (3), the dependent variable is the relative amount of funding that the founder is comfortable asking for compared with his/her original funding plan. The unit is two-hundredth of the relative funding amount. For example, if the founder's original plan is to raise \$1M for the startup and Q3 is equal to 4, it means that the founder feels comfortable about asking for \$1M $\times$ 5 $\times$ 2% = \$100,000 from the investor to fund the company. In column (4), the dependent variable is the startup founder's contact interest rating, which describes the probability that the founder plans to contact this investor. In column (5), the dependent variable is the informativeness of the investor's profile, which describes how informative the provided information is to each experimental subject. All the regressions add subject fixed effects. Standard errors in parentheses are clustered within each subject. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table E2: Test the "Balance the Profile" Hypothesis

| Dependent Variable | $\beta_1$ Quality (1) | $\beta_2$ Availability (2) | $\beta_3$ Funding (3) | $\beta_4$ Contact (4) | $\beta_5$ Informativeness (5) |
|---|---|---|---|---|---|
| # of Female Investor Profiles in the First Half of Study | 1.61 | 1.62 | 0.09 | 0.11 | -0.61 |
| | (1.49) | (1.32) | (0.93) | (0.92) | (0.99) |
| Profile Observations | 43 | 43 | 43 | 43 | 43 |
| R-squared | 0.03 | 0.03 | 0.00 | 0.00 | 0.01 |

*Notes.* This table tests the "balance the profile" hypothesis by investigating 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. "# of Female Investor Profiles in the First Half of Study" stands for the number of female investors' profiles evaluated by the subject in the first half of the study (i.e., among the first 10 profiles evaluated). The dependent variables are the coefficients of "Female Investor" of the following OLS regressions using evaluation results of investor profiles displayed in the second half of the study. $Q_{ik} = \beta_{ik}\text{Female Investor} + \epsilon_{ik}$ for each subject $i$ and $k \in \{1, 2, 3, 4, 5\}$. In Columns (1) - (5), the dependent variables are $\beta_1$, $\beta_2$, $\beta_3$, $\beta_4$, and $\beta_5$, indicating investors' attitudes about female investors compared to similar male investors in terms of quality evaluations, availability evaluations, funding to be raised, contact interest ratings, and perceived informativeness of each profile, separately. Standard errors in parentheses are robust standard errors. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table E3: Homophily Based on Founder's Race

| Dependent Variable | Response Time (Unit: Second) (1) | Q1 Quality (2) | Q2 Availability (3) | Q3 Funding (4) | Q4 Contact (5) | Q5 Informativeness (6) |
|---|---|---|---|---|---|---|
| *Panel A: White Founders* | | | | | | |
| Second Half of Study | -20.59*** | -0.05 | 0.79 | -3.67* | 0.46 | 0.84 |
| | (2.98) | (2.49) | (2.11) | (1.99) | (2.35) | (2.45) |
| Asian Investor | 2.47 | 1.40 | 0.69 | -0.78 | -0.55 | 0.17 |
| | (2.54) | (2.13) | (1.69) | (1.52) | (2.30) | (1.88) |
| Asian Investor × | | -1.63 | -1.70 | 1.10 | 0.94 | -0.71 |
| Second Half of Study | | (3.33) | (2.93) | (3.18) | (3.31) | (3.10) |
| p-value of Asian Investor in the second half of study | | 0.933 | 0.569 | 0.703 | 0.891 | 0.833 |
| Subject FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Mean of Dependent Variables | 42.25 | 63.89 | 63.78 | 54.38 | 66.41 | 71.36 |
| Observations | 700 | 700 | 700 | 700 | 700 | 700 |
| R-squared | 0.45 | 0.26 | 0.33 | 0.50 | 0.34 | 0.42 |
| *Panel B: Minority Founders* | | | | | | |
| Second Half of Study | -12.27*** | 8.48** | 8.87* | 5.74 | 9.44** | 13.84** |
| | (4.72) | (3.37) | (3.92) | (3.85) | (3.56) | (5.55) |
| Asian Investor | -0.22 | -0.99 | -4.46 | -2.40 | 0.47 | -1.20 |
| | (4.91) | (3.80) | (5.32) | (5.54) | (5.40) | (9.11) |
| Asian Investor × | | -6.27 | -0.00 | -4.21 | -2.18 | -6.59 |
| Second Half of Study | | (5.79) | (6.46) | (5.91) | (7.50) | (10.43) |
| p-value of Asian Investor in the second half of study | | 0.085 | 0.294 | 0.176 | 0.823 | 0.287 |
| Subject FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Mean of Dependent Variables | 34.29 | 63.91 | 65.01 | 60.80 | 67.85 | 71.52 |
| Observations | 160 | 160 | 160 | 160 | 160 | 160 |
| R-squared | 0.21 | 0.49 | 0.46 | 0.70 | 0.32 | 0.44 |

*Notes.* This table reports regression results testing how white founders and minority founders (defined as non-white founders) respond to an investor's race differently. The founders are recruited in Wave 1. Panel A tests whether white founders have implicit racial discrimination. Panel B tests whether minority founders have implicit racial discrimination. "Asian Investor" is a dummy variable that is equal to one if the investor has an Asian last name, and zero otherwise. Columns (1)-(5) show the investor quality evaluation, founders' beliefs in the investor's availability, relative amount of funding asked, contact interest ratings, and the informativeness of each investor profile, separately. The "p-value of Asian Investor in the second half of study" provides the p-value of the coefficient of "Asian Investor" when we only include the evaluation results in the second half of the study. All the regressions add subject fixed effect. R-squared is indicated for each OLS regression. Standard errors in parentheses are clustered within each experimental subject. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Table E4: Quantile-Regression Estimates for Startups' Evaluations (Race)

Panel A. Contact Interest Ratings (i.e., $Q_4$)

| | 10th [1] | 20th [2] | 30th [3] | 40th [4] | 50th [5] | 60th [6] | 70th [7] | 80th [8] | 90th [9] | Mean [10] |
|---|---|---|---|---|---|---|---|---|---|---|
| Asian Investor | 7.00 | 4.00 | 3.00 | 3.00 | 2.00 | 0.00 | 0.00 | -1.00 | -1.00 | 0.12 |
| | (4.42) | (3.31) | (2.67) | (2.54) | (2.53) | (1.86) | (2.05) | (1.96) | (2.12) | (1.96) |
| Mean of Dep. Var. | 39 | 50 | 58 | 63 | 70 | 74.5 | 80 | 84 | 92 | 66.68 |
| Observations | 430 | 430 | 430 | 430 | 430 | 430 | 430 | 430 | 430 | 430 |

Panel B. Quality Ratings (i.e., $Q_1$)

| | 10th [1] | 20th [2] | 30th [3] | 40th [4] | 50th [5] | 60th [6] | 70th [7] | 80th [8] | 90th [9] | Mean [10] |
|---|---|---|---|---|---|---|---|---|---|---|
| Asian Investor | 0.00 | 1.00 | 0.00 | 0.00 | -1.00 | -1.00 | -1.00 | -1.00 | -3.00 | -1.34 |
| | (4.64) | (2.72) | (2.84) | (2.86) | (2.38) | (2.36) | (2.28) | (3.45) | (3.18) | (2.21) |
| Mean of Dep. Var. | 37 | 50 | 55.5 | 61 | 67 | 70 | 74 | 80 | 90 | 63.90 |
| Observations | 430 | 430 | 430 | 430 | 430 | 430 | 430 | 430 | 430 | 430 |

*Notes.* This table reports the effects of investors' race on the quantiles and the mean of investors' attractiveness evaluations (i.e., $Q_4$) and quality evaluations (i.e., $Q_1$) of the second half of the experiment in Wave 1. In each of Columns [1]–[9], the dependent variable is the $k$th percentile ($k \in 10, 20, ..., 90$) of the distribution of the investor's perceived attractiveness measured by startups' contact interest ratings (i.e., $Q_4$) in Panel A and perceived quality measured by startups' quality ratings (i.e., $Q_1$) in Panel B; in Column [10], the dependent variable is the average startup's contact interest ratings of the second half profiles in Panel A and the average quality ratings of the second half profiles in Panel B. Standard errors are clustered at the subject level and reported in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

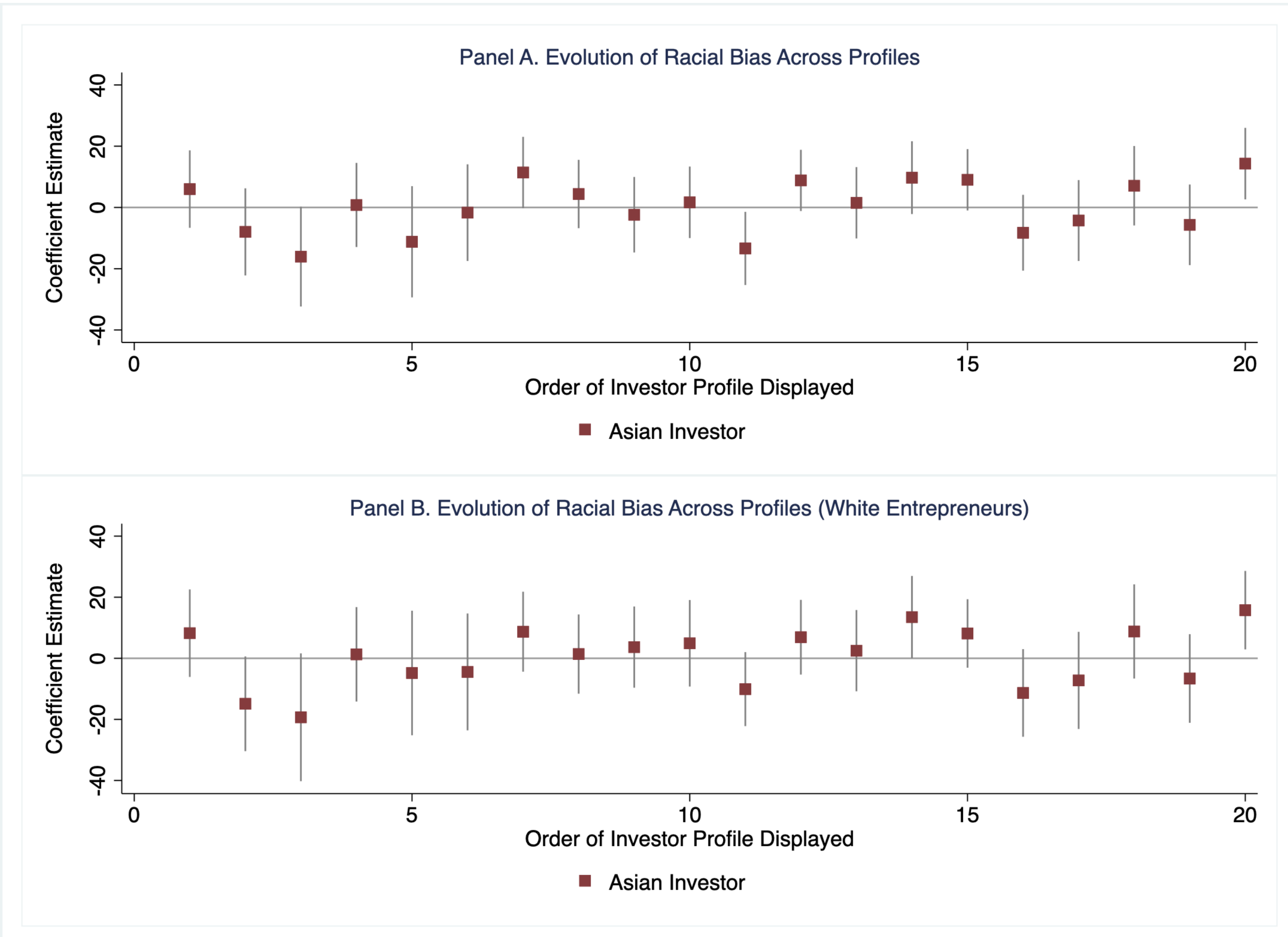


Figure E1: Evolution of Racial Discrimination

*Notes.* This figure demonstrates how the racial discrimination evolves as the study progresses to the end. The horizontal line indicates the order of each investor profile displayed to the experimental subjects (i.e., the $i^{th}$ displayed investor profile). The vertical line indicates the magnitude of the racial discrimination as measured by entrepreneurs' contact interest ratings (i.e., $Q_4$) when we analyze founders' evaluations of only the $i^{th}$ displayed profiles. Panel A uses all subjects' evaluation results, and Panel B uses only white entrepreneurs' evaluation results.

Table E5: Full Names Populating Profile Tool

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

*Notes.* This table lists all the names used for the hypothetical investors. 50 names were selected to be highly indicative of each combination of race and gender. Considering that white and Asian investors account for more than 95% of the venture capital investors and angel investors, we only have four combinations listed above: Asian Female, White Female, Asian Male, White Male. A name drawn from these lists was displayed at the top of each hypothetical investor profile and in the questions used to evaluate the resumes. First and last names were always linked 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. After we generated a list of potential full names, we further checked these names to make sure that there are no names owned by famous investors, such as Kevin Moore, who is one of the leading angel investors with high annual investment volumes and successful exits.

Table E6: Investor Position Categories Populating the Profile

| Position Category | Position | 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 positions listed above are common descriptions of early-stage investors in venture capital companies and angel investment community. In the randomization process, position categories are first randomly drawn according to the distribution VC Senior: VC Junior: Angel=35%:35%:30%. Within each position category, one specific position (e.g., Managing Partner) is randomly drawn from a uniform distribution.

Table E7: Entrepreneurial Experience Description A

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

*Notes.* This table describes the experiences of investors without entrepreneurial experiences. All the descriptions of entrepreneurial experience and non-entrepreneurial experience are drawn from real venture capitalists' or angel investors' personal profiles. We deleted the specific company names to make the description transferable across different investors and industries.

Table E8: Entrepreneurial Experience Description B

| | Description Example |
|---|---|
| No | 1. Previously, (Investor Name) was an analyst at a Capital Management firm, focusing on global growth equities. Later, he joined a private equity firm, conducting market analysis and due diligence.<br>2. Previously, (Investor Name) worked at a large online sales and operations company and later joined an investment bank. His investment experience spans a wide range of industries.<br>3. (Investor Name) performed in various executive roles and began her career as a product development engineer. She has experience in operations, budgeting, and strategic planning.<br>4. Previously, (Investor Name) worked in a consulting company and started his career in a global investment bank. His prior work experience includes consulting, investment banking and venture capital funds.<br>5. Prior to joining the current position, (Investor Name) was an equity research analyst and investor at an investment bank, covering publicly traded stocks.<br>6. (Investor Name) has diverse experience of working in tech companies, sales companies, and an investment bank.<br>7. (Investor Name) was specialized in corporate finance and M&A when working at the investment bank. Later, he moved to a venture capital firm, focusing on early-stage startup investment.<br>8. (Investor Name) started his career as a management consultant at a leading consulting company and later worked in a P&E fund.<br>9. After graduating from college, Investor Name worked in a management consulting company and joined a P&E company later.<br>10. Investor Name started his career as an institutional investment analyst at an asset management company, analyzing investments across asset classes from public equities to venture capital.<br>11. Investor Name started his career as an institutional investment analyst at an asset management company, analyzing investments across asset classes from public equities to venture capital.<br>12. Previously, (Investor Name) held a position in asset management company, executing fixed-income investment, FX trading, and cash management. He also worked on M&A transactions later.<br>13. After graduation, Investor Name worked in a research institution and later joined a consulting company.<br>14. Investor Name started working for an venture capital fund a s an (exit) analyst and responsible for investor relations, controlling and reporting. She keeps a constant eye on the latest M&A trend and market development.<br>15. (Investor Name) has diverse experience in the areas of marketing, finance and international relations. Prior to joining the current company, he was responsible for international relationship at an investment firm.<br>16. After graduation, (Investor Name) started working as an investment analyst for a private equity firm. Later, he joined the job, identifying additional opportunities for financial vehicles to further expand the investment.<br>17. (Investor Name) started his career as an investment analyst in a leading private equity investment firm. He held various operations and business development roles for the portfolio companies.<br>18. (Investor Name) began his career as a commercial banker on Wall Street and then joined a leading consulting company. After leaving consulting, (Investor Name) started investing in early-stage startups.<br>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.<br>20. (Investor Name) was part of the go-to-market team, responsible for building, launching and scaling new business ventures. He specialized in enterprise growth strategy and business operations. |

*Notes.* This table describes the experiences of investors with related entrepreneurial experiences. All the descriptions of entrepreneurial experience and non-entrepreneurial experience are drawn from real venture capitalists or angel investors' personal profiles. We deleted the specific company names to make the description transferable across different investors and industries.

Table E9: Education Background (School List)

| Top Undergraduate (BA/BS) | Top Graduate |
|---|---|
| Brown University | (No Business School) |
| Columbia University | MBA, Columbia Business School |
| Cornell University (2) | MBA, Cornell University (Johnson) |
| Dartmouth College (2) | |
| Harvard University (3) | MBA, Harvard Business School (3)** |
| | JD, Harvard Law School |
| Princeton University | (No Business School) |
| University of Pennsylvania | MBA, University of Pennsylvania (Wharton) (2) |
| 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 (3) | MBA, Stanford Graduate School of Business (3)** |
| | Master of Science, Stanford University |
| | Ph.D, Stanford University |
| University of Chicago | MBA, University of Chicago (Booth)** |

| Common Undergraduate | Common Graduate |
|---|---|
| University of Puget Sound (89) | MBA, La Salle University (Regional 38) |
| University of Cape Town (114) | MBA, University of Denver (97) |
| University of Arizona (81) | MBA, Syracuse University ( Martin J. Whitman School) (54) |
| Clemson University (70) | Master of Science, SUNY Buffalo State College (Regional 104) |
| Lehigh University (50) | Master of Engineering, Stony Brook University–SUNY (91) |
| Morehouse College (154) | MBA, Rochester Institute of Technology (104) |
| Clark University (91) | Master of Arts, Villanova University (46) |
| University of Oklahoma (132) | Master of Science, New Jersey Institute of Technology (97) |
| Hofstra University (162) | Ph.D. University of Nebraska (not ranked) |
| CUNY-Hunter college (Regional 23) | J.D, University of Louisville (192) |
| Franklin and Marshall College (Liberal Arts 38) | MBA, Georgia State University (J.Mack Robinson College) (211) |
| Alfred University (Regional 38) | MBA, Oregon State University (139) |
| Northern Kentucky University (293-381) | |
| Rutgers University–New Brunswick (62) | |
| Kent State University (211) | |
| Wheaton College (Liberal Arts 58) | |
| Salisbury University (Regional 75) | |
| Drexel University (97) | |
| Occidental College (Liberal Arts 39) | |
| DePauw University (Liberal Arts 46) | |

*Notes.* All the schools and degrees listed in the table are based on the profiles of real VC investors or angel investors' educational background that we collected from the public platforms, such as investors' personal websites, LinkedIn, Crunchbase, AngelList, and etc.

Table E10: Investment Experience

| Experience | Description/Criteria | Percentage |
| --- | --- | --- |
| *Senior Position* | | 35% |
| | years of experience: Uniform Distribution 12-30 (integer) | |
| | number of deals involved (N1):See below | |
| | number of successful exits: 10% $\times$ N1, round up | |
| *Junior Position* | | 35% |
| | years of experience: Uniform Distribution 1-6 (integer) | |
| | number of of deals involved (N2): See below | |
| | number of successful exits: 10% $\times$ N2, round up | |
| *Angel Investors* | | 30% |
| | years of experience: | |
| | Low: Uniform Distribution 1-6 (integer) | |
| | High: Uniform Distribution 12-30 (integer) | |
| | number of deals involved (N3): See below | |
| | number of successful exits: 10% $\times$ N3, round up | |

| Experience | Description of Number of Deals | Percentage |
| --- | --- | --- |
| *Senior Position* | | |
| | **Low** Uniform Distribution 1-7 (integer); Example: (1,1,2,3,3,5,6) | 50% |
| | **High** Uniform Distribution 25-75 (integer); Example: (26,30,31,39,44,69,70,75) | 45% |
| | **Extremely high** Uniform Distribution 100-180 (integer); Example: (98,178) | 5% |
| Total | | 100% |
| | | |
| *Junior Position* | | |
| | **Low** Uniform Distribution 1-2 (integer); Example: (1,2) | 50% |
| | **High** Uniform Distribution 6-17 (integer); Example: (6,10,11,17) | 50% |
| Total | | 100% |
| | | |
| *Angel Investors* | | |
| | **Low** Uniform Distribution 1-20 (integer); Example: (1,1,2,5,6,8,10,14,15,17,20) | 50% |
| | **High** Uniform Distribution 20-80 (integer); Example: (18,24,29,31,38,48,57,60,78,85) | 45% |
| | **Extremely high** Uniform Distribution 110-180 (integer); Example: (113,161,175,187) | 5% |
| | | |
| Total | | 100% |

Table E11: Variations 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 | 50% |
| | Drawn Unif [20, 50] to second decimal place | |
| Small Fund | Description: relatively small angel fund | 50% |
| | Drawn Unif [1, 10] to second decimal place | |

*Notes.* To provide more variations within larger funds and smaller funds, I also randomize the AUM (Asset Under Management) and dry powder within each fund size category. The unit of AUM and dry power is $1 million. The distribution of AUM follows the U.S. VC industry AUM distribution in 2018. The amount of dry powder is fixed to be 30%-40% of the fund's AUM. In general, AUM and dry powder is positively correlated, and we assume that larger funds have more AUM and dry powder.

Table E12: Distribution of Page Submission Time

| Profile Index | Mean | SD | Percentile | | |
|---|---|---|---|---|---|
| | | | 10 | 50 | 90 |
| 1 | 133.52 | 85.02 | 64.49 | 112.35 | 253.28 |
| 2 | 64.80 | 43.56 | 15.93 | 57.00 | 138.28 |
| 3 | 52.43 | 38.19 | 16.36 | 42.47 | 108.47 |
| 4 | 47.13 | 29.13 | 18.70 | 38.68 | 105.21 |
| 5 | 65.80 | 90.97 | 18.33 | 35.53 | 134.26 |
| 6 | 39.55 | 24.16 | 16.26 | 30.60 | 81.74 |
| 7 | 38.00 | 25.92 | 13.63 | 29.37 | 83.49 |
| 8 | 40.78 | 27.86 | 13.65 | 32.15 | 83.00 |
| 9 | 40.46 | 29.05 | 14.15 | 30.99 | 80.46 |
| 10 | 29.82 | 16.95 | 12.96 | 24.96 | 54.78 |
| 11 | 34.85 | 21.67 | 13.30 | 31.63 | 69.41 |
| 12 | 28.68 | 16.30 | 12.32 | 23.17 | 52.39 |
| 13 | 31.29 | 19.14 | 13.70 | 25.51 | 68.99 |
| 14 | 35.25 | 20.86 | 13.53 | 29.02 | 70.55 |
| 15 | 30.79 | 19.26 | 11.69 | 23.64 | 62.10 |
| 16 | 29.50 | 16.89 | 11.98 | 23.72 | 57.53 |
| 17 | 28.79 | 15.41 | 11.69 | 26.06 | 56.00 |
| 18 | 26.12 | 13.08 | 11.24 | 22.04 | 44.53 |
| 19 | 27.89 | 17.27 | 10.79 | 26.41 | 42.27 |
| 20 | 26.05 | 14.35 | 11.24 | 21.77 | 45.94 |

*Notes.* This table describes the distribution of the Page Submission Time for each profile. The sample includes 860 valid profiles' evaluation results. All the time is winsorized at 95th.

Table E13: Evaluation Results (Organizational Capital vs. Human Capital)

| Dependent Variable | Q1 Quality | Q2 Investment Interest | Q3 Funding Requested | Q3 Funding Requested | Q4 Contact | Q4 Contact | Q5 Informativeness |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Impact Fund | 0.57 | -0.80 | 0.96 | 0.94 | -0.05 | -0.12 | 0.47 |
| | (1.33) | (1.42) | (1.39) | (0.99) | (1.20) | (0.82) | (1.12) |
| Large Fund | 4.73** | 0.57 | 3.41** | 1.71 | 3.75* | 1.06 | 3.20* |
| | (2.13) | (1.64) | (1.49) | (1.29) | (2.05) | (0.90) | (1.75) |
| Entrepreneurial Experience | 2.78 | 1.71 | 1.23 | -0.06 | 2.71 | 0.72 | 2.34 |
| | (1.87) | (1.81) | (1.92) | (1.16) | (1.79) | (0.96) | (1.86) |
| VC Senior Position | 3.07* | -1.57 | 2.71 | 2.02 | 2.28 | 1.11 | 3.22** |
| | (1.76) | (1.57) | (1.79) | (1.69) | (1.69) | (1.16) | (1.54) |
| VC Junior Position | -2.44 | -4.21** | 0.12 | 1.84 | -2.50 | 0.03 | -2.16 |
| | (2.12) | (1.80) | (1.82) | (1.45) | (2.19) | (1.12) | (2.11) |
| Top School | 1.85 | 0.69 | 0.21 | -0.56 | -0.03 | -1.23 | 1.39 |
| | (1.23) | (1.23) | (1.22) | (1.07) | (1.17) | (0.93) | (1.14) |
| Graduate School | -0.24 | -0.18 | -1.33 | -1.22 | 2.00 | 2.18** | -0.90 |
| | (1.21) | (1.22) | (1.32) | (1.11) | (1.21) | (0.99) | (1.05) |
| Q1 | | | | 0.33*** | | 0.53*** | |
| | | | | (0.07) | | (0.06) | |
| Q2 | | | | 0.21** | | 0.29*** | |
| | | | | (0.09) | | (0.07) | |
| Investor FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 860 | 860 | 860 | 860 | 860 | 860 | 860 |
| R-squared | 0.33 | 0.36 | 0.55 | 0.67 | 0.35 | 0.70 | 0.43 |

*Notes.* This table reports regression results about which fund organizational characteristics and investor individual characteristics that affect startup founders' fund-seeking behaviors. All the founders were recruited by Qualtrics Panel Providers. In columns (1)-(7), the dependent variable is the evaluation results of Q1 (quality evaluation), Q2 (investment interest), Q3 (funding requested), Q3 (funding requested), Q4 (contact interest), Q4 (contact interest), and Q5 (informativeness of each profile). "Impact Fund," "Large Fund," "Entrepreneurial Experience," "VC Senior Position," "VC Junior Position," "Top School" and "Graduate School" are indicative dummy variables that equal to one if the investor works in an impact fund focusing on ESG criteria, works in a large fund, has related entrepreneurial experience, is a senior investor in the VC fund, is a junior investor in the VC fund, graduates from a prestigious university, or has a graduate degree. These variables are equal to 0 if the investor does not have such characteristics. "Q1" is the evaluation results of investor quality. "Q2" is the evaluation results of the investor's interest in the founder's startup. All the regression results add investor fixed effect and use the robust standard errors reported in parentheses. Results are similar when using the Simes method to implement multiple hypothesis testing. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table E14: Implicit Gender and Racial Discrimination (Full Sample)

| Dependent Variable | Response Time (Unit: Second) (1) | Q1 Quality (2) | Q2 Availability (3) | Q3 Funding (4) | Q4 Contact (5) | Q5 Informativeness (6) |
|---|---|---|---|---|---|---|
| *Panel A: Gender* | | | | | | |
| Second Half of Study | -17.71*** | 4.03** | 3.58** | 0.08 | 4.17** | 2.87 |
| | (2.23) | (1.90) | (1.64) | (1.53) | (1.75) | (1.75) |
| Female Investor | 0.88 | 6.65** | 4.74* | 4.28** | 6.29** | 2.30 |
| | (1.74) | (2.69) | (2.56) | (1.96) | (2.68) | (1.47) |
| Female Investor × | | -11.13*** | -7.52*** | -6.42** | -7.66** | -3.31 |
| Second Half of Study | | (2.92) | (2.66) | (2.46) | (2.89) | (2.00) |
| p-value of Female Investor in the second half of study | | 0.011 | 0.100 | 0.321 | 0.271 | 0.568 |
| Subject FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Mean of Dependent Variables | 40.00 | 66.71 | 65.36 | 57.14 | 69.04 | 74.57 |
| Observations | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 |
| R-squared | 0.39 | 0.39 | 0.48 | 0.62 | 0.40 | 0.48 |
| *Panel B: Race* | | | | | | |
| Second Half of Study | -17.88*** | 0.24 | 0.90 | -3.04* | 0.63 | 2.12 |
| | (2.25) | (1.98) | (1.79) | (1.70) | (1.95) | (2.09) |
| Asian Investor | 3.09 | 0.96 | 0.21 | -0.90 | -0.08 | 0.00 |
| | (1.94) | (1.68) | (1.56) | (1.46) | (1.84) | (1.90) |
| Asian Investor × | | -0.69 | -0.12 | 1.89 | 1.76 | -0.99 |
| Second Half of Study | | (2.69) | (2.44) | (2.54) | (2.69) | (2.62) |
| p-value of Asian Investor in the second half of study | | 0.817 | 0.890 | 0.939 | 0.371 | 0.863 |
| Subject FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Mean of Dependent Variables | 40.00 | 66.71 | 65.36 | 57.14 | 69.04 | 74.57 |
| Observations | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 |
| R-squared | 0.39 | 0.38 | 0.47 | 0.62 | 0.39 | 0.48 |

*Notes.* This table reports regression results of how founders' response time and evaluation results respond to an investor's gender and race in the first and second half of the study. All responses collected from 51 candidates are used in this table, including 43 valid candidates and 8 noisy candidates. Panel A tests the implicit discrimination based on investor's gender. Panel B tests the implicit discrimination based on investor's race. "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. "Second Half of Study" is an indicator variable for investor profiles shown among the last ten investor resumes viewed by an experimental subject. In column (1), the dependent variable is startup founders' response time, which is defined as the number of seconds before each page submission, winsorized at the 95th percentile (40.77 seconds on average). Columns (2)-(6) show the quality evaluation, founders' beliefs in the investor's availability, relative amount of funding asked, contact interest ratings, and the perceived informativeness of each investor profile, separately. The "p-value of Female Investor (or Asian Investor) in the second half of study" provides the p-value of the coefficient of "Female Investor" (or "Asian Investor") when we only include the evaluation results in the second half of the study. All the regressions add subject fixed effect. R-squared is indicated for each OLS regression. Standard errors in parentheses are clustered within each experimental subject. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table E15: Homophily Based on Founder's Gender (Full Sample)

| Dependent Variable | Response Time (Unit: Second) (1) | Q1 Quality (2) | Q2 Availability (3) | Q3 Funding (4) | Q4 Contact (5) | Q5 Informativeness (6) |
|---|---|---|---|---|---|---|
| *Panel A: Male Founders* | | | | | | |
| Second Half of Study | -17.90*** | 4.31* | 4.90** | 1.20 | 4.93** | 4.16* |
| | (2.00) | (2.32) | (2.10) | (1.99) | (2.14) | (2.29) |
| Female Investor | 0.38 | 7.46** | 7.07** | 5.34** | 8.70** | 3.60** |
| | (2.07) | (3.54) | (3.38) | (2.61) | (3.52) | (1.51) |
| Female Investor × | | -13.81*** | -11.17*** | -9.46*** | -11.41*** | -6.04** |
| Second Half of Study | | (3.96) | (3.45) | (3.19) | (3.81) | (2.50) |
| p-value of Female Investor in the second half of study | | 0.004 | 0.065 | 0.064 | 0.091 | 0.176 |
| Subject FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Mean of Dependent Variables | 39.97 | 64.14 | 64.54 | 54.06 | 67.18 | 73.13 |
| Observations | 700 | 700 | 700 | 700 | 700 | 700 |
| R-squared | 0.43 | 0.33 | 0.34 | 0.52 | 0.32 | 0.44 |
| *Panel B: Female Founders* | | | | | | |
| Second Half of Study | -17.23*** | 3.44 | 0.79 | -2.22 | 2.51 | 0.21 |
| | (5.70) | (3.40) | (2.45) | (2.17) | (3.07) | (2.51) |
| Female Investor | 2.02 | 4.65 | -0.64 | 1.77 | 0.68 | -0.71 |
| | (3.22) | (3.64) | (3.00) | (2.54) | (3.20) | (3.23) |
| Female Investor × | | -4.36 | 1.11 | 0.85 | 1.50 | 3.04 |
| Second Half of Study | | (2.58) | (2.71) | (2.80) | (2.72) | (2.60) |
| p-value of Female Investor in the second half of study | | 0.790 | 0.630 | 0.030 | 0.223 | 0.074 |
| Subject FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Mean of Dependent Variables | 40.08 | 72.33 | 67.15 | 63.87 | 73.10 | 77.73 |
| Observations | 320 | 320 | 320 | 320 | 320 | 320 |
| R-squared | 0.30 | 0.52 | 0.74 | 0.78 | 0.58 | 0.59 |

*Notes.* This table reports regression results of how female founders and male founders respond to an investor's gender differently. The founders are recruited in Wave 1. All the 1020 responses collected from 51 candidates are used in this table, including 43 valid candidates and 8 noisy candidates. Panel A tests whether male founders have implicit gender discrimination. Panel B tests whether female founders have implicit gender discrimination. "Female Investor" is a dummy variable that is equal to one if the investor has a female first name, and zero otherwise. Columns (1)-(5) show the investor quality evaluation, founders' beliefs in the investor's availability, relative amount of funding asked, contact interest ratings, and the informativeness of each investor profile, separately. The "p-value of Female Investor in the second half of study" provides the p-value of the coefficient of "Female Investor" when we only include the evaluation results in the second half of the study. All the regressions add subject fixed effect. R-squared is indicated for each OLS regression. Standard errors in parentheses are clustered within each experimental subject. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table E16: Quantile-Regression Estimates for Startups' Evaluations (Gender) (Full Sample)

Panel A. Contact Interest Ratings (i.e., $Q_4$)

| | 10th [1] | 20th [2] | 30th [3] | 40th [4] | 50th [5] | 60th [6] | 70th [7] | 80th [8] | 90th [9] | Mean [10] |
|---|---|---|---|---|---|---|---|---|---|---|
| Female Investor | 3.00 | -5.00 | -3.00 | -6.00** | -4.00* | -4.00* | -2.00 | -5.00** | -5.00** | -1.50 |
| | (6.30) | (3.45) | (2.73) | (2.46) | (2.31) | (2.16) | (1.86) | (2.47) | (2.12) | (1.35) |
| Quantile of Dep. Var. | 40 | 52 | 61 | 66 | 73 | 79 | 83 | 88 | 95 | 69.03 |
| Observations | 510 | 510 | 510 | 510 | 510 | 510 | 510 | 510 | 510 | 510 |

Panel B. Quality Ratings (i.e., $Q_1$)

| | 10th [1] | 20th [2] | 30th [3] | 40th [4] | 50th [5] | 60th [6] | 70th [7] | 80th [8] | 90th [9] | Mean [10] |
|---|---|---|---|---|---|---|---|---|---|---|
| Female Investor | -3.00 | -6.00** | -8.00*** | -9.00*** | -7.00*** | -7.00** | -9.00*** | -4.00 | -4.00* | -4.28*** |
| | (5.14) | (2.82) | (2.85) | (2.59) | (2.59) | (3.03) | (2.59) | (3.07) | (2.20) | (1.61) |
| Quantile of Dep. Var. | 37.5 | 51 | 58 | 64 | 70 | 73.5 | 80 | 87 | 93 | 66.71 |
| Observations | 510 | 510 | 510 | 510 | 510 | 510 | 510 | 510 | 510 | 510 |

*Notes.* This table reports the effects of investor's gender on the quantiles and the mean of investors' attractiveness evaluations (i.e., $Q_4$) and quality evaluations (i.e., $Q_1$) of the second half of the experiment in Wave 1. All the 1020 responses collected from 51 candidates are used in this table, including 43 valid candidates and 8 noisy candidates. In each of Columns [1]–[9], the dependent variable is the $k$th percentile ($k \in 10, 20, ..., 90$) of the distribution of the investor's perceived attractiveness measured by startups' contact interest ratings (i.e., $Q_4$) in Panel A and perceived quality measured by startups' quality ratings (i.e., $Q_1$) in Panel B; in Column [10], the dependent variable is the average startup's contact interest ratings of the second half profiles in Panel A and the average quality ratings of the the second half profiles in Panel B. Standard errors are clustered at the subject level, and reported in parentheses. $*p < 0.10, **p < 0.05, ***p < 0.01$

Table E17: Heterogeneous Effect Based on Investor's Seniority (Full Sample)

| 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 | -19.61*** | 8.82*** | 6.72** | 4.33* | 8.90*** | 5.65** |
| | (2.52) | (3.22) | (2.91) | (2.51) | (3.14) | (2.34) |
| Female Investor | -0.84 | 9.57** | 7.09 | 6.99** | 9.01* | 3.08 |
| | (3.15) | (4.60) | (4.34) | (3.11) | (4.53) | (2.40) |
| Female Investor × | | -17.99*** | -13.82*** | -9.22** | -12.52** | -7.27** |
| Second Half of Study | | (6.04) | (5.00) | (4.35) | (5.79) | (3.46) |
| p-value of Female Investor in the second half of study | | 0.075 | 0.118 | 0.807 | 0.332 | 0.310 |
| Subject FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Mean of Dependent Variables | 43.96 | 68.98 | 65.76 | 58.45 | 71.08 | 76.81 |
| Observations | 357 | 357 | 357 | 357 | 357 | 357 |
| R-squared | 0.56 | 0.44 | 0.57 | 0.71 | 0.44 | 0.55 |
| *Panel B: Junior Investors* | | | | | | |
| Second Half of Study | -17.93*** | 2.59 | 2.73 | -2.11 | 2.70 | 2.55 |
| | (2.66) | (2.40) | (2.21) | (2.38) | (2.58) | (2.71) |
| Female Investor | -0.53 | 3.57 | 2.31 | 1.57 | 2.16 | 0.34 |
| | (2.92) | (2.71) | (2.42) | (2.80) | (2.57) | (2.45) |
| Female Investor × | | -7.28** | -3.04 | -2.86 | -4.80 | -1.17 |
| Second Half of Study | | (3.04) | (3.18) | (3.59) | (3.46) | (3.32) |
| p-value of Female Investor in the second half of study | | 0.247 | 0.996 | 0.714 | 0.429 | 0.719 |
| Subject FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Mean of Dependent Variables | 38.33 | 64.01 | 62.96 | 56.16 | 66.44 | 72.53 |
| Observations | 357 | 357 | 357 | 357 | 357 | 357 |
| R-squared | 0.36 | 0.67 | 0.70 | 0.71 | 0.65 | 0.62 |

*Notes.* This table reports regression results of how senior investors' gender information and junior investors' gender information affect startups' evaluation results. All responses collected from 51 candidates are used in this table, including 43 valid candidates and 8 noisy candidates. Panel A tests whether startup founders have implicit gender discrimination for senior VC investors. Panel B tests whether startup founders have implicit gender discrimination for junior VC investors. "Female Investor" is a dummy variable that is equal to one if the investor has a female first name, and zero otherwise. Columns (1)-(5) show the investor quality evaluation, founders' beliefs in the investor's availability, relative amount of funding asked, contact interest ratings, and the informativeness of each investor profile, separately. The "p-value of Female Investor in the second half of study" provides the p-value of the coefficient of "Female Investor" when we only include the evaluation results in the second half of the study. All the regressions add subject fixed effect. R-squared is indicated for each OLS regression. Standard errors in parentheses are clustered within each experimental subject. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$