# Impact Investing and the Venture Capital Industry: Experimental Evidence*

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**Abstract**

This paper studies the effect of startups' ESG characteristics on venture capitalists' investments by linking investors' behavior in an incentivized experiment to their real-world portfolio data. I find that investors perceive impact ventures to be less profitable and harder to evaluate than similar profit-driven startups. Investors' interest in impact ventures positively correlates with their social preferences, supporting the non-pecuniary motivation for impact investing. Impact ventures are also associated with better ex-post performance at the global level. The paper uses a dynamic Bayesian model to demonstrate how these identified beliefs and preferences affect impact investment in the venture capital industry.

**Key Words:** Sustainable Finance, Field Experiments, Venture Capital, Entrepreneurship
**JEL Classification:** C93, D83, G11, G24, Q56

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# 1 Introduction

Impact investing is an investment discipline targeting positive environmental, social, and governance (ESG) impact and has recently entered the mainstream and attracted massive attention from practitioners, policymakers, and researchers (Bialkowski and Starks, 2016; Hong, Wang and Yang, 2021). According to Morningstar, ESG funds captured \$51.1 billion of net new money from investors in 2020, reaching their fifth consecutive annual record.[1] Among various asset classes in the impact investing landscape, the private market attracts a large amount of allocated impact investing capital, accounting for 38% of the total assets under management.[2] As important environmental and social challenges might be best addressed by new firms through innovation, these impact investing capital in the private market is crucial for financial markets to contribute to the sustainable transition of society. The venture capital (VC) industry plays a key role here by fostering impact ventures with their expertise and capital. While the media often claim impact ventures enjoy higher profitability and lower cost of capital from the VC industry, this "doing well by doing good" thesis in the entrepreneurial financing setting often stems from anecdotal evidence and does not match with the recently documented lower financial returns of impact VC funds (Barber, Morse and Yasuda, 2020; Kovner and Lerner, 2015).[3] Given the importance of VC in fostering innovative impact ventures, this paper studies the effect of startups' ESG characteristics on VCs' expectations of startups' financial performance and investment decisions.

VCs' entrepreneurial investment process has several distinct features compared to trading stocks in the secondary market. These distinctions might lead to different opinions on green assets' financial performance and different motivations behind VCs' investment strategies. First and foremost, startups tend to be more financially constrained than publicly-listed companies. Because corporate goodness can be more costly to financially constrained firms (Hong, Kubik and Scheinkman, 2012), findings that socially responsible investment (SRI) in public equities are perceived to outperform conventional investments cannot be easily transferred to private equity SRIs (Derwall, Guenster, Bauer and Koedijk, 2005; Edmans, 2011; Hartzmark and Sussman, 2019; Kempf and Osthoff, 2007; Lins, Servaes and Tamayo, 2017). Secondly, significant information asymmetry exists in the private capital markets. The increased complexity of impact ventures might lead to additional difficulties in their evaluation process, causing adverse effects on their fundraising. Thirdly, the entrepreneurial financing process is essentially a two-sided matching process (Sørensen, 2007). Sorting and related strategic thinking might affect investors' decisions. For example, if profit-driven investors expect impact ventures to choose impact funds for collaboration, they may strategically prefer solely profit-driven ventures due to higher obtainability and availability in the pre-investment screening stage. This strategic mechanism may serve as a new channel to explain investors' SRI decisions in the private market

[1]See "Money invested in ESG funds more than doubles in a year" CNBC News.

[2]Private equity is also one of the most popular asset classes considered by impact investors based on the GIIN 2020 Annual Impact Investor Survey. See Global Impact Investing Network (GIIN) 2020 Annual Impact Investor Survey. In this paper, "sustainable investment" and "impact investment" are used interchangeably.

[3]Impact ventures refer to startups that apply groundbreaking technologies to solve difficult ESG challenges. In this paper, "Impact ventures" and "ESG startups" are used interchangeably to refer to startups that aim for positive ESG impacts.

The argument for impact ventures' better financial performance relies on the assumption that both consumers and investors opt for brands that focus on ESG issues. Other suggested benefits may encompass top talent acquisition, improved social image, and reputation, etc. See "ESG Investing in 2021: The Ultimate Guide for Startups."

where sorting generally exists (Chang, Gomez and Hong, 2021; Chen and Song, 2013).

Despite the importance of understanding how VCs evaluate impact ventures, empirically testing this question is challenging due to data limitations. Firstly, standard databases generally record completed deals, which are equilibrium outcomes based on the endogenous matching process between VCs and startups. Researchers rarely directly observe investors' portfolio selection process and evaluation results of startups' financial performance. Secondly, startups — unlike public firms — do not have a matured ESG rating system.

To address these empirical challenges above, this paper implements an incentivized resume rating (IRR) experiment with real US-based VCs following the experimental paradigm created by Kessler, Low and Sullivan (2019). To implement this experiment, I have worked with several real-world accelerators that are closely connected to prestigious universities. We developed a machine learning-powered "Nano-Search Financing Tool" to improve matching US-based VCs with startups in these accelerators. These VCs were invited to try this tool by evaluating multiple synthetic startup profiles with randomized startup characteristics, including ESG characteristics (i.e., impact ventures vs. profit-driven ventures).[4] The VCs then indicate their willingness to contact each presented startup and evaluate multiple dimensions of the startup profile (i.e., profitability, availability, and risk). Profitability evaluation is based on investors' judgments on startups' potential financial returns and these subjective individual-level evaluations can be miscalibrated. After the profile evaluation part, investors will receive an unexpected \$15 Amazon gift card. They can accept it or anonymously donate a portion of the \$15 to real startup teams in the collaborative incubators. This donation game directly measures investors' social preferences.

To elicit investors' honest evaluations, this IRR experiment provides the following two incentives that can increase the stakes involved in this experiment. The first incentive is a "matching incentive" provided to all the participants (Kessler et al., 2019). Despite knowing all the profiles are hypothetical, investors are still willing to provide their true preferences to match their preferred real startups from these incubators. The second incentive is a "monetary incentive" provided to a *randomly* selected subgroup of investors (Armona, Fuster and Zafar, 2019). This incentive only elicits investors' expectations of startups' future one-year profitability by mimicking how investing in startups generates financial returns; i.e., the more accurate judgments investors make based on startups' ex-post performance, the more financial rewards they can receive. This paper shows that these two incentives generate similar profitability evaluation results. Both incentives guarantee that the more truthfully investors reveal their individual-level investment preferences, the more benefits they can obtain from participating in this experiment. Therefore, providing honest evaluations becomes the dominant strategy for rational investors compared to distorting the evaluations.

The sample size of the experiment is comparable to Kessler et al. (2019). Approximately 70 US-based VCs participated and evaluated more than 1,200 synthetic startup profiles. Experimental results provide the following main findings. Firstly, aiming for environmental and social impacts reduces investors' expectations of the startup's future financial returns. However, this effect mainly exists when investors evaluate attractive startups (i.e., startups that receive higher contact interest ratings from investors). For example, quantile regressions show that the conditional 95th percentile of impact ventures' received profitability ratings ranks

[4] Corporate governance (G) has a well-researched causal impact on firms' financial performance. This paper only focuses on companies' environmental and social aspects (i.e., E and S).

roughly 5 percentiles lower than that of similar profit-driven startups' received ratings. Surprisingly, impact investors also give lower profitability ratings to impact ventures. Results from quantile regressions are robust after controlling investors' rating levels. When focusing on more attractive startups (based on higher contact interest ratings), Ordinary least squares (OLS) regressions yield similar results, indicating that investors' profitability ratings on average decrease by 2.94 percentile ranks for impact ventures. This is equivalent to a 6.6% decrease when compared to the average level of investors' profitability ratings. The measurement of attractiveness is produced by other orthogonally randomized startup characteristics.

Secondly, the paper also discovers several other factors that potentially impose negative effects on impact ventures' fundraising outcomes from the VC industry. One factor is the potential extra difficulties in evaluating impact ventures. In the experiment, investors on average spend eight or ten more seconds evaluating attractive impact ventures compared to the time they spend evaluating similar profit-driven ventures. While both "taste-driven preferences" towards impact ventures and the "more complexity" of impact ventures' evaluations can explain this extra allocated attention, further tests support the latter. Results show that investors' additional time spent on impact ventures is significantly *negatively* correlated with their donation amount in the donation game. Moreover, instead of allocating more time to the documented "preferred" startup characteristics, investors only spend significantly more time when assessing more complicated startups, such as those with multiple founders or advantages. Given that impact ventures are still not common startups yet, their evaluations are likely to involve added complexity.

Another potential factor is the existence of sorting or market segregation based on ESG. When examining investors' implicit preferences, the experiment detects weak evidence on the sorting channel. While impact investors expect impact ventures to be more likely to collaborate with them, profit-driven investors expect profit-driven ventures to be more likely to collaborate with them. The result is consistent with the field experimental evidence in Zhang (2022), which finds that this positive assortative matching behavior based on ESG indeed exists in US-based startups' fundraising process. Although the evidence on sorting in this paper is not as strong as other main findings, results suggest that professional US-based VCs rationally expect this fundraising behavior of US-based startups and might adjust their investment strategies accordingly. Since profit-driven funds continue to dominate the VC industry, the added difficulties in evaluating impact ventures and perceived lower availability could jeopardize impact ventures' fundraising.

Thirdly, the experimental evidence supports the non-pecuniary motivation of impact investing. The lower expectation of impact ventures' profitability does not reduce impact investors' contact interest ratings of impact ventures. Investors who are more willing to contact impact ventures also behave more generously in the donation game. This finding is consistent with Riedl and Smeets (2017), confirming that social preferences are also correlated with SRI decisions in the VC industry. Contrary to the hypothesis that risk-adjusted returns of impact ventures might outperform those of conventional startups, experimental results show that profit-driven investors on average give 3.63 percentage points lower contact interest ratings to impact ventures compared to similar profit-driven startups. Again, this effect mainly exists when investors evaluate attractive startup profiles.

As each experimental participant's identity is observable, the paper further checks the correlations between the participants' evaluations in the experiment and their affiliated VC companies' real-world portfolios. Results show that VCs with more ESG startups in their firms' investment portfolios have a significantly higher contact interest in impact ventures. However, this close connection with real-world investment portfolios only exists when using investors' evaluations of attractive startups. Moreover, investors who are classified as impact investors based on their self-reported information indeed have more ESG-related investments in their portfolios. These "self-reported" impact investors' VC firms are also more likely to emphasize impact investing strategies on their official websites. The close link between the experimental data and participants' real-world investment decisions justifies the validity of the experiment.

To test the accuracy of investors' expectations of impact ventures' financial performance, the paper uses the outcome test method by further checking impact ventures' financial performance after the experiment is completed. Between 07/31/2020 and 07/31/2021 (i.e., the one-year period after the experiment), impact ventures are significantly correlated with a roughly 4 percentage points higher likelihood to raise new funding from the VC industry and roughly 2 percentage points lower chance to go out of business. Between 07/31/2020 and 01/31/2023 (i.e., the 2.5-year period after the experiment), Impact ventures are found to correlate with a roughly 0.7 percentage point higher likelihood of successful exits at the global level. This is equivalent to an increase of around 34% in the successful exit rate when compared to the average successful exit rate during the tested period. However, this paper does not find significant outperformance of US-based impact ventures in the medium run. This result is consistent with Cole, Melecky, Mölders and Reed (2020), showing that market frictions related to impact investing might be more salient in developing countries. Impact ventures that aim for positive environmental impact also significantly correlate with a 1.0 percentage point higher likelihood of successful exits. When conducting similar outcome tests based on recruited investors' portfolio companies, results show that similar short-run outperformance still exists. However, in the medium run, the outperformance in terms of successful exits becomes weaker, potentially due to the sample size.

Any detected post-funding outperformance of impact ventures does *not* mean that impact ventures are more profitable in the pre-selection stage. Instead, it suggests that VCs might underinvest in potentially profitable impact ventures in the pre-selection stage due to miscalibrated beliefs (Ewens and Townsend, 2020). Unlike some experimental results, impact ventures' short-run and medium-run outperformance are based on correlational evidence. Due to this standard limitation of the outcome test method, readers should interpret this part as providing suggestive evidence.

Lastly, this paper extends the dynamic Bayesian model introduced by Bohren, Imas and Rosenberg (2019) by incorporating preferences. "Preference" in this paper mainly refers to "taste-driven" preference, which is not affected by subjects' beliefs. This model explains how (miscalibrated) beliefs and preferences might affect the potential evolvement of impact investment in a dynamic setting. Basically, taste-driven support for ESG has two effects: (1) a positive effect that directly increases the amount of impact investing capital, and (2) a negative effect (i.e., the backfire channel) that leads to lower expectations in impact ventures' profitability when startup's profitability is not fully observed by investors. Although the positive effect generally dominates over the negative effect, any exaggeration of early-stage impact investment, such as greenwashing, can intensify this backfire channel and generate negative externalities.

This paper mainly contributes to the following strands of literature. Firstly, it contributes to the burgeoning literature on VC and impact investing.[5] On the one hand, Barber et al. (2020) show that limited partners (LP), especially LPs like development organizations, accept lower financial returns from dual-objective VC funds. The heterogeneous effect and positive willingness to pay for impact directly support the hypothesis that impact investing is driven by the non-pecuniary hypothesis. On the other hand, Jeffers, Lyu and Posenau (2021) show that for market rate-seeking impact funds, risk-adjusted returns of impact funds are similar to risk-adjusted returns of benchmark VC funds. Hence, risk, rather than non-pecuniary motives, explains the lower financial returns of impact funds. Consistent with both papers, this paper shows that professional US-based VCs expect impact ventures to generate lower financial returns. The experimental results provide extra support to the "non-pecuniary motive" hypothesis by showing that VCs' ESG attitudes are positively correlated with their social preferences. Importantly, profit-driven VCs are less enthusiastic about impact ventures. As financial intermediaries, VCs' investment preferences should reflect their LPs' preferences. While Barber et al. (2020) document LPs' non-pecuniary motivations when investing in impact VC funds, this paper complements the literature by documenting VCs' non-pecuniary motivations when investing in ESG startups. Moreover, by directly observing how VCs evaluate multiple startups with *randomly* assigned ESG characteristics, this paper discovers several potential barriers that impede impact ventures' fund-raising outcomes from profit-driven investors.

Secondly, the paper adds to the rising experimental and survey literature on sustainable finance. Riedl and Smeets (2017) link individual investors' administrative data from a large mutual fund with their responses in an incentivized experiment. They find that investors' SRI decisions are explained by "social signaling" and "social preferences." Heeb, Kölbel, Paetzold and Zeisberger (2021) implement a framed field experiment, suggesting that pro-social individual investors are "warm glow optimizers" rather than "financial optimizers" when evaluating general assets. Krüger (2015) conduct a survey with institutional investors to study how they consider climate risks in their investment decisions. Bauer, Ruof and Smeets (2021) run incentivized field surveys with members of a Dutch pension fund and find that participants usually support engagement on sustainability criteria. By implementing an IRR experiment with US-based VCs and linking investors' experimental results with real-world portfolio data, this paper complements the literature by examining how US-based VCs evaluate ESG startups' performance and the accuracy of these evaluations.

Thirdly, this paper also joins the debate in corporate social responsibility (CSR) literature. The influential thesis "doing well by doing good," rationalized by rich theories and promoted by the media, often argues that corporate social responsibility might create value (Hong and Liskovich, 2015). However, recent empirical evidence challenges this profit angle (Cheng, Hong and Shue, 2013; Colonnelli and Gormsen, 2020; Hong and Kacperczyk, 2009; Krüger, 2015). Specifically, Hong et al. (2012) supports the "Doing Well After Doing Good" thesis by showing corporate goodness can be sensitive to financial constraints. This paper is consistent with their theoretical framework, showing that aiming for ESG reduces profit-driven VCs' interest in a financially constrained firm (i.e., a startup). This could be attributed to several factors

[5] Cole, Jeng, Lerner, Rigol and Roth (2022) document that impact investors are more likely to invest in disadvantaged areas and invest in "pioneer companies". Alakent, Goktan and Khoury (2020) find that VC-backed companies are less likely to adopt CSR practices. Geczy, Jeffers, Musto and Tucker (2021) note that although impact funds rarely tie compensation to ESG impact, they incorporate impact goals into governance contracts. Theoretical papers related to sustainable finance in the private market include Green and Roth (2021), Oehmke and Opp (2020), Gupta, Kopytov and Starmans (2022), Chowdhry, Davies and Waters (2019), etc.

such as investors having lower expectations of impact ventures' profitability, the added complexity involved in evaluating impact ventures, and potentially the perception of there being a lower availability of impact ventures.

Lastly, this paper contributes to the entrepreneurial finance literature on VCs' investment criteria. Bernstein, Korteweg and Laws (2017) provides the first experimental evidence on VCs' investment process by demonstrating the importance of startup founders' human capital. Block, Fisch, Vismara and Andres (2019) implement the conjoint analysis method with real private equity investors and document that revenue growth is the most important investment criterion. Zhang and Ebrahimian (2020) extends this literature by estimating a dynamic search-and-matching model with bargaining between VCs and startups to investigate the influence of human and non-human assets on the matching equilibrium outcomes. Given the rising attention to sustainable finance, this paper complements the literature by showing that startups' ESG characteristics also influence VCs' investment decisions and expectations of startups' financial performance.

This paper proceeds as follows. Section 2 presents the experimental design. Section 3 analyzes investors' evaluations of startups' ESG-related characteristics. Section 4 tests the accuracy of investors' beliefs using the standard outcome test method. Section 5 uses a dynamic Bayesian model to demonstrate the potential evolvement of impact investing in the VC industry and related policy implications. Section 6 concludes.

## 2 Experimental Design

The Incentivized Resume Rating (IRR) experiment is an experimental paradigm created by Kessler et al. (2019) to study discrimination in a more ethical way. Unlike conventional lab experiments with real investors, the IRR experiment requires researchers to provide an experimental environment that closely mimics the real-world context (i.e., a field context). The only difference between the IRR experiment and a conventional natural field experiment is that participants are informed of the experiment's research nature and can obtain real benefits from their participation in the IRR experiment. Similar to discriminatory preference, investors' ESG preference also belongs to socially sensitive preference. Without high stakes, people have the motivation to tilt their claimed preferences in favor of supporting ESG to create positive social images. This generally leads to the overestimation of pro-social preferences using a traditionally unincentivized survey method, as pointed out by Bauer et al. (2021). Given the similarities between discriminatory preference and ESG preference, this paper applies the IRR experimental method to study how VCs evaluate ESG startups.

To implement the IRR experiment, I collaborated with two incubators and developed a "Nano-Search Financing Tool," which is essentially a machine learning algorithm-based matching tool to assist investors in identifying preferred investment opportunities. In our experiment, investors are asked to evaluate multiple randomly generated startup profiles following the Crunchbase format. Investors are aware that all startup profiles are fictional. However, they are willing to reveal their true investment preferences to match their preferred real startups in these incubators and maximize their potential financial reward.

This experimental setting closely mimics the real world. It is not unique to the VC industry to develop data-driven methods to identify the best deals from thousands of potential investment opportunities in the screening stage. For example, Techstars, Social+ Capital, and Citylight Capital have all done extensive work on developing machine learning algorithms to facilitate their deal sourcing.[6] Investors chose to participate in this experiment mainly to build closer connections with startups from prestigious universities and get more potential high-quality deal sources. The incubators, who collaborated with this project, usually work with startup teams from prestigious universities in North America, such as Stanford University, Columbia University, and University of British Columbia. Many of their startups have international backgrounds and have run successful fundraising campaigns. Considering that some startup characteristics, such as founders' personalities, are difficult to quantify, these data-driven methods are often used before investors invite founders to the face-to-face due diligence process. Therefore, this experiment mainly captures investors' preferences in the *pre-selection* stage.

## 2.1 *Recruitment Process and Sample Selection*

This IRR experiment was mainly implemented between 03/2020 and 07/2020. I sent invitation emails and instructional posters to the 15,000+ US-based VCs, whose information is collected by Zhang (2020). Both the recruitment emails and posters emphasized the matching purpose of this tool (see Online Appendix Figures A5 and A6 for the recruitment emails, Figures A7 and A8 for the instruction posters). Nonetheless, I also notify them that their anonymized data will be used for some research purposes as required by IRB. In total, 69 VCs from 68 different VC funds chose to participate in this experiment, providing 1,216 total startup profile evaluation results.[7] The number of recruited experimental participants is comparable to Kessler et al. (2019).

Table 1 summarizes the observed background information of all recruited VCs and compares it with the background information of US-based VCs recorded in the Pitchbook database.[8] Panel A shows that recruited investors' sectors of interest are diverse and representative, covering all the major industries that VCs typically focus on (Bernstein et al., 2017). Panel B shows that 67.1% of recruited investors focus on the Seed Stage. Panel C shows that the sample investors are representative in terms of gender, with 20.0% female investors. This is consistent with the NVCA 2018 VC report, showing that women hold 21% of investment positions in the VC industry. Furthermore, 86% of recruited investors are in senior positions, as their contact information is more readily available in existing databases. Roughly 11% of investors explicitly claim that their investment strategies involve ESG criteria or that their sectors of interest are typical ESG sectors, such as Clean Energy.

Sample selection bias might arise for unobservable reasons.[9] The major concern is that the recruited investors might have systematically different views on impact investing compared to normal US VCs. Since it is feasible to link experimental subjects with their VC firms' investment histories, Panel E further provides the financial information of the 69 recruited investors' VC companies. Results show that the recruited investors on average have more active portfolio companies, more exits, more dry powder, and a longer

[6]See "Using Machine Learning In Venture Capital" and "Venture Capital Due Diligence: The Screening Process."

[7]At the beginning of the study, each investor evaluates 32 profiles. Six investors completed the 32-profile version of the evaluation task. However, to recruit more investors, later participants only need to evaluate 16 profiles. One investor participated twice for different funds. Results are similar after removing the first 6 investors.

[8]See https://pitchbook.com/.

[9]For example, participants might be more pro-social since they are willing to participate in academic research studies. They may also be more interested in the application of data-driven methods in facilitating VCs' deal flows.

history of investment when compared to VC companies recorded in Pitchbook. During the COVID-19 pandemic, only more active VC companies still considered new investment deals and therefore had the incentive to participate in this experiment. However, the fraction of ESG-related investments of recruited VCs is similar to that of the VCs recorded in Pitchbook, suggesting that recruited investors are unlikely to have systematically different ESG attitudes when compared to other VC investors.

### 2.2 *Survey Tool Structure*

The detailed experimental design is the same as that employed in Zhang (2020) and Zhang and Ebrahimian (2020). In brief, investors who are interested in this matching tool will open the survey link inserted in the recruitment email. The tool contains two sections. After acknowledging the consent form, investors enter the profile evaluation section (i.e., the IRR experiment) to assess startup profiles. Participants also need to answer several background questions after the profile evaluation section. The second section contains a donation game, which is used to elicit investors' social preferences. Figure 1 provides the experimental flowchart that demonstrates the tool's structure.

***A. Consent Form and Instruction Page***

Both consent forms and recruitment emails invite investors to "try a matching tool that helps identify matched startups." When elaborating on the research purpose, the experimental design explicitly avoids mentioning the purpose of studying startups' ESG characteristics. To help investors understand the incentive structure, an extra instruction page is provided, emphasizing "the more accurately they reveal their preferences, the better outcomes the matching algorithm will generate (and the higher the financial return that the lottery winner will obtain)." Participants are also asked to assume that the provided startups are in their preferred industries and investment stages to pass the "qualify/disqualify test".[10] To provide the matching service, this tool also collects each investor's interested industry and stage after the profile evaluation section.

***B. Profile Evaluation Section***

***Profile Creation and Variation*** — The IRR experiment essentially follows the factorial experimental design, which dynamically varies multiple startup characteristics simultaneously and independently. The backend Javascript code randomly varies different startup characteristics simultaneously and independently across profiles to create hypothetical startups. The variable of interest in this paper is the startup's mission (i.e., impact ventures versus profit-driven ventures). Other randomized variables can provide quality variations, enabling the distributional analysis in Section 3. The validity of randomization is shown in Online Appendix Table A4 and Table A5.

To create largely realistic profiles, the presentation format mimics the Crunchbase format by emphasizing the key elements of a startup. [11] Investors like Plug and Play Tech Centers are known to access these public platforms to seek potential deals that fit their portfolios. However, these platforms only provide publicly

[10]Venture capitalists only invest in their interested sectors or stages. The qualify/disqualify test, as a quick decision-making exercise, is based on many factors such as industry, stage, and prior market knowledge. It tells investors whether the startup is worth any further examination.

[11]Crunchbase is a commercial platform that provides public information about startups mainly in the US. Other similar platforms include AngelList and Pitchbook.

available information, which is mirrored in our format. This avoids confidential startup characteristics, such as the proposed contract or various requirements of ownership and control rights. Moreover, the wording describing startup founders' experiences is extracted from real startup founders' biographies.

***Manipulating Startup's ESG Characteristics*** — To randomize a company's ESG characteristics, a startup characteristic called "mission" is introduced. This variable indicates whether the startup is a profit-driven venture or an impact venture. Startups often list this information on their Crunchbase profiles and company websites. Some well-known ESG startups, such as Planted Green and Footprint, have also specifically chosen their company names to signal that they are impact ventures. Therefore, it is normal for impact ventures to disclose their intention to promote sustainability and generate positive ESG impact.

I randomly assign the following wording to each generated startup's mission: "For profit" (i.e., profit-driven ventures), "For profit, consider IPO within 5 years" (i.e., profit-driven venture with IPO plans), or "Besides financial gains, also care about the social and environmental impacts" (i.e., impact ventures). To maximize the experimental power, the variable "mission" is randomly drawn from the following distribution: profit-driven ventures (25%, Control Group), profit-driven ventures with IPO plans (25%, Treatment 1 Group), and impact ventures (50%, Treatment 2 Group).[12] This reflects the fact that when compared to profit-driven ventures, it is very rare for impact ventures to file IPOs in the real world. Table 2 provides all the randomization details of other startup characteristics. The construction process of detailed startup characteristics is provided in Online Appendix Section A.

To test investors' implicit preferences, I introduce a short break after investors evaluate the first half of the startup profiles (i.e., the first eight profiles) by providing them with a progress screen. Investors can also go back to previous screens and revise their evaluations. Qualtrics can record the time spent on evaluating each profile, which is crucial to approximate the investors' attention and measure their tiredness. Additionally, each profile has a startup ID to indicate the evaluation progress.

***Evaluation Questions (Test Mechanisms)***—The mainstream mechanisms explaining investors' socially responsible investment (SRI) preferences include the following two parts. For belief-based mechanisms, investors may have optimistic risk-return expectations for impact ventures (Jeffers et al., 2021). Investors may expect impact ventures to generate higher financial returns or maintain lower risks. Given the two-sided matching nature of the entrepreneurial financing process, one extra potential belief-based mechanism is investors' expectation of the startup's availability, defined by the startup's likelihood to collaborate with this investor rather than other venture capitalists. For taste-based mechanisms, strong pro-social preferences can also drive SRI decisions. These pro-social preferences may stem from the improvement of investors' self-image or social image (i.e., social signaling).

To test these mechanisms, evaluation questions in this experiment include three mechanism questions and two decision questions. As for the mechanism questions, $Q_1$ (i.e., "profitability evaluation") asks investors to evaluate the percentile rank of each startup's profitability compared to firms they have previously invested in. Investors need to drag a bar, which stands for their evaluations of the startup's probability of generating a

[12]According to Kessler et al. (2019), while using a 50% versus 50% ratio can increase the statistical power of an experiment, this approach may also signal to participants the researcher's intent to study certain research questions, potentially making the IRR experiment more difficult to detect less pro-social decisions. Thus, in the real world, VCs may be even less enthusiastic about impact ventures than what is documented in this paper.

higher return. $Q_2$ (i.e., "availability evaluation") requires investors to evaluate how likely it is for the startup to accept their investment offer rather than other investors'. $Q_5$ (i.e., "risk evaluation") asks investors to evaluate the percentile rank of each startup's risk compared to firms they have previously invested in. $Q_5$ was not in the original design but was added later based on investors' feedback. Considering that only a few investors answered $Q_5$, risk-related results are only reported in the Online Appendix (see Online Appendix Table A10).

As for the decision questions, $Q_3$ (i.e., "contact interest ratings") requires investors to indicate how likely they are to get the startup's contact information or pitch deck. $Q_4$ (i.e., "investment interest ratings") asks investors to indicate how much money they would invest in the startup compared to their average investment amount.[13] Investment interest ratings (i.e., "$Q_4$") are much noisier than contact interest ratings (i.e., "$Q_3$") when testing investors' attitudes about impact ventures. This is because the experiment does not provide the amount of funding required by each startup or any soft information about startup teams in the pre-selection stage. Hence, the main results in this paper mainly come from evaluations of $Q_3$ rather than those of $Q_4$.

Screenshots of all the evaluation questions are provided in Online Appendix Figure A3 and Figure A4. Since these evaluations generate continuous outcome variables, the IRR experiment can get away from typical confounders that arise from the "cutoff" rule used in correspondence tests or outcome tests (Ewens and Townsend, 2020; Kessler et al., 2019).

***Background Questions*** — After the evaluation section, investors provide their standard background information for the following two purposes. Firstly, it helps to check how representative the sample is. Secondly, it enables the relevant heterogeneous effect analysis. Specifically, it is important to check whether impact investors and profit-driven investors have divergent views on impact ventures. The collected background information includes investors' preferred industries, stages, special investment philosophies (e.g., only investing in social ventures and women-led startups, whether caring about ESG), and standard demographic information (i.e., gender, race, educational background).

***Donation Game*** — To measure investors' social preferences, a donation game is added at the end of the survey tool. Similar to Riedl and Smeets (2017), if investors' social preferences are positively correlated with their SRI decisions, this suggests that social preference is a possible factor that drives investors' taste-driven preferences towards impact ventures. In this donation game, investors are informed that they will receive an *unexpected* \$15 Amazon Gift Card for their participation in this study. Investors can decide whether to donate a portion of the provided \$15 to the displayed startup founders. For example, if an investor donates \$3, this investor will receive a \$12 Amazon Gift Card. Therefore, investors' donation decisions are incentivized by real monetary rewards. The donated money will be used to purchase a small gift for real startups in the incubators and bring them anonymous encouragement during the pandemic recession.

[13] $Q_4$ asks the relative investment amount rather than the absolute investment magnitude because different investors have different ranges of targeted investment amounts. For example, conditional on investing the same amount of money, an investor who usually invests \$500,000 in each startup might have more investment interest in the candidate startup compared to another investor who usually invests \$1,000,000. To accommodate these situations, I make $Q_4$ as standardized and general as possible.

## 2.3 *Incentives*

One key point of the IRR experimental design is its incentive structure, which ideally satisfies the following two conditions. Firstly, it should guarantee that the more truthfully investors reveal their investment preferences, the more benefits they can obtain from this research (i.e., incentive alignment). Secondly, it should involve enough stakes to elicit sensitive preferences in finance-related settings.

Taking advantage of the field context of this experiment, I provide a "matching incentive" (Kessler et al., 2019) to all the investors, which essentially uses *real* investment opportunities to elicit investment preferences. To increase the sample size, I also provide an extra "monetary incentive" (Armona et al., 2019) to a randomly selected subset of investors. This paper later shows that investors' evaluations of other startup characteristics are consistent with the extant VC literature. Moreover, investors' ratings significantly correlate with their real-world investment decisions, further justifying the validity of the incentive.

***Matching Incentive*** — For roughly 4,000 randomly selected investors who receive the recruitment email (Version 1), I only provide the "matching incentive" following Kessler et al. (2019). After each investor evaluates all startup profiles, a machine learning algorithm is used to identify matching startups from the collaborative incubators. If the matched startups are also interested in the investor's investment philosophy, they will contact the investor for a potential collaboration opportunity. The matching algorithm uses all the investors' evaluation answers to identify their preferences. Therefore, all five evaluation questions are incentivized by this incentive. A description of the algorithm is provided in the consent form.

***Monetary Incentive*** — To increase the sample size, I provide both the "matching incentive" and an extra "monetary incentive" as used by Armona et al. (2019) to the remaining randomly selected investors who received the Version 2 recruitment email. This "monetary incentive" is essentially a lottery in which two experimental participants will be randomly selected to receive $500 each plus an extra monetary return closely related to the accuracy of their evaluations of each startup's profitability. The more accurate their evaluations are of each startup's future financial returns, the more money they will obtain as a lottery winner.[14] However, this is only used to incentivize the "profitability evaluation question" (i.e., "Q1"). The accuracy of evaluation results will be determined based on the Pitchbook data published in the next twelve months after the experiment is completed. The two lottery winners were separately informed that they would receive the award at the end of July 2020. The evaluation algorithm is provided in the consent form (Version 2).

***Justification*** — One concern with adding the "monetary incentive" is the possibility of attracting participants who do not value the matching incentive, which results in extra noise. Another concern is that the "monetary incentive" essentially elicits each subject's judgment of how the market evaluates each startup's profitability. This might be different from the subject's own judgment of each startup's profitability as incentivized by the "matching incentive." To address these concerns, I have compared the evaluation results

[14]For example, consider if Peter Smith, one hypothetical experimental participant, is chosen as the lucky draw winner. In his survey, he indicates that male teams are more likely to generate higher financial returns on average. In that case, the researcher can construct a portfolio containing more real startups with male teams. After one year, based on the financial performance of real startups in Pitchbook, this portfolio containing more startups with male teams generates a 10% return. Thus, Peter Smith receives $500 + $500*10% = $550 as his finalized monetary compensation one year after he participates in the survey. $500*10%=$50 is the "extra monetary return."

of investors who receive only the "matching incentive" and those who receive both incentives. Online Appendix Table A6 shows that these two incentive structures do not cause systematically different evaluations, especially the profitability ratings. The interaction terms between the incentive structure and the startup's ESG characteristics are not significantly different from zero.[15]

# 3 Results

Table 3 reports the average treatment effect (ATE) of startups' ESG characteristics on investors' evaluations. The dependent variables of Columns (1) to (4) are investors' profitability evaluations, availability evaluations, contact interest ratings, and investment interest ratings, respectively. Panel A compares evaluations of impact ventures and all types of profit-driven ventures (i.e., both profit-driven ventures and those with an IPO plan). Panel B compares evaluations of impact ventures and solely profit-driven ventures. "Has ESG Characteristics" is a dummy variable that equals one if the startup aims for positive environmental and social impacts besides financial gains, and zero otherwise. "Has IPO Plan" is a dummy variable that equals one if the startup is profit-driven and considers IPO within five years, and zero otherwise. All the regressions add investor fixed effects to allow some investors to have more generous ratings. Standard errors in parentheses are clustered at the investor level. The p-values of "Has ESG Characteristics" have been adjusted to Bonferroni-Holm p-values due to the multiple hypothesis testing problem. Table 3 shows very weak average treatment effects (i.e., ATEs). For example, although the coefficient of "Has ESG Characteristics" in Panel A indicates that aiming for environmental and social impacts lowers investors' evaluations of the startup's profitability ratings by 2.75 percentile ranks, it is weakly significant at the 10% level. The coefficients of "Has ESG Characteristics" in other columns are not significant.

Generating insignificant ATEs is a common outcome when eliciting socially sensitive preferences using the IRR experiment (Kessler et al., 2019). This might occur due to multiple factors. Firstly, as documented by Zhang (2020), the magnitude and direction of an evaluator's sensitive preferences can vary depending on the candidates' quality. If the treatment effects of ESG only exist among high-quality startups, then the ATE of ESG cannot capture this. Secondly, impact investors and profit-driven investors might hold opposing beliefs and attitudes towards impact ventures, neutralizing the group-level ATE. Thirdly, investors' *explicit* ESG preferences and *implicit* ESG preferences might differ, leading to opposing evaluations at the start and at the end of the experiment. Lastly, as consent forms notify investors of the research purpose as required by the IRB, investors might behave more pro-socially. Hence, it is crucial to test distributional effects, heterogeneous effects, and implicit preferences when researchers analyze socially sensitive behaviors using the IRR experimental method.

## 3.1 (Distributional Effect) Investors Expect Impact Ventures to Underperform.

The distributional effect might exist due to the following two reasons. Firstly, investors have incentives to evaluate attractive startups more carefully as only high-quality startups are likely to receive funding from

[15] Among investors who received only the "matching incentives", 17 investors participated in the experiment. Among investors who received both the "monetary incentive" and the "matching incentive", 52 investors participated in the experiment.

them. This leads to less noise in evaluations of attractive startups, making it more likely to detect significant results. Secondly, impact ventures still belong to the "minority" group in the entrepreneurial community given that profit-driven ventures are the mainstream. Based on the discrimination theory (Morgan and Várdy, 2009), information signaling high-quality candidates is generally perceived as noisier for a "minority" group, which shifts evaluators' priors upward to a lesser extent when compared to similar signals from the "majority" group. Hence, "discrimination" against the "minority" group (i.e., ESG startups) is more likely to happen when investors evaluate attractive candidates. OLS regressions only examine the effect of "ESG characteristics" on the conditional *mean* of investors' evaluations. To detect any distributional effect, I first use the following quantile regression.

$$Y_{ij} = \alpha(\tau) + \beta(\tau)X_{ij} + \epsilon_{ij}(\tau)$$
$$\text{where} \qquad Q_{Y_{ij}|X_{ij}}(\tau) = X_{ij}\beta(\tau), \qquad Q_{\epsilon_{ij}(\tau)|X_{ij}}(\tau) = 0$$

where $Y_{ij}$ is the evaluation rating from investor $i$ for startup profile $j$. $X_{ij}$ is a dummy variable indicating whether the startup aims for ESG. $Q_{Y|X}(\tau)$ is the $\tau^{th}$ conditional quantile of Y. In OLS regression, we assume $E(Y|X) = \beta X$ and the coefficient $\beta$ stands for the effect of X on the conditional *mean* of Y (i.e., $E(Y|X)$). In Quantile regressions, by assuming $Q_{Y|X}(\tau) = X\beta(\tau)$, $\beta(\tau)$ is the effect of X on the $\tau^{th}$ conditional *quantile* of Y (i.e., $Q_{Y|X}(\tau)$). The estimation of $\beta(\tau)$ requires using all evaluated profiles.[16]

Table 4 reports quantile regression results about the effects of aiming for ESG on different conditional quantiles and conditional mean of investors' profitability evaluations and attractiveness evaluations. Panel A focuses on profitability evaluations (i.e., $Q_1$). Panel B focuses on attractiveness evaluations, measured by investors' contact interest ratings (i.e., $Q_3$). In all the columns, the dependent variable is the startup's received profitability rating (i.e., $Q_1$) in Panel A and the contact interest rating (i.e., $Q_3$) in Panel B. In each of the Columns (1) to (10), the reported coefficient of "Has ESG Characteristics" stands for the effect of aiming for ESG on the $k$th conditional percentile ($k \in 5, 15, 25, ..., 95$) of the startup's received profitability rating (i.e., $Q_1$) in Panel A and the contact interest rating (i.e., $Q_3$) in Panel B. In Column (11), the reported coefficient of "Has ESG Characteristics" using OLS regressions stands for the effect of aiming for ESG on the conditional mean of $Q_1$ in Panel A and $Q_3$ in Panel B. Standard errors in parentheses are clustered at the investor level.

Panel A of Table 4 shows that aiming for ESG lowers investors' profitability evaluations of impact ventures. Considering that startups' ESG characteristics are randomly assigned, the control group (i.e., profit-driven ventures) and treatment group (i.e., impact ventures) are similar in both observable and unobservable dimensions. Hence, experimental results precisely show that similar startups receive lower profitability and contact interest ratings due to their ESG objectives. However, this effect mainly exists among relatively high-quality startups and is less salient among low-quality startups.In general, the profitability evaluations of impact ventures in the four quantiles between the 65th and 95th percentiles decrease by at least 5 percentile ranks. These results are statistically significant at least at the 5% level, equivalent to an 11.3% decrease

[16] $\beta(\tau) = \underset{\beta \in R^k}{\text{argmin}} E(\rho_\tau(Y - X\beta))$ and $\rho_\tau$ is proportional to the absolute value function.

compared to the average profitability evaluations. However, the five quantiles between the 5th and 45th percentiles decrease by only 1 to 2 percentile ranks and all coefficients are not statistically significant. VCs are generally very selective in their startup selection process. Given that the negative ESG effect mainly exists among startups whose profitability is above the median compared to recruited investors' portfolio companies, impact ventures can be severely hurt by these profitability evaluations during their fundraising process.

Panel B of Table 4 shows that impact ventures also receive lower contact interest ratings. Similarly, this effect mainly exists among attractive startups which are more likely to be contacted by investors. For startups whose contact interest ratings are in the 65th and 75th quantiles of the attractiveness distribution, pursuing ESG goals reduces the likelihood of investors contacting the startup by 7 to 9 percentage points. These results are statistically significant at the 1% level and equivalent to a decrease of at least 12.8% compared to the average contact interest ratings. For startups whose contact interest ratings are below the 60th quantile, the ESG effect is also negative and ranges between 0 to -3 percentage points. However, it is not statistically significant. Combined with the results shown in Panel A, the experiment indicates that investors are on average less willing to contact impact ventures when compared to similar profit-driven ventures, as they expect impact ventures to generate lower financial returns, thus confirming the theoretical prediction of Pástor, Stambaugh and Taylor (2021).

To facilitate the readers' understanding of results in quantile regressions above, Figure 2 visualizes the results provided in Table 4. Assume that a high-quality profit-driven startup receives a profitability rating equal to "85" and at the 95th quantile of all profit-driven startups' profitability ratings. When the startup exogenously becomes an impact venture, under the standard assumption of "rank invariance",[17] its new profitability rating decreases to roughly "80". As shown in Panel A of Figure 2, the slopes of the upper gray lines are all negative, indicating that relatively more profitable startups' profitability evaluations decrease when they exogenously change from profit-driven startups to impact ventures. Similar negative slopes also exist for the upper gray lines in Panel B, which indicates that more attractive startups' received contact interest ratings also decrease when these startups become impact ventures. However, the flatter slopes of gray lines below the median suggest that the negative effect of aiming for ESG is not salient for unattractive startups.

The discovered distributional effects of investors' expectations of impact ventures are aligned with the hypothesis that people are more likely to opt for impact investing as long as they are doing well and face fewer performance pressures. Bauer et al. (2021) shows that, among people expecting much lower retirement benefits due to COVID-19, the percentage of investors favoring sustainable investment is also lower than groups expecting milder negative impacts from economic hardship. If impact ventures are expected to underperform profit-driven ventures, profit-driven funds will have fewer motivations to support impact investing at the cost of their financial performances, especially when they face performance pressures. The tension between profits and impact is likely to exist when investors evaluate attractive startups.

***Robustness Check*** As shown in Online Appendix Table A7, the distributional effects are robust after evaluations of the first two or three profiles are removed. This mitigates concerns about learning effects.

[17] The "rank invariance" assumption means that the startup's received profitability ratings are still at the 90th quantile of all impact ventures after the exogenous change. It's a standard assumption when researchers need to use quantile regressions.

These distributional effects might be driven by a few experimental subjects with extreme attitudes against impact investing, yet Online Appendix Table A8 shows that results are still robust after evaluations of a few experimental subjects with the strongest ESG attitudes are removed.

Since $Q_1$ is about the percentile rank of startups' profitability compared to investors' previous portfolio companies, some VCs might give uniformly better or worse profitability ratings due to their historical fund performances. Online Appendix Table A9 shows that quantile regression results based on $Q_1$ still hold after controlling for each investor's profitability rating level, which is measured by each investor's median of $Q_1$ or "leave-one-out" median of $Q_1$. [18]

***Confirm Quantile-regression Results Using "Objective" Attractiveness*** Quantile regression results show that aiming for ESG mainly hurts attractive startups when they raise funding from early-stage VCs. Another alternative method that can test this effect is to generate an "objective" attractiveness measurement of each startup using other orthogonally randomized startup team and project characteristics. Researchers can then check whether aiming for ESG reduces investors' evaluations of these more "objectively" attractive startups using OLS regressions. When compared to using quantile regressions, this method is slightly noisier due to the following two reasons. Firstly, researchers need to impose functional form assumptions when using other startup characteristics to predict startups' attractiveness. Secondly, while the estimation of quantile regression coefficients uses all the startup profiles (i.e., the full sample), this method only uses a subset of startup profiles (i.e., those relatively attractive startup profiles).

To implement this method, I first generate an "objective" attractiveness measure (i.e., $\hat{Q_3}$) for each startup profile using the following OLS regression for each investor $i$:

$$Y_{ij} = \alpha_i + \beta_i X_{ij} + \epsilon_{ij}$$

where $Y_{ij}$ is the contact interest rating received by startup profile $j$, which is evaluated by investor $i$. $X_{ij}$ includes the other orthogonally randomized startup team and project characteristics used in Online Appendix Table A11. These startup characteristics include "Serial Founder," "Ivy League Educational Background," "Number of Founders," "US Founder," "Number of Comparative Advantages," "Has Positive Traction, "Number of Employees," "Company Age," "Company Age$^2$," "B2B Startup," and "Domestic Market."

Table 5 reports the effect of aiming for ESG on investors' evaluations using OLS. Unlike Table 3, Table 5 only uses "objectively" attractive startup profiles whose received $\hat{Q_3}$ is above 50. The dependent variable is the profitability evaluation (i.e., $Q_1$) in Columns (1) and (2), and the contact interest rating (i.e., $Q_3$) in Columns (3) and (4). The sample contains "objectively" attractive startup profiles (i.e., $\hat{Q_3} \geq 50$) evaluated by all the investors in Columns (1) and (3), and "objectively" attractive startup profiles evaluated by profit-driven investors in Columns (2) and (4). All the regressions add investor fixed effects to control for the effect from any fixed investor characteristics. Standard errors in parentheses are clustered at the investor level.

Table 5 confirms previous quantile regression results that aiming for ESG mainly hits attractive startups. Columns (1) and (2) show that compared to profitability ratings received by "objectively" attractive profit-

[18]Ideally, researchers can add fixed effects in quantile regressions to address this concern. However, unlike OLS, quantile regression is a nonlinear model. Adding fixed effects to nonlinear models requires that the number of profiles evaluated by each investor should be comparable to the number of total investors. Given that one investor only evaluates 16 profiles, adding fixed effects to quantile regressions is infeasible in this IRR experimental setting.

driven ventures, profitability ratings received by similar attractive impact ventures on average decrease by 2.9 percentile ranks. Results are statistically significant at the 10% level and equivalent to an 6.5% decrease compared to the average profitability evaluations. Column (3) shows that investors on average give 2.98 percentage points lower contact interest ratings to "objectively" attractive impact ventures compared to similar profit-driven ventures. The negative coefficient is statistically significant at the 5% level and equivalent to an 5.4% decrease compared to the average contact interest ratings. In Column (4), it is shown that when profit-driven investors evaluate objectively attractive startups, the negative effect of pursuing ESG goals increases to -3.63 percentage points, which is roughly a 6.6% decrease. The negative coefficient is statistically significant at the 1% level. This is consistent with results in Table 6 and Table 7, showing that although investors expect attractive impact ventures to generate lower financial returns, this expectation mainly reduces profit-driven investors' contact interest ratings.

***Validity of IRR Experiment*** Some readers might be concerned that the significant results above are just noises, and that the IRR experimental method cannot elicit investors' preferences. To justify the validity of the experimental design, I borrow the results of Zhang and Ebrahimian (2020) and show them in the Online Appendix Table A11. Using the same experimental data, Zhang and Ebrahimian (2020) finds that several other startup characteristics, such as startup founders' educational backgrounds, entrepreneurial experiences, as well as the startup's traction, can strongly affect investors' evaluations based on the same IRR experiment. These results are consistent with both the VC literature and anecdotal evidence, verifying that the IRR experiment is a valid preference elicitation technique.

***Link with Real-world Investment Portfolios*** As I can observe the identity of each experimental subject, Online Appendix Table A12 further tests correlations between investors' real-world investment portfolios recorded in the Pitchbook and their evaluations in the IRR experiment. Results show that having more ESG startups in the portfolio companies of the investor's affiliated VC firm is significantly correlated with giving higher contact interest ratings to ESG startups. However, this correlation is only significant when using investors' evaluations of attractive startups (i.e., $\hat{Q}_3 \geq 50$). When adding investors' evaluations of unattractive startups, this correlation becomes noisy and insignificant. Hence, results suggest a close connection between investors' evaluations of attractive startups in the experiment and their VC firms' real-world investment portfolios.

Online Appendix Table A13 further links investors' self-reported background information about their ESG characteristics with the real-world investment decisions of their affiliated VC companies. Results show that investors who claim to care more about impact investing and work in ESG-related industries in the background information section are indeed significantly associated with more ESG-related startups in their investment portfolios. Moreover, their companies are also more likely to emphasize their impact investing strategies on their official websites. This correlation also brings some validity to the self-reported background information of each investor in the experiment.

Table 6 reports quantile regression results based on profit-driven investors' evaluated profiles. Since profit-driven investors dominate among the recruited investors, most results are similar to those in Table 4. In Panel A, the three conditional quantiles between the 55th and 75th percentiles decrease by 5 to 10 percentile ranks for impact ventures' profitability evaluations. In Panel B, the three conditional quantiles between the 65th and 85th percentiles decrease by 4 to 8 percentage points for impact ventures' received contact interest ratings. This suggests that profit-driven investors' decisions are influenced by their beliefs about startups' profitability. As impact ventures are viewed as less lucrative, it is natural that profit-driven investors have less interest in approaching them at the pre-selection stage.

Table 7 reports quantile regression results based on impact investors' evaluated profiles. Investors are classified as impact investors if they claim to care about ESG or adopt impact investing in their indicated investment philosophies, or if their preferred industries are ESG-related, such as climate tech.[19] Results show that although impact investors also view impact ventures as less profitable in general, this belief does not reduce their contact interest ratings. In Panel A, all quantiles above the 65th percentile of the profitability distribution decrease by 5 to 13 percentile ranks, and the results are statistically significant. However, in Panel B, impact investors' contact interest ratings do not significantly decrease across the whole spectrum of startups' attractiveness. This suggests the existence of taste-driven preferences toward impact ventures among impact investors. Unlike profit-driven investors, impact investors are willing to forgo a portion of their profits to generate positive environmental and social impacts from their investment decisions.

Surprisingly, quantile regressions and OLS regressions above show that compared to purely profit-driven ventures, profit-driven startups that consider IPO within five years generally do not receive higher profitability evaluations or higher contact interest ratings. The only exception is that very top startups with an IPO plan, whose received profitability ratings are at the 95th quantile, are considered to be significantly more profitable by impact investors. This can happen due to the following reasons. Firstly, only the most promising startups can successfully issue an IPO. As shown in Table 7, a potential IPO plan only benefits very top startups' profitability evaluations and can hurt middle-level startups' profitability evaluations. Secondly, few impact ventures successfully issued an IPO before, which helps to explain the negative coefficient of "Has IPO Plan" in Panel B of Table 7. Thirdly, recruited investors are mainly early-stage VCs. Considering that it usually takes eight to ten years for an early-stage startup to successfully issue a high-impact IPO, emphasizing an IPO plan within five years might be less appropriate for early-stage startups except for the very top ones.[20] Lastly, startups with an IPO plan might demonstrate lower availability to early-stage investors. As shown in Panel B of Table 3, the coefficient of "Has IPO Plan" is -1.87 with a p-value equal to 0.185.

### 3.2 Investors Pay More Attention to Attractive Impact Ventures.

Table 8 tests whether investors allocate more attention to ESG startups compared to similar profit-driven startups. Attention is measured by investors' response time, which is defined as the number of seconds

[19] The discrepancy between the preferences of impact investors and conventional investors is crucial for the theoretical work discussing the equilibrium outcome of sustainable investment (Pástor, Stambaugh and Taylor, 2020). To identify impact investors, I collect investors' preferred industries and investment philosophies in the "Background Question" section. Some participants mentioned whether they aim for impact investments or target green industries. For example, one investor explicitly wrote, "We aim for anything with positive environmental or social impacts, such as Renewable Energy, Energy Efficiency, etc". Therefore, I can identify impact investors and profit-driven investors based on these indicated preferences.

[20] See the article "How Long Do Firms Take from Founding to IPO?" by Justin Garosi, August 18, 2021. To transition from an early-stage startup to a public company (i.e., post-IPO company), Google took six years, Facebook took eight years, and Uber took ten years.

before each page submission, winsorized at the 95th percentile (Huang, Li, Lin, Tai and Zhou, 2021; Kessler et al., 2019). On average, investors spend 59.23 seconds on each profile. Column (1) tests all the evaluation results. Columns (2) to (6) focus on the high-stake situation where investors indicate a higher likelihood of contacting the startup. I choose five thresholds to define high stake situations (i.e., $Q_3 > 30$, $Q_3 > 40$, $Q_3 > 50$, $Q_3 > 60$, $Q_3 > 70$). All the regressions add investor fixed effects. Standard errors in parentheses are clustered at the investor level. Since regressions control $Q_1$ and $Q_2$, Table 8 mainly shows investors' attention allocation decisions which cannot be explained by investors' beliefs.

Results show that conditional on receiving similar profitability and availability evaluations, impact ventures on average receive more attention from investors. This effect mainly exists among attractive startups which receive higher contact interest ratings. For example, when $Q_3 > 30$, investors spend 8.41 more seconds on impact ventures' profiles, accounting for 14.2% of investors' average spent time on each profile. When $Q_3 > 40$, the extra allocated attention to ESG startups increases to 10.17 seconds. All the results are statistically significant at the 5% level. Online Appendix Table A14 and Table A15 show that results are still similar after evaluations of the first two profiles have been removed or when attractive startups are defined by "objective" attractiveness measurements (i.e., $\hat{Q}_3$), respectively. Online Appendix Table A16 finds that both impact investors and profit-driven investors spend more time on ESG-related startups.

There are two potential explanations of why investors allocate more attention to impact ventures. The first interpretation is that impact ventures are harder to evaluate compared to similar profit-driven ventures. Hence, investors need to spend more effort and time to assess impact ventures. The second interpretation is that profit-driven investors might also have taste-driven preferences toward impact ventures. Based on the "attention discrimination" theory (Bartoš, Bauer, Chytilová and Matějka, 2016), evaluators should rationally spend more attention on the more preferred group in a "cherry-picking" market (i.e., selecting high-quality candidates), such as in the entrepreneurial finance market.

To examine which explanation is more valid, I implement the following two tests. Firstly, I check which other startup characteristics also affect investors' allocated attention in Online Appendix Table A17. As suggested by Table A17, recruited investors might have potential taste-driven preferences toward startup founders who graduated from Ivy League colleges or are located in the US.[21] However, Table A17 shows that investors do not allocate more time to these preferred startups. Instead, investors spend more attention on more complicated startups, such as those with multiple founders and multiple comparative advantages. While investors on average spend four to six more seconds on relatively complicated startups, they spend eight to ten more seconds on impact ventures, suggesting that ESG startups present more complexity.

Secondly, I check the correlation between investors' additional time spent on impact ventures and their donation amount in the donation game. If the "taste-driven preference" explanation dominates, we should expect the correlation to be *positive*, which means that more pro-social investors should demonstrate more taste-driven preferences toward impact ventures. However, as shown in Online Appendix Table A18, the

[21]As shown in Column (5) of Online Appendix Table A11, coefficients of "Ivy League Educational background" and "US Founder" are still significantly positive after the regression controls for $Q_1$ and $Q_2$. This suggests that investors prefer Ivy League startups and US startups, and this preference cannot be explained by profitability evaluations and availability evaluations. One possible explanation is the existence of taste-driven preferences. In contrast, any positive effects of "Number of Founders" or "Number of Comparative Advantages" on investors' contact interest ratings can be fully absorbed by investors' profitability evaluations and availability evaluations.

correlation is significantly *negative*. Both tests support the explanation that it is harder for investors to evaluate impact ventures. This extra difficulty in the impact ventures' evaluation process can be another obstacle for impact ventures to raise funding from VCs.

### 3.3 Implicit Preferences and Potential Sorting

"Implicit preference" refers to a preference that affects individuals' decisions in an unconscious manner. Bertrand, Chugh and Mullainathan (2005) discuss the economic importance of implicit preference, which can influence behaviors in meaningful ways. Zhang (2020) discovers that in the IRR experimental setting, investors' implicit preference based on startup founders' gender has a stronger correlation with investors' real-world portfolios than their explicit preference. The effect of implicit preference is stronger under the conditions of greater ambiguity or subjectivity, heavier cognitive load, and more inattentiveness to tasks. Given the huge amount of screening workload for VCs in the pre-selection stage, it is helpful to also test investors' implicit preferences.

To test for implicit preferences, the experiment deliberately inserts a break, showing a progress screen after the first half of the startup profiles. Kessler et al. (2019) provides two methods to test implicit preferences. The first one is to compare evaluations of the first half profiles and the second half profiles *within* each block. The second one is to compare evaluations of the first half profiles of the study and evaluations of the second half profiles of the study. The logic behind both methods is that when investors become more rushed or fatigued, their implicit preferences are more likely to emerge and affect their judgments. Since only the second method is pre-registered for this experiment, I report results from comparing investors' evaluations in the first half and second half of the study.[22] Similar to the Implicit Association Test (IAT), the IRR experiment also measures implicit preferences by using subjects' response time in the assigned experimental task.

Table 9 reports regression results of impact investors' and profit-driven investors' implicit preferences regarding startups' ESG characteristics. Panel A focuses on impact investors' evaluations. Panel B focuses on profit-driven investors' evaluations. "Second Half of Study" is an indicator variable for startup profiles shown in the second half of the experiment. Fixed effects for subjects are included in all specifications. In Column (1), the dependent variable is investors' response time, which is defined as the number of seconds before each page submission, winsorized at the 95th percentile. Columns (2) to (5) show the profitability evaluations, availability evaluations, contact interest ratings, and investment interest ratings, respectively. R-squared is indicated for each OLS regression. Standard errors in parentheses are clustered at the investor level.

Results of Table 9 find weak evidence that sorting potentially exists along the ESG dimension between startups and investors. Column (1) of Panel A and Panel B shows that investors on average spend roughly 27 seconds less on evaluating startup profiles in the second half of the study. This indicates that investors are more fatigued or rushed as the experiment progresses to the end. Importantly, in Column (3) of Panel A, the coefficient of "Has ESG Characteristics" is 10.39, which is statistically significant at the 5% level. After implementing multiple hypothesis test, both Bonferroni-Holm p-value and Sidak-Holm p-value are still

[22] The pre-registered analysis plan for this experiment (AEARCTR-0004982) is not publicly accessible, but can be requested.

around 0.05. This indicates that impact investors on average expect impact ventures to be 10.39 percentage points more likely to accept their investment offers instead of collaborating with other investors in the first half of the study. Although this effect decreases in the second half of the study, impact investors' overall availability evaluations are more positive for impact ventures.

Unlike impact investors, profit-driven investors appear to think the opposite. In Column (3) of Panel B, the coefficient of the interaction term between "Has ESG Characteristics" and "Second Half of Study" is -5.89, which is statistically significant at the 5% level. When the sample only includes evaluations of profiles displayed in the second half of the experiment, the coefficient of "Has ESG Characteristics" in Column (3) is -4.38.[23] Its Bonferroni-Holm p-value and Sidak-Holm p-value are 0.016. This suggests that when investors become more rushed or more familiar with the evaluation process, they view impact ventures as roughly 4 percentage points less likely to collaborate with them.

This paper acknowledges that evidence on sorting is slightly weak becomes it is discovered based on testing investors' implicit preferences and the number of impact investors is not large in this experiment. Hence, readers can take this result with caution. However, through field experiments with real US-based startup founders, Zhang (2022) discovers that positive assortative matching based on ESG indeed exists in US startups' fundraising process. In the US, ESG startups are more likely to approach impact VCs while profit-driven startups are more likely to approach profit-driven VCs. Consistent with Zhang (2022), the sorting evidence in this paper shows that on the investor side, professional VCs might realize the existence of sorting and segmentation based on ESG between investors and startups. Then the lower availability evaluations can also hurt impact ventures' fundraising outcomes from profit-driven investors.[24] Since the entrepreneurial financing process in the VC industry is a two-sided matching process, investors may differ not only in their risk-return models but also in their perceptions of how likely impact ventures are to collaborate with them.

### 3.4 Investors Who Are More Supportive to ESG Also Donate More.

Riedl and Smeets (2017) show that social preferences can explain mutual fund investors' socially responsible investment (SRI) decisions. Because the donation game assesses the pro-social tendencies of each recruited VC based on their anonymous donation amount, it is valuable to examine the relationship between investors' ESG attitudes and their donation behavior when incentivized by real money. A significant positive correlation between social preferences and impact investing decisions suggests that VCs' pro-social tendencies may play a role in their decisions to invest in socially responsible ventures.

Table 10 reports regression results for correlations between investors' attitudes towards startups' ESG characteristics and their anonymous donation behaviors.[25] In Columns (1) and (2), the dependent variable "Donate or Not" is an indicator that equals one if the investor donates any positive amount of money to

[23]Similarly, the coefficient of "Has IPO Plan" in Column (3) becomes -3.32 in the second half of study, which is statistically significant at the 10% level. This indicates that profit-driven startups that consider IPO within five years indeed demonstrate lower availability when compared to other profit-driven startups based on investors' implicit preferences.

[24]Zhang and Ebrahimian (2020) show that investors' availability evaluations are significantly positively correlated with the investors' contact interest ratings.

[25]Since one VC participated in the experiment twice for different VC companies, the number of observations is 70 instead of 69. Results are robust after removing this investor.

startups, and equals zero otherwise. In Columns (3) and (4), the dependent variable "Donate All or Not" is an indicator that equals one if the investor donated all \$15 to the startup, and equals zero otherwise. In Columns (5) and (6), the dependent variable is the amount of money donated by the investor and the unit is dollars. "ESG Attitude" is calculated based on $Q_3$. It is the coefficient $\beta_i$ of the following regression, which uses each individual investor $i$'s evaluation results: $Q_{3ij} = \beta_{0i} + \beta_i \text{Has ESG Characteristics}_{ij} + \gamma_i \text{Has IPO Plan}_{ij} + \epsilon_{ij}$. It stands for the causal effect of "being an impact venture" on the investor's contact interest ratings (i.e., $Q_3$). Control variables include the investor's preferred industries and stages. Probit regressions are used in Columns (1) to (4) and OLS regressions are used in Columns (5) and (6). R-squared reports Pseudo R2 for Probit regressions and R-squared for OLS regressions. Standard errors in parentheses are robust standard errors.

Table 10 shows that investors' attitudes toward impact ventures are indeed positively correlated with their social preferences as indicated by their anonymous donation decisions. In Columns (1) to (4), all coefficients of Probit models are positive and statistically significant at the 5% level. This shows that 1 positive unit of investors' "ESG Attitude" is associated with a roughly 1% higher likelihood of donating money to startups and a 1% higher likelihood of donating all the \$15 during the experiment. Since Probit models are nonlinear models, marginal effects are estimated at the level of the mean of "ESG Attitude." In Columns (5) to (6), coefficients of OLS models are also positive and statistically significant at the 5% level. This indicates that, on average, investors who have one more positive unit of "ESG Attitude" donate an additional \$0.04 to startup teams. Results are still robust after controlling for the effect of startups' ESG characteristics on investors' profitability ratings.

Since investors' "ESG attitudes" are represented by the coefficient estimated by OLS, these attitudes potentially involve measurement errors and lead to attenuation bias in estimated correlations between investors' "ESG attitudes" and their donation behaviors. Some may argue that the low stake amount of \$15 in the donation game could lead to additional noise in investors' donation decisions, potentially underestimating the true correlation between social preferences and SRI decisions. This suggests that social preferences may have an even greater impact on investors' SRI decisions in the US private equity market than the estimated correlation value implies.

# 4 Accuracy of Expectations

To test the accuracy of investors' expectations regarding the underperformance of impact ventures, the paper compares the *ex-post* financial performance of impact ventures and profit-driven ventures after the experiment was completed. The paper first tests the short-term performance of different startups between 07/31/2020 and 07/31/2021, given that the "monetary incentive" primarily elicits investors' expectations during the one-year period after the experiment. Furthermore, since venture capitalists' investment cycles are usually longer than one year, the paper also examines the medium-term performance of different startups between 07/31/2020 and 01/31/2023, which is the 2.5-year period after the experiment. The deal-level data used in the analysis were obtained from the Pitchbook Database. Similar to other mainstream VC databases, Pitchbook only observes completed deals instead of the entire pool of startups considered by VC investors.

Therefore, this section provides only suggestive evidence of whether impact ventures underperform profit-driven ventures, conditional on having successfully raised funding.

This method essentially follows the "outcome test" in the discrimination literature (Becker, 1993; Ewens and Townsend, 2020; Fisman, Paravisini and Vig, 2017; Hebert, 2020). If investors' pre-selection judgments are fully accurate and taste-driven investment preferences do not exist, impact ventures should perform ex post equally as well as profit-driven ventures. After screening out less lucrative impact ventures, rational investors can achieve similar financial performance by investing in either profit-driven ventures or impact ventures. If investors underinvest or overinvest in impact ventures in the pre-selection stage due to miscalibrated beliefs or taste-driven preferences against or towards ESG, respectively, then impact ventures should significantly underperform or outperform profit-driven ventures, conditional on being funded. To classify startups as impact ventures or profit-driven ventures, the paper follows Barber et al. (2020) and implements the following two steps. .

**Step 1:** The paper identifies a startup as an ESG-related company if any ESG-related keywords from Online Appendix Table B1 appear in the startup's description of business models or industry background. The selected ESG-related keywords come from the following three main sources: 1) The ESG-related keywords to identify impact investors used by Barber et al. (2020); 2) KPMG 2021 UK Mid-market PE Review Report, which publishes a list of keywords to identify deals with an ESG component; 3) Prestigious impact ventures' official websites. The following variables in Pitchbook are used to indicate the startup's type: "Description" (i.e., description of the startup's business model), "Keywords" (i.e., selected keywords to indicate the startup's primary business model), "PrimaryIndustrySector", "PrimaryIndustryGroup", and "PrimaryIndustryCode".

**Step 2:** Two research assistants (RAs) independently read the descriptions and online resources of the ESG startups selected in Step 1 and remove startups that are unrelated to generating ESG impact. In cases where there are disagreements between the RAs, the author makes the final judgment. There are 377 ambiguous cases. However, dropping these cases or adding them back produces similar results. This method labels 5,326 startups as ESG-related impact ventures, accounting for approximately 5.38% of the full sample. The manual verification step is helpful in removing additional noise that may result from using the "keyword" method.

To measure the short-run performance of each startup, the paper uses the following two standard measures from the entrepreneurial finance literature (Ewens and Rhodes-Kropf, 2015; Ewens and Townsend, 2020; Gompers, Kovner, Lerner and Scharfstein, 2010; Hochberg, Ljungqvist and Lu, 2007; Nanda, Samila and Sorenson, 2020): 1) Whether a startup has raised a follow-on round of VC investment during the one-year period after the experiment (i.e., 07/31/2020-07/31/2021). 2) Whether a startup has "gone bankrupt" or has been "out of business". Pitchbook provides the ownership status of a startup in 10/2021, indicating whether the startup has been out of business. I further check each startup's website status at the same time to justify the data quality. Results are similar when measuring "out of business" by using the "exittype" variable recorded in Pitchbook.

To measure the medium-run performance of each startup, the paper checks for a successful exit within the 2.5-year period following the experiment (i.e., 07/31/2020-01/31/2023). A "successful exit" is defined as either an IPO or an exit at a reported value at least twice the total capital invested, which is in line with previous studies on venture capital performance (Ewens and Rhodes-Kropf, 2015). Since most impact ventures do not exit through IPOs, it is crucial to include other types of exits, such as include mergers and acquisitions and selling to other investors, in order to accurately measure the medium or long-term performance of startups.[26]

Table 11 compares the ex-post performance of impact ventures and profit-driven ventures. The sample contains all the startups which have received funding between 01/01/2017 and 07/31/2020 based on the Pitchbook data. Panel A examines the performance of global startups. Panel B focuses on the performance of U.S. startups, defined as startups whose headquarters are located in the U.S. Panel C focuses on startups that just raised their early-stage funding. Panel D examines startups that mainly aim for positive environmental impacts. In Columns (1) and (2) of each panel, the dependent variable is an indicator that equals one if the startup has successfully raised a new round of funding from the VC industry during 07/31/2020-07/31/2021. In Columns (3) and (4), the dependent variable is an indicator that equals one if the startup's business status is "out of business" in 10/2021. "Out of Business" is defined as either "File Bankruptcy" or "Out of Business" in Pitchbook. Results are similar if I include situations in which startups' websites do not function anymore or measure "Out of Business" by using the "exittype" in 07/2021. In Columns (5) and (6), the dependent variable is an indicator that equals one if the startup has experienced a successful exit during 07/31/2020-01/31/2023, and zero otherwise. Columns (2), (4), and (6) include the following control variables that are last updated startup characteristics before 07/31/2020: number of deals, founding years, and log the total raised amount of the latest deal. Standard errors in parentheses are clustered at the headquarter location level.

The results from Table 11 suggest that impact ventures exhibit better ex-post fundraising and business performance, particularly in the US, during the one-year period after the experiment. Panel A Columns (1) and (2) show that in the whole world, impact ventures have about 3.9 to 4.4 percentage points higher likelihood of raising the next round of funding from investors. Columns (3) and (4) show that impact ventures have about a 2 percentage points higher possibility to avoid bankruptcy or go out of business. Panel B shows that the outperformance of impact ventures is still robust in the US, which is consistent with increasing attention to sustainable finance among US investors. Basically, US impact ventures have about a 4 percentage points higher likelihood of entering the next round compared to the US conventional ventures, and they are also 2.1 percentage points less likely to go bankrupt. Results are similar in Panel C and Panel D.

Panel A of Table 11 shows that global impact ventures are associated with a higher likelihood of successful exits, with a range of 0.7 to 0.9 percentage points, which is significant at the 1% level in Column (5) and the 5% level in Column (6). This translates to an increase of around 34% in the successful exit rate, given the average successful exit rate of only 2.08 percent for global startups during the tested period. Similarly, Panel D suggests that impact ventures that aim for environmental impact are correlated with a higher likelihood of successful exits, ranging from 1.0 to 1.4 percentage points higher than profit-driven ventures, which is also statistically significant. This translates to an increase of around 49% compared to the average successful

[26] In this paper, other types of exits include mergers and acquisitions, selling to other investors, buyouts/LBO, reverse mergers, public investment second offering, and share repurchase by the management team.

exit rate of startups that target environmental impact.

The positive correlations indicate that VCs might under-invest in impact ventures at the global level and those that specifically aim for environmental impact. However, Panels B and C indicate that the correlations between impact ventures and successful exits are not significant for US-based startups and weakly significant for early-stage startups. These findings are consistent with Cole et al. (2020), which suggests that the potential underinvestment in impact ventures as indicated by medium-run performance is more likely to be observed in non-US startups due to market frictions related to impact investing in developing countries.

Table 12 conducts similar outcome tests based on startups invested by the experimental subjects' affiliated VC companies. The results of the short-run outperformance are even more salient in this sub-sample. Columns (1) to (4) show that impact ventures are associated with a 10.6 percentage points higher likelihood to raise another round of funding and a 3.2 percentage points lower chance to go bankrupt than profit-driven startups. A similar phenomenon is also seen in US startups. These correlations are robust after including various control variables and fixed effects. However, for the medium-run performance, Columns (5) and (6) show that these positive correlations are much weaker potentially due to the sample size. Hence, this paper cannot reject the hypothesis that recruited VCs' beliefs are rational based on the medium-run performance. However, Table 11 suggests that underinvestment in impact ventures might still exist at the global level and especially among startups addressing environmental challenges. It should be noted that any detected outperformance might gradually fade away in the future as the market slowly moves to the following equilibrium status and market frictions gradually disappear (Pástor et al., 2021).

Since experimental results find a taste-driven preference towards impact ventures, any detected ex-post "outperformance" of impact ventures conditional on being funded can only stem from investors' miscalibrated beliefs. The detected "outperformance" does not mean that impact ventures are more profitable than similar conventional ventures in the *pre-selection* stage. Investors' overall expectations of the underperformance of impact ventures can still be correct. However, they may underestimate impact ventures' performance and underinvest in lucrative impact ventures in the pre-selection stage, leading to the outperformance of funded impact ventures at the global level. This suggests that there is still room to improve impact investing in the venture capital industry. Figure 1 Panel C of Ewens and Townsend (2020) provides a clean illustration of the logic behind this test of miscalibrated beliefs, which is also used by Fisman et al. (2017).

It has been documented in the literature that without exploiting exogenous variations, the static outcome test does not identify investors' preferences or their nature due to potential omitted variable bias issues and the two-sided matching nature of the entrepreneurial financing process. The outcome test also relies on the implicit assumption that majority groups and minority groups follow similar unobservable quality distributions, which should share similar higher moments, such as variances (Heckman, 1998; Neumark, 2012). By exploiting Brown and Forsythe's F statistic, I find that conditional on receiving funding from the VC industry, the variance of impact ventures' performance is not statistically larger than profit-driven ventures' performance. Hence, the concern about different distributions of ESG startups and profit-driven startups is unlikely to be the major driver of the observed correlations. Despite these limitations of an outcome test per se, combining experimental evidence in Section 3 and these correlations in the outcome test can still provide researchers with suggestive evidence about whether investors' beliefs are miscalibrated.

In the discrimination and expectation literature, several models have provided micro-foundations for how inaccurate beliefs can arise and persist. For example, investors may form biased stereotypes using the representativeness heuristic that deviates from reality (Bordalo, Coffman, Gennaioli and Shleifer, 2016). Also, as impact ventures are less prevalent than conventional ventures, investors can make less accurate predictions when confronted with this group due to the coarse categorization of experiences with impact ventures (Fryer, Jackson et al., 2008). Moreover, several papers have documented that individuals extrapolate from recent experiences when forming expectations (Armona et al., 2019; Kuchler and Zafar, 2019). If the extrapolation does not accurately predict the future, investors can form biased beliefs. These mechanisms can potentially coexist and all contribute to investors' miscalibrated beliefs. In the Online Appendix, I provide some empirical evidence that extrapolation might exist.

The experiment and the outcome test show that investors have a taste-driven preference toward impact ventures and a potential (miscalibrated) belief-driven preference against impact ventures. Section 5 exploits a dynamic Bayesian model in a partial equilibrium setting to understand how these preferences affect the potential evolvement of impact investing in the venture capital industry. The model also demonstrates that any exaggeration of early-stage impact investing (i.e., greenwashing) can also lead to an underestimation of impact ventures' expected financial returns. With the help of this theoretical framework, it is easier to clarify various concepts about investors' ESG preferences and understand relevant policy implications.

# 5 Theoretical Framework

This model extends the theoretical framework of Bohren et al. (2019) to the sustainable finance setting in the venture capital industry. As Bohren et al. (2019) studies discrimination questions, their model does not incorporate taste-driven preferences when studying the dynamic implications of these preferences. Also, it is rare to empirically identify taste-driven support for minority groups in the empirical discrimination literature. However, several empirical studies (Ilhan, Krueger, Sautner and Starks, 2021; Riedl and Smeets, 2017) have documented that one of investors' motivations behind SRI is a taste-driven preference. Therefore, the partial equilibrium model in this paper adds taste-driven preferences that support ESG, which changes several conclusions in the dynamic setting and is more customized to the situation of impact investing.

## 5.1 Model Set-up

Startups. — Assume startups are classified into two categories: impact ventures (I) and profit-driven ventures (P). Consider a startup with an observable type $g \in \{I, P\}$ and unobservable ability of generating profits for the investor i, $a \sim N(\mu_g, \frac{1}{\tau_a})$, with mean $\mu_g \in R$ and precision $\tau_a > 0$. Given that some startups may reject the investor's offer due to other outside options and increase the investor's searching cost, let $a = \alpha + \beta$ where $\alpha$ denotes the startup's own potential to generate profits for the investor. $\beta$ denotes the startup's likelihood of accepting the investor's offer and is directly related to the investor's searching cost. The startup experiences a sequence of stages $t = 1, 2, ...$ In each stage, the startup's potential of generating profits can change due to random shocks, with hidden quality/profitability $q_t = a + \epsilon_t$ where $\epsilon_t \sim N(0, \frac{1}{\tau_\epsilon})$ is an independent random shock with precision $\tau_\epsilon > 1$. In this section, "quality" and "profitability" are used interchangeably.

Investors. — Investors evaluate the startup's performance. For simplicity, assume that one investor evaluates one startup in each stage and provides an evaluation/rating $v_t \in R$. Before assessing the startup at the stage t, the investor observes the startup's type g, its previous performance in previous stages $h_t = (v_1, ..., v_{t-1})$, where $h_1 = \emptyset$ if the startup does not have any historical performance. The investor also observes the signal $s_t = q_t + \eta_t$ of the quality provided by the current stage startup, where $\eta_t \sim N(0, \frac{1}{\tau_\eta})$ is also an independent random shock with precision $\tau_t > 0$.

Preferences and Beliefs. — An investor's type $\theta_i$ determines her taste-driven preference towards impact ventures and her beliefs about impact ventures, including 1) her subjective beliefs about the potential of different types of startups to make profits, 2) her subjective beliefs about the likelihood of different types of startups to accept her offer, and 3) her subjective beliefs about other investors' tastes and beliefs. In our setting, investors are also classified into two categories: impact investors ($\theta_1$) and profit-driven investors ($\theta_2$).

To understand the aggregate preference, the investor also forms a subjective belief about the distribution of other investors' types, $\hat{\pi}_i \in \Delta(\Theta)$. If $\hat{\pi}_i \neq \pi$, the investor forms an inaccurate belief about the distribution of all the investors' types. Specifically, $\hat{\pi}_i$ can affect $\hat{\beta}_g^i$ if sorting exists in the dimension of investors' and startups' ESG characteristics. In this situation, more impact investors can decrease impact ventures' likelihood of accepting profit-driven investors' offers.

**Optimal Evaluations.** Each investor chooses the evaluation that maximizes her expected payoffs based on her taste and posterior belief. $c_g^i$ denotes a type-specific taste parameter and $c_P^i$ is normalized to 0. In the real world, a profit-driven early-stage investor may also consider investing in expected low-quality impact ventures because she expects later-stage investors to have more taste-driven preferences towards impact ventures. This extra payoff from later-stage investors' preferences can also be counted in $c_g^i$. $c_g^i$ can be further decomposed as $c_g^i = c_{gS}^i + \hat{c}_{gL}^i$ where $c_{gS}^i$ stands for the investor's own taste parameter and $\hat{c}_{gL}^i$ stands for the investor's expectation of later-stage investors' taste parameter.

The investor's subjective prior belief about the startup's average ability is $\hat{\mu}_g^i = \hat{\alpha}_g^i + \hat{\beta}_g^i$. If $\hat{\mu}_g^i \neq \mu_g^i$, then the investor's subjective belief may be inaccurate and different from the true population's average ability. Specifically, her subjective prior belief about the startup's availability is $\hat{\beta}_g^i(\hat{\pi}_i)$, which is a function of her belief about other investors' preferences. Intuitively, a "hot" startup has many alternative fundraising options and is less available to each particular investor. Since the venture capital industry is competitive, making accurate judgments on startups' quality/profitability is important for venture capitalists' investment decisions. Hence, for an investor with type $\theta_i$, her optimal evaluation strategy follows:

$$v_i(h, s, g) \equiv \text{argmax}_{v \in R} \hat{E}_i[-(v - (q - c_g^i))^2 | h, s, g] \tag{1}$$

Based on the investor's payoff function, her optimal evaluation conditional on observing the startup's historical performance h, signal s, and type g is

$$v_i(h, s, g) = \hat{E}_i[q | h, s, g] - c_g^i \tag{2}$$

If the investor gives different evaluations to impact ventures and profit-driven ventures with the same evaluation history and current signal, I denote this differential treatment as

$$D_i(h,s) \equiv v_i(h,s,P) - v_i(h,s,I) \tag{3}$$

If impact investment goes well in the venture capital industry, it is expected to see $D(h,s) \equiv E_\pi[D_i(h,s)] < 0$ and the investment community prefers impact ventures on the aggregate level. Unlike preferences, $D_i(h,s)$ stands for behaviors, such as contact interest and investment interest.

### 5.2 Different Evaluations of Profit-driven Ventures and Impact Ventures

This part illustrates how various belief-driven preferences and taste-driven preferences affect investors' evaluations of different types of startups. This part also provides a theoretical foundations to empirically test the nature of preferences and interpret the observed experimental results.

Consider a just established startup of type g that is evaluated by an investor who has subjective prior beliefs $(\hat{\alpha}_I, \hat{\alpha}_P)$, $(\hat{\beta}_I, \hat{\beta}_P)$, $(\hat{\mu}_I, \hat{\mu}_P)$, and preference parameter $c_F$ and who observes signal $s_1$. Then the investor's prior belief about the startup's quality is normally distributed, i.e., $q_1 \sim N(\hat{\mu}_g, \frac{1}{\tau_q})$, where $\tau_q \equiv \frac{\tau_a \tau_\epsilon}{\tau_a + \tau_\epsilon}$. The conditional distribution of the initial signal is $s_1|q_1 \sim N(q_1, \frac{1}{\tau_\eta})$, and the investor's posterior belief about quality conditional on observing $s_1$ is $q_1|s_1 \sim N(\frac{\tau_q \hat{\mu}_g + \tau_\eta s_1}{\tau_q + \tau_\eta}, \frac{1}{\tau_q + \tau_\eta})$. Based on (2), the investor's optimal evaluation is equal to

$$v(h_1, s_1, g) = \frac{\tau_q \hat{\mu}_g + \tau_\eta s_1}{\tau_q + \tau_\eta} - c_g = \frac{\tau_q(\hat{\alpha}_g + \hat{\beta}_g) + \tau_\eta s_1}{\tau_q + \tau_\eta} - c_g \tag{4}$$

Intuitively, higher signals, more taste towards impact ventures, and higher subjective beliefs in the startup's availability and profitability all lead to higher evaluations, such as higher contact interest ratings or investment interest ratings. Conditional on observing the same signal and historical performance, the investor's differential evaluation of profit-driven ventures and impact ventures is equal to

$$D(h_1, s_1) = (\frac{\tau_q}{\tau_q + \tau_\eta})(\hat{\mu}_P - \hat{\mu}_I) + c_I = (\frac{\tau_q}{\tau_q + \tau_\eta})(\hat{\alpha}_P - \hat{\alpha}_I + \hat{\beta}_P - \hat{\beta}_I) + c_{IS} + c_{IL} \tag{5}$$

This means that if the investor gives lower evaluations to impact ventures, it can be driven by the following four mechanisms: 1) lower expectation of its potential to make profits ($\hat{\alpha}_I$), 2) lower expectation of its availability ($\hat{\beta}_I$), 3) her taste against impact ventures ($\hat{c}_{IS}$), or 4) her expectation of later-stage investors' taste against impact ventures ($\hat{c}_{IL}$). The experimental results directly identify the first two channels for profit-driven investors (i.e., $\hat{\alpha}_I < \hat{\alpha}_P, \hat{\beta}_I < \hat{\beta}_P$) and the existence of taste towards impact ventures (i.e., $\hat{c}_{IS} + \hat{c}_{LS} < 0$). However, this experiment per se cannot separate $\hat{c}_{IS}$ from $\hat{c}_{IL}$.[27]

[27] Based on equation (5), there is another situation that is consistent with both experimental results and outcome test findings. Basically, even if investors' beliefs of startups' financial returns are accurate, underestimating later-stage or future investors' taste-driven preferences towards impact ventures can also lead to impact ventures' better performances of raising next-round

***Potential Evolvement of Impact Investing in the VC Industry***

PROPOSITION 1 (Subjectivity of Judgement):*Initial belief-driven bias against impact ventures is decreasing in the precision of the signal $\tau_\eta$. As the signal becomes perfectly accurate, $\tau_\eta \to \infty$, any differential treatments of impact ventures and profit-driven ventures are only driven by the investor's own taste parameters (i.e., $c_{IS}$) or her belief of later-stage investors' taste parameters (i.e., $c_{IL}$).*

This result is straightforward based on equation (5). As $\tau_\eta$ increases, $\hat{\alpha}$ and $\hat{\beta}$ play a less important role. However, a better precision of signal does not affect any taste-driven parameters. Intuitively, when the startup's quality and availability are perfectly observed, investors do not need to use its group membership to infer this information. $D_i(h,s) \to c_{iIS} + c_{iIL}$, and the aggregate investment decision from the whole investment community becomes $D_(h,s) = E_\pi(D_i(h,s)) \to E_\pi(c_{IS} + c_{IL})$.

In the situation where both $\alpha$ and $\beta$ cannot be accurately observed, the existence of impact investors can further lower investors' expectations of impact ventures' quality. Based on the experimental results and extant literature (Barber et al., 2020), impact investors have taste-driven preference towards impact ventures (i.e., $c_{IS} < 0, c_{IL} < 0$). No evidence shows that profit-driven investors have an animus against impact ventures. Therefore, the aggregate level of taste-driven preferences in the investment community should be biased towards impact ventures (i.e., $E_\pi(c_{IS}) < 0, E_\pi(c_{IL}) < 0$). Inverting equation (4), I can calculate the signal required to receive evaluation $v$ in period 1

$$\begin{aligned} s(v, \hat{\mu}_g, t=1) = & \quad (\tfrac{\tau_q+\tau_\eta}{\tau_\eta})[v + c_g] - (\tfrac{\tau_q}{\tau_\eta})\hat{\mu}_g \\ = & \quad (\tfrac{\tau_q+\tau_\eta}{\tau_\eta})[v + c_{gL} + c_{gS}] - (\tfrac{\tau_q}{\tau_\eta})(\hat{\alpha}_g + \hat{\beta}_g) \end{aligned} \tag{6}$$

Based on equation (6), conditional on receiving the same evaluation in period 1, the existence of previous-round impact investors means that impact ventures can produce a lower signal of quality and receive the same amount of investment and support as profit-driven ventures. This channel can lower the current-round investors' expectations in impact ventures' profitability (i.e., $Q1$).

PROPOSITION 2 (Impossibility of Belief Reversal): *Suppose there is a representative investor with a belief-driven preference against impact ventures (i.e., $\hat{\mu}_I < \hat{\mu}_P$) and a taste-driven preference towards impact ventures (i.e., $c_I < 0$). Then fixing a funding history, belief-driven preference against impact ventures never reverses (i.e., if $\hat{\mu}_I(h_t) < \hat{\mu}_P(h_t)$, then $\hat{\mu}_I(h_{t+1}) < \hat{\mu}_P(h_{t+1})$). There exists a cutoff $\bar{c}(t)$ such that*
*when $c_I < \bar{c}(t)$, belief-driven preference against impact ventures increases across periods (i.e., $\hat{\mu}_P(h_{t+1}) - \hat{\mu}_I(h_{t+1}) > \hat{\mu}_P(h_t) - \hat{\mu}_I(h_t)$);*
*when $c_I > \bar{c}(t)$, belief-driven preference against impact ventures decreases across periods (i.e., $\hat{\mu}_P(h_{t+1}) - \hat{\mu}_I(h_{t+1}) < \hat{\mu}_P(h_t) - \hat{\mu}_I(h_t)$).*

Similar to the dynamic setting without taste-driven parameters (Bohren et al., 2019), any belief-driven preference against impact ventures will not reverse when $C_I < 0$. However, taste-driven support for impact investing in previous rounds of investment can reduce current round investors' expectations of impact ventures' profitability (i.e., "backfire channel"). Intuitively, profit-driven ventures need to send a stronger

funding and lower likelihood of going bankrupt. However, this still means that investors underinvest impact ventures due to miscalibrated beliefs.

signal of profitability to receive a similar amount of investment in the previous rounds due to a lack of taste-driven support for them. Therefore, given the same histories and signals, investors should rationally expect profit-driven ventures to be of higher profitability. When taste-driven support is strong enough (i.e., $c_I < \bar{c}(t)$), belief-driven preference against impact ventures does not decrease across time periods, even if investors receive more signals about each startup's profitability and availability.

PROPOSITION 3 (Possibility of Investment Reversal): *The direction of differential treatments (i.e., the sign of $D(h_t, s_t)$) can reverse between periods t and t + 1, depending on the relative strength of belief-driven preference (i.e., $\hat{\mu}_P - \hat{\mu}_I$) and taste-driven preference (i.e., $c_{IS} + c_{IL}$).*

Despite lower expectations in impact ventures' profitability, taste-driven bias towards impact ventures can sometimes help to improve the overall impact investment based on equation (5). However, the realized amount of impact investment depends on the magnitude of the following different forces: 1) belief-driven bias against impact ventures, and 2) taste-driven bias towards impact ventures. Unlike Bohren et al. (2019), taste-driven preferences can lead to evaluation reversion even though belief cannot reverse.[28] Based on the current experimental results, the first force dominates in profit-driven investors' decisions and offsets the second force for impact investors. However, it should be noted that taste-driven preference towards impact ventures can sometimes backfire due to market inefficiency.

PROPOSITION 4 (Helpful Taste and Harm of Exaggeration/Greenwashing): *Taste-driven preference towards impact ventures always helps if it is accurately observed and reported. When $t \to \infty$, $|C_I|$ increases $D(h_t, s_t)$ by $\frac{\tau_\eta}{\tau_\epsilon + \tau_\eta}|C_I|$. However, exaggerating taste-driven impact investing in early-stage financing can intensify the backfire channel and reduce the aggregate impact investment.*

When taste-driven impact investment is truthfully reported and correctly recognized by other investors, these taste parameters *always* improve the overall impact investment and dominate the previous "backfire channel" (see the Proof in the paper Appendix). Figure 3 simulates the model and confirms that when there is no initial belief-driven bias, impact investments will converge to the amount of $\frac{\tau_\eta}{\tau_\epsilon + \tau_\eta}|C_I|$ in the long run. Also, when the signal of profitability is more precise (i.e., $\tau_\eta$ is larger), taste-driven preference towards ESG can play a more important role in the investment process.

However, due to various social image concerns or the documented greenwashing phenomenon,[29] people are often inclined to exaggerate their pro-social behaviors. This can lead to an illusion of "ubiquitous impact investment" of previous-round investors, amplifying the "backfire channel" and leading current-round investors to further underestimate impact ventures' profitability. When the current-round investors' real taste-driven preference is not strong enough to neutralize this amplified belief-driven bias, the overall impact investment gets hindered due to this exaggerated information. Therefore, exaggerating early-stage, taste-driven support for ESG might lead to underestimation of impact ventures' profitability and underinvestment in impact ventures by profit-driven investors.[30]. This demonstrates the negative externalities of

[28] The dynamic "evaluation reversion" story proved in Bohren et al. (2019) also applies to the sustainable finance setting if some investors realize that other investors form miscalibrated beliefs about impact ventures' profitability. In this situation, we might expect investors' aggregate-level evaluations to be more likely to favor impact ventures in the later rounds or on the public market.

[29] "Green investing: the risk of a new mis-selling scandal" FEBRUARY 20 2022, Financial Times

[30] Any exaggeration of impact investing, such as greenwashing, can actually hurt impact ventures' fundraising outcomes through two channels. Besides causing the underestimation of impact ventures' quality/profitability, exaggeration can also

any greenwashing in the early-stage investment process.

***Policy Implications*** The experimental results and the model above provide the following policy suggestions to improve impact investing in the venture capital industry. First and foremost, any action of reducing information asymmetry is extremely helpful as the key obstacle of impact investing is investors' lower expectations of its profitability. Founders of impact ventures should also show more signals of their company's lucrative prospects, such as objective data about the company's promising revenues or patents. Second, the current promotion of sustainable finance should still last in order to improve investors' taste-driven preference towards green firms because accurately observed taste-driven support always helps to increase impact investment. It is helpful to reward real impact investing behaviors and prevent greenwashing in the early-stage investment process. To sum up, impact investing benefits from better information transparency.

# 6 Conclusion

This paper examines how US VCs evaluate startups' ESG characteristics and their expectations of financial performance for impact ventures. This question is important, given that the private equity market attracts a significant amount of allocated impact investing capital, and the venture capital industry plays a pivotal role in fostering startups that can potentially solve environmental and social challenges through innovation.

The paper first utilizes an Incentivized Resume Rating experiment with real US VCs to study the impact of startups' ESG characteristics on VC investment decisions. The results demonstrate that targeting positive environmental and social impacts reduces VCs' expectations of startups' future financial returns, especially among attractive startups. Furthermore, the experiment supports the non-pecuniary motivation of impact investing, as investors' ESG attitudes positively correlate with their social preferences. Notably, profit-driven investors give lower contact interest ratings to impact ventures compared to similar profit-driven startups, indicating that they perceive the overall financial performances of impact ventures to be less appealing. Additionally, the experiment identifies other factors that might negatively affect impact ventures' fundraising outcomes from profit-driven investors, including the complexity of evaluating impact ventures and the perceived lower availability to profit-driven investors due to sorting. These findings provide practical guidance on impact ventures' fundraising strategies within the VC industry.

The paper further investigates whether investors' expectations of impact ventures' underperformance are accurate. Using an outcome test method, it compares the performance of impact ventures to that of profit-driven ventures during the one-year period after the experiment's completion. The results indicate that between 07/31/2020-07/31/2021, impact ventures are more likely to obtain another round of funding and less likely to go out of business. The post-funding short-run outperformance also holds among impact ventures invested in by recruited investors. In terms of medium-run ex-post performance, global impact ventures have a 0.7 percentage point higher likelihood of successful exits. However, the outperformance of US-based startups is not significant. This suggests that VCs may have underinvested in impact ventures in the pre-selection stage at the global level. However, the medium-run ex-post outperformance is mainly

reduce profit-driven investors' evaluations of impact ventures' availability (i.e., $\beta$). Considering that impact ventures seem to have more outside options due to the "increase" of impact investors, these startups become less available to profit-driven investors.

driven by non-US startups.

Lastly, a dynamic Bayesian model illustrates how (miscalibrated) beliefs against ESG and taste-driven preferences towards ESG might affect the development of impact investment in a partial equilibrium setting. By demonstrating how greenwashing in the early-stage investment can lead to underestimation of impact ventures' financial performances, the model also provides several policy implications to improve impact investing in the VC industry.

Future research can replicate this experiment in other countries and at different times. It would also be interesting to examine investors' evaluations of companies that only aim for either environmental impact, social impact, or governance impact, separately. Furthermore, it would be helpful to investigate other factors that can drive venture capitalists' taste-driven preferences towards ESG, which is one of the keys to promoting sustainable finance in the private market.

## Appendix

To prove Propositions 2, 3 and 4, I first show that the following lemma from Bohren et al. (2019) still holds when taste parameters are included in the model.

LEMMA 1: *Suppose a representative investor has a normally distributed subjective prior distribution of ability with mean $\hat{\mu}$ and precision $\tau_a$ for a startup of type $g$. The investor also has preference-driven preference towards impact ventures. Then following any history $h_t$ for $t \geq 2$, the subjective posterior distribution of ability $f_a(a|h_t)$ is normally distributed with mean*

$$\hat{\mu}\left(h_t\right) \equiv \frac{\tau_a \hat{\mu}+\tau_{\epsilon \eta} \sum_{n=1}^{t-1} s\left(v_n, \hat{\mu}\left(h_n\right), n\right)}{\tau_a+(t-1) \tau_{\epsilon \eta}} \tag{A1}$$

and precision of ability $a$ at time $t$ $\tau_a(t) \equiv \tau_a+(t-1)\tau_{\epsilon\eta}$ where

$$s\left(v, \hat{\mu}\left(h_t\right), t\right) \equiv\left(\frac{\tau_q(t)+\tau_\eta}{\tau_\eta}\right)\left(v+c_I\right)-\left(\frac{\tau_q(t)}{\tau_\eta}\right) \hat{\mu}\left(h_t\right) \tag{A2}$$

is the signal required to receive an investor's evaluation or treatment $v$. The investor's belief at time $t$ is $\hat{\mu}(h_t)$ and the precision of profitability/quality is $\tau_q(t) \equiv \tau_a(t)\tau_\epsilon / \left(\tau_a(t)+\tau_\epsilon\right)$.

PROOF:

Suppose the representative investor has a normally distributed prior distribution of startup's ability $f_a(a|h_1) \sim N(\hat{\mu}, \frac{1}{\tau_a})$ and taste-driven preference towards impact ventures (i.e., $c_{IS} < 0, c_{IL} < 0$). Since $s_t = a + \epsilon_t + \eta_t$, then $f_s(s|a) \sim N(a, \frac{1}{\tau_{\epsilon\eta}})$ where $\tau_{\epsilon\eta} \equiv \tau_\eta\tau_\epsilon / \left(\tau_\eta + \tau_\epsilon\right)$. Conditional on observing $s_1$,

$$v_1=\frac{\tau_q \hat{\mu}+\tau_\eta s_1}{\tau_q+\tau_\eta}-c_I \tag{A3}$$

then based on observing $v_1$, $s_1$ should be

$$s_1=s\left(v_1, \hat{\mu}, 1\right)=\left(\frac{\tau_q+\tau_\eta}{\tau_\eta}\right)\left(v_1+c_I\right)-\left(\frac{\tau_q}{\tau_\eta}\right) \hat{\mu} \tag{A4}$$

If $h_2 = (v_1)$,

$$f_a\left(a \mid h_2\right)=\frac{f_v\left(v_1 \mid a, h_1\right) f_a\left(a \mid h_1\right)}{\int_{-\infty}^{\infty} f_v\left(v_1 \mid a^{\prime}, h_1\right) f_a\left(a^{\prime} \mid h_1\right) d a^{\prime}}=\frac{f_s\left(s\left(v_1, \hat{\mu}, 1\right) \mid a\right) f_a\left(a \mid h_1\right)}{\int_{-\infty}^{\infty} f_s\left(s\left(v_1, \hat{\mu}, 1\right) \mid a^{\prime}\right) f_a\left(a^{\prime} \mid h_1\right) d a^{\prime}},$$

Recall that if random variable $X \sim f_X(x), -\infty < x < +\infty$, then $Y = aX+b \sim f_Y(y) = \frac{1}{|a|} f_X\left(\frac{y-b}{a}\right), \quad -\infty < y < +\infty$ where $a, b$ are all constants and $a \neq 0$. Then $s\left(v_1, \hat{\mu}, 1\right) = \left(\frac{\tau_q+\tau_\eta}{\tau_\eta}\right)\left(v_1+c_I\right)-\left(\frac{\tau_q}{\tau_\eta}\right)\hat{\mu} = \left(\frac{\tau_q+\tau_\eta}{\tau_\eta}\right) v_1 + [(\frac{\tau_q+\tau_\eta}{\tau_\eta})c_I - \left(\frac{\tau_q}{\tau_\eta}\right)\hat{\mu}]$, and $f_v\left(v \mid a, h_1\right) = \left(\frac{\tau_q+\tau_\eta}{\tau_\eta}\right) f_s(s(v, \hat{\mu}, 1) \mid a)$. Hence, the posterior distribution $f_a\left(a \mid h_2\right) \sim N(\hat{\mu}(h_2), \tau_a(2))$ where $\hat{\mu}(h_2) = \frac{\tau_a\hat{\mu}+\tau_{\epsilon\eta}s(v_1,\hat{\mu},1)}{\tau_a+\tau_{\epsilon\eta}}, \tau_a(2) = \tau_a + \tau_{\epsilon\eta}$.

Since both the prior and likelihood function follow normal distributions, it is feasible to recurse the process above. At time $t$, conditional on observing $s_t$, the evaluation becomes

$$v_t = \frac{\tau_q(t)\hat{\mu}(h_t) + \tau_\eta s_t}{\tau_q(t) + \tau_\eta} - c_I \tag{A5}$$

Then the signal required to receive the evaluation $v_t$ is

$$s(v_t, \hat{\mu}(h_t), t) \equiv \left(\frac{\tau_q(t) + \tau_\eta}{\tau_\eta}\right)(v_t + c_I) - \left(\frac{\tau_q(t)}{\tau_\eta}\right)\hat{\mu}(h_t) \tag{A6}$$

Then the posterior distribution of ability following history $h_{t+1} = (h_t, v_t)$ is still normally distributed with mean

$$\hat{\mu}(h_{t+1}) \equiv \frac{\tau_a(t)\hat{\mu}(h_t) + \tau_{\epsilon\eta} s(v_t, \hat{\mu}(h_t), t)}{\tau_a(t) + \tau_{\epsilon\eta}} \tag{A7}$$

and precision $\tau_a(t+1) = \tau_a(t) + \tau_{\epsilon\eta}$

If $\hat{\mu}(h_1) = \hat{\mu}$ and $\tau_a(1) = \tau_a$, then $f_a(a \mid h_t) \sim N(\hat{\mu}(h_t), \tau_a(t))$ where

$$\hat{\mu}(h_t) = \frac{\tau_a\hat{\mu} + \tau_{\epsilon\eta}\sum_{n=1}^{t-1} s(v_n, \hat{\mu}(h_n), n)}{\tau_a + (t-1)\tau_{\epsilon\eta}} \tag{A8}$$

$$\tau_a(t) = \tau_a + (t-1)\tau_{\epsilon\eta} \tag{A9}$$

PROOF OF PROPOSITION 2:

Suppose $\hat{\mu}_I(h_t) < \hat{\mu}_P(h_t)$, then the difference in signals required for an impact venture and a profit-driven venture to receive $v_t$ becomes

$$s(v_t, \hat{\mu}_P(h_t), t) - s(v_t, \hat{\mu}_I(h_t), t) = -\left(\frac{\tau_q(t)}{\tau_\eta}\right)(\hat{\mu}_P(h_t) - \hat{\mu}_I(h_t)) - \frac{\tau_q + \tau_\eta}{\tau_\eta} c_F$$

Based on (A7), the difference in the belief is updated as follows

$$\begin{aligned}
\hat{\mu}_P(h_{t+1}) - \hat{\mu}_I(h_{t+1}) &= \left(\frac{\tau_a(t)}{\tau_a(t) + \tau_{\epsilon\eta}}\right)(\hat{\mu}_P(h_t) - \hat{\mu}_I(h_t)) \\
&\quad + \left(\frac{\tau_{\epsilon\eta}}{\tau_a(t) + \tau_{\epsilon\eta}}\right)(s(v_t, \hat{\mu}_P(h_t), t) - s(v_t, \hat{\mu}_I(h_t), t)) \\
&= \underbrace{\left(\frac{\tau_a(t) - \tau_{\epsilon\eta}\tau_q(t)/\tau_\eta}{\tau_a(t) + \tau_{\epsilon\eta}}\right)(\hat{\mu}_P(h_t) - \hat{\mu}_I(h_t))}_{\text{belief updating channel}} - \underbrace{\frac{\tau_{\epsilon\eta}}{\tau_a(t) + \tau_{\epsilon\eta}}\frac{\tau_q(t) + \tau_\eta}{\tau_\eta} c_I}_{\text{backfire channel}}
\end{aligned} \tag{A10}$$

where $\frac{\tau_a(t) - \tau_{\epsilon\eta}\tau_q(t)/\tau_\eta}{\tau_a(t) + \tau_{\epsilon\eta}} = \frac{\tau_a(t)[\tau_\eta\tau_\epsilon + \tau_a(t)(\tau_\eta + \tau_\epsilon)]}{(\tau_\eta + \tau_\epsilon)(\tau_a(t) + \tau_\epsilon)} \in (0, 1)$.

If investors have an initial belief-driven preference against impact ventures (i.e., $\hat{\mu}_I < \hat{\mu}_P$) and taste-driven preference towards impact ventures (i.e., $c_I < 0$), then the right-hand side will always be positive. This indicates that the difference in beliefs about average ability for profit-driven ventures and impact ventures with the same history can never reverse. In other words, investors' expectations of impact ventures' profitability will always be lower than their expectations of profit-driven ventures' profitability.

It should be noted that two channels simultaneously play a role here. Similar to the dynamic Bayesian model in Bohren et al. (2019), the "belief updating channel" means that belief-driven bias should never reverse, and will shrink as more signals are revealed. What's interesting in the impact investing setting is the existence of a "backfire channel". After realizing previous-round investors have some taste-driven preference towards impact ventures, current-round investors will further lower their expectations of impact ventures' profitability. Let $A(t) = \frac{\tau_a(t) - \tau_{\epsilon\eta}\tau_q(t)/\tau_\eta}{\tau_a(t)+\tau_{\epsilon\eta}}, B(t) = \frac{\tau_{\epsilon\eta}}{\tau_a(t)+\tau_{\epsilon\eta}}\frac{\tau_q(t)+\tau_\eta}{\tau_\eta}, S(t) = \hat{\mu}_P(h_t) - \hat{\mu}_I(h_t)$, then $S(t+1) = A(t)S(t) - B(t)C_I$ where $A(t) \in (0,1), B(t) > 0$.

$$
\begin{aligned}
\text{(A11)}\quad S(t) =& A(t-1)S(t-1) - B(t-1)C_I \\
=& A(t-1)[A(t-2)S(t-2) - B(t-2)C_I] - B(t-1)C_I \\
=& A(t-1)A(t-2)S(t-2) - [A(t-1)B(t-2) + B(t-1)]C_I \\
=& A(t-1)A(t-2)...A(1)S(1) - [B(t-1) + B(t-2)A(t-1) + B(t-3)A(t-2)A(t-1) + \\
& ... + B(1)A(2)A(3)...A(t-1)]C_I
\end{aligned}
$$

$$
\text{(A12)}\quad [\hat{\mu}_P(h_{t+1}) - \hat{\mu}_I(h_{t+1})] - [\hat{\mu}_P(h_t) - \hat{\mu}_I(h_t)] = S(t+1) - S(t) = [A(t)-1]S(t) - B(t)C_I
$$

Let $\bar{c}(t) = \frac{[A(t)-1]S(t)}{B(t)} = -S(t) < 0$,

When $C_I < \bar{c}(t) < 0, S(t+1) - S(t) < 0$, i.e., $\hat{\mu}_P(h_{t+1}) - \hat{\mu}_I(h_{t+1}) < \hat{\mu}_P(h_t) - \hat{\mu}_I(h_t)$, belief-driven bias against impact ventures increases from t to t+1.

When $\bar{c}(t) < C_I < 0, S(t+1) - S(t) > 0$, i.e., $\hat{\mu}_P(h_{t+1}) - \hat{\mu}_I(h_{t+1}) > \hat{\mu}_P(h_t) - \hat{\mu}_I(h_t)$, belief-driven bias against impact ventures shrinks from t to t+1.

Intuitively, when the taste-driven preference towards impact ventures is very small (i.e., $C_I \to 0^-$), belief updating channel dominates, and belief-driven bias should decrease as more signals are revealed. However, when the taste-driven preference towards impact ventures is very large (i.e., $C_I \to \infty$), the backfire channel dominates. Impact ventures need to be extremely profitable in order to receive a similar amount of funding and support. Hence, given the same signal and history, expectations of impact ventures' profitability should be lower. Based on the expression of $S(t)$ (i.e, equation A11), in the situation where there is no initial belief-driven bias against impact ventures (i.e., $S(1) = 0$), the existence of taste-driven preference towards impact ventures (i.e., $C_I < 0$) can still lead to belief-driven preference against impact ventures in later funding rounds.

PROOF OF PROPOSITION 3:

Given belief $\hat{\mu}_P(h_t)$ and $\hat{\mu}_I(h_t)$, based on (A5), evaluation or treatment in period t is equal to

$$(A13)\qquad D\left(h_t,s_t\right)=\left(\frac{\tau_q(t)}{\tau_q(t)+\tau_\eta}\right)\left(\hat{\mu}_P\left(h_t\right)-\hat{\mu}_I\left(h_t\right)\right)+C_I$$
$$=\frac{\tau_q(t)}{\tau_q(t)+\tau_\eta}S(t)+C_I$$
$$=\frac{\tau_q(t)}{\tau_q(t)+\tau_\eta}[A(t-1)A(t-2)...A(1)]S(1)+\{1-[B(t-1)+B(t-2)A(t-1)$$
$$+B(t-3)A(t-2)A(t-1)+...+B(1)A(2)A(3)...A(t-1)]\}C_I$$

The sign of $D(h_t,s_t)$ depends on the relative magnitude of $S(t)$ and $C_I$. As the coefficient of $S(1)$ is always positive (i.e., $\frac{\tau_q(t)}{\tau_q(t)+\tau_\eta}[A(t-1)A(t-2)...A(1)]>0$), initial belief-driven bias against impact ventures can always hurt later-round impact investment.

PROOF OF PROPOSITION 4:

According to A(13), when $S(1)=0$, the coefficient of $C_I$ is decreasing in t. Therefore, we only need to prove that when $t\to\infty$ and $S(1)=0, D(h_t,s_t)<0$, which means that the coefficient of $C_I$ should be bounded by zero.

Claim 1: $A(t)=\frac{\tau_a(t)}{\tau_a(t)+\tau_\epsilon}\in(0,1)$

PROOF:

$$A(t)=\frac{\tau_a(t)-\tau_{\epsilon\eta}\tau_q(t)/\tau_\eta}{\tau_a(t)+\tau_{\epsilon\eta}}=\frac{\tau_a(t)-\tau_{\epsilon\eta}\frac{\tau_a(t)\tau_\epsilon}{(\tau_a(t)+\tau_\epsilon)\tau_\eta}}{\tau_a(t)+\frac{\tau_\epsilon\tau_\eta}{\tau_\epsilon+\tau_\eta}}$$
$$=\frac{\tau_a(t)[1-\frac{\tau_{\epsilon\eta}\tau_\epsilon}{(\tau_a(t)+\tau_\epsilon)\tau_\eta}]}{\tau_a(t)+\frac{\tau_\epsilon\tau_\eta}{\tau_\epsilon+\tau_\eta}}=\frac{\tau_a(t)[\frac{\tau_a(t)\tau_\eta+\tau_\epsilon\tau_\eta-\tau_{\epsilon\eta}\tau_\epsilon}{(\tau_a(t)+\tau_\epsilon)\tau_\eta}]}{\tau_a(t)+\frac{\tau_\epsilon\tau_\eta}{\tau_\epsilon+\tau_\eta}}\ \text{recall}\ \tau_{\epsilon\eta}\equiv\tau_\eta\tau_\epsilon/\left(\tau_\eta+\tau_\epsilon\right)$$
$$=\frac{\tau_a(t)[\frac{\tau_a(t)\tau_\eta+\frac{\tau_\eta^2\tau_\epsilon}{\tau_\eta+\tau_\epsilon}}{(\tau_a(t)+\tau_\epsilon)\tau_\eta}]}{\tau_a(t)+\frac{\tau_\epsilon\tau_\eta}{\tau_\epsilon+\tau_\eta}}=\frac{\tau_a(t)\frac{\tau_a(t)+\frac{\tau_\epsilon\tau_\eta}{\tau_\epsilon+\tau_{eta}}}{\tau_a(t)+\tau_\epsilon}}{\tau_a(t)+\frac{\tau_\epsilon\tau_\eta}{\tau_\epsilon+\tau_\eta}}=\frac{\tau_a(t)}{\tau_a(t)+\tau_\epsilon}\in(0,1)$$

Claim 2: $B(t)=\frac{\tau_\epsilon}{\tau_a(t)+\tau_\epsilon}\in(0,1)$

PROOF:

$$B(t)=\frac{\tau_{\epsilon\eta}}{\tau_a(t)+\tau_{\epsilon\eta}}\frac{\tau_q(t)+\tau_\eta}{\tau_\eta}=\frac{\tau_{\epsilon\eta}}{\tau_a(t)+\tau_{\epsilon\eta}}\frac{\frac{\tau_a(t)\tau_\epsilon}{\tau_a(t)+\tau_\epsilon}+\tau_\eta}{\tau_\eta}$$
$$=\frac{\tau_{\epsilon\eta}}{\tau_a(t)+\tau_{\epsilon\eta}}\frac{\tau_a(t)(\tau_\epsilon+\tau_\eta)+\tau_\epsilon\tau_\eta}{\tau_\eta(\tau_a(t)+\tau_\epsilon)}$$
$$=\frac{\tau_\epsilon\tau_\eta}{\tau_a(t)(\tau_\epsilon+\tau_\eta)+\tau_\epsilon\tau_\eta}\frac{\tau_a(t)(\tau_\epsilon+\tau_\eta)+\tau_\epsilon\tau_\eta}{\tau_\eta(\tau_a(t)+\tau_\epsilon)}$$
$$=\frac{\tau_\epsilon}{\tau_a(t)+\tau_\epsilon}$$

Then $A(t) + B(t) = 1$ for all $t$. Also, $S(t+1) = A(t)S(t) - (1 - A(t))C_I$

$$\begin{aligned}
S(t+1) + C_I =& A(t)(S(t) + C_I) \\
=& [A(1)A(2)...A(t)](S(1) + C_I) \text{Recall } S(1) = 0 \\
=& \prod_{s=1}^{t} A(s)C_I \\
S(t+1) =& (\prod_{s=1}^{t} A(s) - 1)C_I \in (0, -C_I)
\end{aligned}$$

Claim 3: $\frac{\tau_q(t)}{\tau_q(t)+\tau_\eta} \to \frac{\tau_\epsilon}{\tau_\epsilon+\tau_\eta}$
PROOF: recall that when $t \to \infty, \tau_a(t) \to \infty$

$$\frac{\tau_q(t)}{\tau_q(t) + \tau_\eta} = \frac{\tau_a(t)\tau_\epsilon}{\tau_a(t)(\tau_\epsilon + \tau_\eta) + \tau_\eta\tau_\epsilon} \to \frac{\tau_\epsilon}{\tau_\epsilon + \tau_\eta}$$

Therefore, for $t \to \infty$,

$$\begin{aligned}
D\left(h_t, s_t\right) =& \left(\frac{\tau_q(t)}{\tau_q(t) + \tau_\eta}\right)\left(\hat{\mu}_P\left(h_t\right) - \hat{\mu}_I\left(h_t\right)\right) + C_I \\
=& (\frac{\tau_q(t)}{\tau_q(t) + \tau_\eta})S(t) + C_I < (1 - \frac{\tau_q(t)}{\tau_q(t) + \tau_\eta})C_I \to \frac{\tau_\eta}{\tau_\epsilon + \tau_\eta}C_I
\end{aligned}$$

As $\tau_\epsilon > 0, \tau_\eta > 0$, $D(h_t, s_t) < 0$. Therefore, any accurately observed taste-driven preference towards impact ventures can always help to improve the aggregate impact investment.

(Harm of Exaggeration/Greenwashing) Previously, we assume that $C_I$ is constant across different periods, indicating that the belief of the previous round investor's taste parameters are the same as the current round investor's taste parameters. If $C_I$ is no longer considered to be constant in different rounds,

$$\begin{aligned}
D\left(h_t, s_t\right) =& \left(\frac{\tau_q(t)}{\tau_q(t) + \tau_\eta}\right)\left(\hat{\mu}_P\left(h_t\right) - \hat{\mu}_I\left(h_t\right)\right) + C_I \\
=& \frac{\tau_q(t)}{\tau_q(t) + \tau_\eta}S(t) + C_I \\
=& \frac{\tau_q(t)}{\tau_q(t) + \tau_\eta}[A(t-1)A(t-2)...A(1)]S(1) - [B(t-1) + B(t-2)A(t-1) \\
&+ B(t-3)A(t-2)A(t-1) + ... + B(1)A(2)A(3)...A(t-1)]\hat{C}_I^{\text{previous round}} + C_I^{\text{current round}} \\
=& \frac{\tau_q(t)}{\tau_q(t) + \tau_\eta}[A(t-1)A(t-2)...A(1)]S(1) - K(t)\hat{C}_I^{\text{previous round}} + C_I^{\text{current round}}
\end{aligned}$$

where $K(t) = B(t-1) + B(t-2)A(t-1) + B(t-3)A(t-2)A(t-1) + ... + B(1)A(2)A(3)...A(t-1)$.

When $\hat{C}_I^{\text{previous round}} < C_I^{\text{current round}}/K(t)$ due to over-estimating previous round investors' taste parameters, the backfire channel is amplified and $D\left(h_t, s_t\right)$ becomes even more positive. This can happen when previous-round investors exaggerate their taste-driven preference towards impact investing.

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Table 1: Summary Statistics of Investors

Panel A: Investor Stated Interest Across Sectors

| Sector (Repeatable) | N | Fraction (%) | Fraction (% Pitchbook) |
|---|---|---|---|
| Information Technology | 39 | 55.7% | 58.3% |
| Consumers | 10 | 14.3% | 28.4% |
| Healthcare | 17 | 24.3% | 22.1% |
| Clean Technology | 3 | 4.3% | 0.7% |
| Business-to-Business | 7 | 10.0% | 8.5% |
| Finance | 11 | 15.7% | 9.7% |
| Media | 4 | 5.8% | 8.0% |
| Energy | 5 | 7.1% | 15.9% |
| Education | 3 | 4.3% | 2.2% |
| Life Sciences | 2 | 2.9% | 9.9% |
| Transportation & Logistics | 4 | 5.7% | 5.7% |
| Others | 6 | 8.6% | 12.8% |
| Industry Agnostic | 6 | 8.6% | 26.1% |

Panel B: Investor Stated Interest Across Stages

| Stage (Repeatable) | N | Fraction (%) | Fraction (% Pitchbook) |
|---|---|---|---|
| Seed Stage | 47 | 67.1% | 41.9% |
| Series A | 45 | 64.3% | 31.8% |
| Series B | 17 | 24.3% | 15.0% |
| Series C or Later Stages | 5 | 7.1% | 11.2% |

Panel C: Investor Stated Demographic Information

| | N | Mean | Mean (Pitchbook) |
|---|---|---|---|
| Female Investor | 69 | 0.20 | 0.24 |
| Minority Investor | 64 | 0.42 | 0.43 (Namsor) |
| Senior Investor | 69 | 0.86 | 0.80 |

Panel D: Investor Stated Investment Philosophy

| | N | Mean | S.D |
|---|---|---|---|
| Cold Email Acceptance | 69 | 0.74 | 0.44 |
| Prefer ESG | 69 | 0.11 | 0.32 |
| Direct Investment | 69 | 0.94 | 0.24 |

*Continued*

Panel E: Available Venture Capital Companies' Financial Performance

| | | | | Percentile | | |
|---|---|---|---|---|---|---|
| | N | Mean | S.D | 10 | 50 | 90 |
| *Recruited Sample* | | | | | | |
| Total Active Portfolio | 54 | 41.40 | 44.51 | 10 | 24 | 102 |
| Total Exits | 46 | 32.74 | 48.39 | 1 | 9 | 110 |
| VC Company Age | 52 | 11.75 | 8.95 | 3 | 8.5 | 25 |
| AUM (Unit: $1 Million) | 33 | 547.46 | 1029.10 | 30 | 111.7 | 1700 |
| Dry Powder (Unit: $1 Million) | 33 | 163.86 | 307.04 | 6.43 | 44.35 | 313.59 |
| Fraction of Previous ESG Investments | 69 | 0.06 | 0.10 | 0 | 0.03 | 0.13 |
| *Pitchbook Sample (US VC Funds)* | | | | | | |
| Total Active Portfolio | 5,015 | 21.16 | 47.71 | 1 | 9 | 47 |
| Total Exits | 3,725 | 22.75 | 57.07 | 1 | 6 | 52 |
| VC Company Age | 3,898 | 9.67 | 11.02 | 1 | 6 | 21 |
| AUM (Unit: $1 Million) | 1,802 | 2419.19 | 30574.22 | 10 | 100 | 1300 |
| Dry Powder (Unit: $1 Million) | 2,017 | 137.54 | 615.08 | 0.12 | 15.24 | 250 |
| Fraction of Previous ESG Investments | 4,325 | 0.06 | 0.16 | 0 | 0 | 0.20 |

*Notes.* This table reports descriptive statistics for the investors who have participated in the lab-in-the-field experiment (i.e., Experiment A). In total, 69 different investors from 68 institutions, mostly venture funds, provided evaluations of 1216 randomly generated startup profiles. Panel A reports the sector distribution of investors. Each investor can indicate their interest in multiple industries. "Others" includes HR tech, Property tech, infrastructure, etc. "Industry Agnostic" means the investor does not have strong preferences based on sector. Panel B reports the stage distribution of investors, and each investor can invest in multiple stages. "Seed Stage" includes pre-seed, angel investment, and late-seed stages. "Series C or later stages" includes growth capital, series C, D, etc. Panel C reports the demographic information of these recruited investors. "Female Investor" is an indicator variable which equals to one if the investor is female, and zero otherwise. "Minority Investor" is an indicator variable which equals to one if the investor is Asian, Hispanic, or African American, and zero otherwise. Investors who prefer not to disclose their gender or race are not included in these variables. Since Pitchbook does not record investors' racial information, this paper uses Namsor to predict each investor's ethnicity using their full names. "Senior Investor" is equal to one if the investor is in a C-level position, or is a director, partner, or vice president. It is zero if the investor is an analyst (intern) or associate investor. "Cold Email Acceptance" is an indicator variable which equals one if the investor feels that sending cold call emails is acceptable as long as they are well-written, and zero if the investor feels that it depends. "Prefer ESG" is an indicator variable which equals one if the investor prefers ESG-related startups, and zero otherwise. "Direct Investment" is an indicator variable which equals to one if the investor can directly make the investment, and zero if their investment is through limited partners or other channels. Panel E provides the financial information of the 68 VC funds that these investors work for. "Fraction of Previous ESG Investments" represents the fraction of ESG-related startups in relevant VC companies' portfolio startups based on the available information before 02/29/2020 when the experiment started. ESG-related startups are identified by the Keyword method described in Section 4. Certain VC companies' financial information is partially missing in the Pitchbook Database.

Table 2: Randomization of Startup Profile Components

| Profile Component | Randomization Description | Analysis Variable |
|---|---|---|
| *Startup Team Characteristics* | | |
| First and Last Names | Drawn from list of names that are indicative of selected race and gender (See names in Online Appendix Tables A1) | White Female (25%)<br>Asian Female (25%)<br>White Male (25%)<br>Asian Male (25%) |
| Number of Founders | The team can have 1 founder or 2 co-founders | 1 Founder (8/16) |
| Age | Founders' age is indicated by the graduation year<br>Young Founders: Old Founders=50% : 50%<br>Young Founders' graduation years: uniformly distributed between 2005 and 2019.<br>Old Founders' graduation years: uniformly distributed between 1980 and 2005. | Age |
| Educational Background | Drawn from top school list and common school list (See school list in Online Appendix Table A2) | Top School (8/16) |
| Entrepreneurial Experiences | The team can have serial founder(s) or only first-time founder(s) | Serial Founder (8/16) |
| *Startup Project Characteristics* | | |
| Company Age | Founding dates are randomly drawn from the following four years {2016, 2017, 2018, 2019} | Company Age |
| Comparative Advantages | Randomly drawn from a comparative advantage list (See Online Appendix Table A3), the number of drawn advantages is between 1 to 4 | 1 Advantage (4/16)<br>2 Advantages (4/16)<br>3 Advantages (4/16)<br>4 Advantages (4/16) |
| Traction | Half randomly selected profiles generate no revenue<br>Half randomly selected profiles generate positive revenue. Previous monthly return: uniform distribution [5K, 80K]; Growth rate: uniform distribution [5%, 60%] | Positive traction (8/16) |
| Company Category | Randomly assigned as either B2B or B2C | B2B (8/16) |
| Number of Employees | Randomly assigned with one of four categories | 0-10 (8/16);10-20 (8/16)<br>20-50 (8/16); 50+ (8/16) |
| Target Market | Randomly assigned as either domestic market or international market | Domestic (8/16) |
| Mission | Randomly assigned with one of three categories "For profit", "For profit, consider IPO within 5 years", "Besides financial gains, also care about the social and environmental impacts" | For profit (25%)<br>For profit, IPO (25%)<br>For profit, ESG (50%) |
| Location | Randomly assigned as either U.S. or Outside the U.S. | U.S. (70%) |
| *Previous Funding Situation* | | |
| Number of Existing Investors | Randomly assigned as one of the four categories with equal probability {0,1,2,3+} | Number of investors |

*Notes.* This table provides the randomization of each startup profile's components and the corresponding analysis variables. Profile components are listed in the order that they appear on the hypothetical startup profiles. Weights of characteristics are shown as fractions when they are fixed across subjects 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: Average Treatment Effects of Startups' ESG Characteristics on Investors' Evaluations

| Dependent Variable | Q1<br>Profitability<br>(1) | Q2<br>Availability<br>(2) | Q3<br>Contact<br>(3) | Q4<br>Investment<br>(4) |
|---|---|---|---|---|
| *Panel A* | | | | |
| Has ESG Characteristics | -2.75* | 0.30 | -1.27 | -0.41 |
| | (1.39) | (1.11) | (1.55) | (0.25) |
| Investor FE | Yes | Yes | Yes | Yes |
| Observations | 1,216 | 1,184 | 1,216 | 1,176 |
| R-squared | 0.31 | 0.53 | 0.47 | 0.34 |
| *Panel B* | | | | |
| Has ESG Characteristics | -2.65 | -0.64 | -2.68 | -0.36 |
| | (1.65) | (1.24) | (1.87) | (0.28) |
| Has IPO Plan | 0.20 | -1.87 | -2.82 | 0.11 |
| | (1.88) | (1.40) | (2.18) | (0.36) |
| Investor FE | Yes | Yes | Yes | Yes |
| Observations | 1,216 | 1,184 | 1,216 | 1,176 |
| R-squared | 0.31 | 0.53 | 0.47 | 0.34 |

*Notes.* This table describes how recruited investors evaluated startups' ESG characteristics. Panel A compares the evaluation results of impact ventures and general profit-driven ventures (i.e., combining both pure profit-driven ventures and profit-driven ventures with an IPO plan). Panel B compares evaluation results of impact ventures, profit-driven ventures with an IPO plan, and pure profit-driven ventures. "Has ESG Characteristics" is a dummy variable that is equal to one if the startup aims for positive environmental and social impacts besides financial profits, and zero otherwise. "Has IPO Plan" is a dummy variable that is equal to one if the startup is profit-driven and considers IPO within five years, and zero otherwise. In column (1), the dependent variable is the profitability evaluation, which indicates the percentile rank of each startup profile compared with investor's previous invested startups in terms of its potential financial return. In column (2), the dependent variable is the availability evaluation, which indicates how likely the investors feel the startup team will accept his/her investment rather than other investors. In column (3), the dependent variable is the contact interest rating, which describes the probability that the investor wants to contact this startup. In column (4), the dependent variable is the investment interest, which describes the relative investment amount compared with the investor's general investment amount. For example, if the investor's average investment amount is $1 million and $Q_4$ is equal to 0.5, then it means the investor only wants to invest $500,000 in this startup. All the regressions add investor fixed effects. Standard errors in parentheses are clustered at the investor level. P-values of "Has ESG Characteristics" have been adjusted to Bonferroni-Holm p-values due to multiple hypothesis testing problem. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 4: Quantile-Regression Estimates for Investors' Evaluations on Startups' Profitability and Attractiveness

Panel A. Profitability (i.e., $Q_1$)

| | 5th (1) | 15th (2) | 25th (3) | 35th (4) | 45th (5) | 55th (6) | 65th (7) | 75th (8) | 85th (9) | 95th (10) | Mean (11) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Has ESG Characteristics | 0.00 | -1.00 | -2.00 | -2.00 | -1.00 | -6.00* | -10.00*** | -5.00** | -5.00** | -5.00** | -2.65 |
| | (2.13) | (1.72) | (2.34) | (2.39) | (2.92) | (3.16) | (3.08) | (2.37) | (2.35) | (2.54) | (1.65) |
| Has IPO Plan | 0.00 | 2.00 | 1.00 | 3.00 | 0.00 | 0.00 | -5.00 | -2.00 | -4.00 | 2.00 | 0.20 |
| | (2.91) | (2.77) | (2.95) | (2.61) | (3.79) | (3.41) | (3.40) | (2.57) | (2.54) | (2.76) | (1.88) |
| Quantile of Dep. Var. | 10 | 17 | 25 | 31 | 40 | 49 | 55 | 61 | 71 | 85 | 44.29 |
| Observations | 1,216 | 1,216 | 1,216 | 1,216 | 1,216 | 1,216 | 1,216 | 1,216 | 1,216 | 1,216 | 1,216 |

Panel B. Attractiveness (i.e., $Q_3$)

| | 5th (1) | 15th (2) | 25th (3) | 35th (4) | 45th (5) | 55th (6) | 65th (7) | 75th (8) | 85th (9) | 95th (10) | Mean (11) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Has ESG Characteristics | -2.00 | -1.00 | -1.00 | 0.00 | -2.00 | -3.00 | -9.00*** | -7.00*** | -5.00 | 0.00 | -2.68 |
| | (2.61) | (2.27) | (2.73) | (3.76) | (3.14) | (3.54) | (3.11) | (2.25) | (3.30) | (0.11) | (1.87) |
| Has IPO Plan | -3.00 | 0.00 | -2.00 | -5.00 | -2.00 | -4.00 | -8.00** | -7.00** | -1.00 | 0.00 | -2.82 |
| | (3.81) | (3.04) | (3.73) | (4.24) | (3.38) | (3.83) | (3.12) | (2.75) | (3.84) | (0.12) | (2.18) |
| Quantile of Dep. Var. | 1 | 15 | 25.5 | 40 | 50 | 61 | 72 | 80 | 97 | 100 | 54.71 |
| Observations | 1,216 | 1,216 | 1,216 | 1,216 | 1,216 | 1,216 | 1,216 | 1,216 | 1,216 | 1,216 | 1,216 |

*Notes.* This table reports the effects of being an impact venture on different conditional quantiles and conditional mean of startups' received profitability evaluations and attractiveness evaluations. The dependent variable is the startup's received profitability rating (i.e., $Q_1$) in Panel A and contact interest rating (i.e., $Q_3$) in Panel B. In each of Columns (1)–(10), the reported coefficient of "Has ESG Characteristics" stands for the effect of aiming for ESG on the $k$th conditional percentile ($k \in 5, 15, 25, ..., 95$) of the startup's received profitability rating (i.e., $Q_1$) in Panel A and contact interest rating (i.e., $Q_3$) in Panel B. In Column (11), the reported coefficients of "Has ESG Characteristics" using OLS regressions stand for the effects of aiming for ESG on the conditional mean of $Q_1$ in Panel A and $Q_3$ in Panel B. Standard errors in parentheses are clustered at the investor level. $*p < 0.10, **p < 0.05, ***p < 0.01$

Table 5: Effect of Attractive Startups' ESG Characteristics on Investors' Evaluation ($\hat{Q}_3 \geq 50$)

| Dependent Variable | Q1 Profitability | Q1 Profitability | Q3 Contact | Q3 Contact |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | All Investors | Profit-driven Investors | All Investors | Profit-driven Investors |
| Has ESG Characteristics | -2.94* | -2.90* | -2.98** | -3.63*** |
| | (1.49) | (1.58) | (1.22) | (1.30) |
| Has IPO Plan | -0.72 | -0.90 | -3.09** | -3.08** |
| | (2.13) | (2.29) | (1.41) | (1.47) |
| Investor FE | Yes | Yes | Yes | Yes |
| Observations | 671 | 600 | 671 | 600 |
| R-squared | 0.39 | 0.38 | 0.43 | 0.45 |

*Notes.* This table tests the effect of aiming for ESG on investors' evaluations of attractive startups. The sample only includes relatively attractive startup profiles, whose received "objective" contact interest ratings (i.e., $\hat{Q}_3$) are above 50. $\hat{Q}_3$ are predicted using OLS models based on other orthogonally randomized startup characteristics used in Online Appendix Table A11. These startup characteristics include "Serial Founder", "Ivy League Educational background", "Number of founders", "US Founder", "Number of Comparative Advantages", "Has Positive Traction", number of employees, "Company Age", "Company Age$^2$", "B2B Startup", and "Domestic Market". In Columns (1) and (2), the dependent variable is the profitability evaluation (i.e., $Q_1$). In Columns (3) and (4), the dependent variable is the contact interest rating (i.e., $Q_3$). In Columns (1) and (3), the sample contains "objectively" attractive startup profiles (i.e., $\hat{Q}_3 \geq 50$) evaluated by all the investors. In Columns (2) and (4), the sample contains "objectively" attractive startup profiles (i.e., $\hat{Q}_3 \geq 50$) evaluated by profit-driven investors. "Has ESG Characteristics" is an indicator that equals one if the startup has an ESG-related mission, and zero otherwise. "Has IPO Plan" is an indicator that equals one if the startup is profit-driven and considers IPO within five years, and zero otherwise. All the regressions add investor fixed effects. Standard errors in parentheses are clustered at the investor level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 6: Quantile-Regression Estimates for Profit-driven Investors' Evaluations on Startups' Profitability and Attractiveness

Panel A. Profitability (i.e., $Q_1$)

| | 5th (1) | 15th (2) | 25th (3) | 35th (4) | 45th (5) | 55th (6) | 65th (7) | 75th (8) | 85th (9) | 95th (10) | Mean (11) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Has ESG Characteristics | 1.00 | 0.00 | -4.00 | -2.00 | -1.00 | -7.00** | -10.00*** | -5.00* | -2.00 | -2.00 | -2.44 |
| | (2.23) | (1.89) | (2.75) | (2.54) | (2.74) | (3.46) | (3.17) | (2.69) | (2.65) | (2.96) | (1.77) |
| Has IPO Plan | 1.00 | 2.00 | 1.00 | 3.00 | 0.00 | -0.00 | -5.00 | -2.00 | -1.00 | 0.00 | 0.47 |
| | (2.65) | (2.82) | (3.41) | (2.89) | (3.74) | (3.71) | (3.52) | (2.82) | (2.57) | (2.32) | (2.06) |
| Quantile of Dep. Var. | 10 | 15 | 25 | 31 | 40 | 49 | 54 | 61 | 71 | 85 | 43.92 |
| Observations | 1,088 | 1,088 | 1,088 | 1,088 | 1,088 | 1,088 | 1,088 | 1,088 | 1,088 | 1,088 | 1,088 |

Panel B. Attractiveness (i.e., $Q_3$)

| | 5th (1) | 15th (2) | 25th (3) | 35th (4) | 45th (5) | 55th (6) | 65th (7) | 75th (8) | 85th (9) | 95th (10) | Mean (11) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Has ESG Characteristics | -2.00 | -4.00* | -2.00 | -0.00 | -1.00 | -4.00 | -8.00** | -7.00*** | -4.00** | 0.00 | -3.02 |
| | (2.88) | (2.14) | (2.97) | (3.98) | (3.75) | (3.94) | (3.73) | (2.58) | (1.73) | (0.14) | (2.03) |
| Has IPO Plan | -3.00 | -8.00*** | -2.00 | -5.00 | -1.00 | -4.00 | -4.00 | -7.00** | 0.00 | 0.00 | -2.35 |
| | (3.85) | (2.73) | (4.10) | (4.64) | (4.03) | (4.44) | (3.45) | (3.21) | (2.50) | (0.11) | (2.38) |
| Quantile of Dep. Var. | 1 | 15 | 25 | 40 | 50 | 61 | 73 | 80 | 97 | 100 | 54.57 |
| Observations | 1,088 | 1,088 | 1,088 | 1,088 | 1,088 | 1,088 | 1,088 | 1,088 | 1,088 | 1,088 | 1,088 |

*Notes.* This table reports the effects of being an impact venture on different conditional quantiles and conditional mean of profit-driven investors' profitability evaluations and attractiveness evaluations. The dependent variable is the startup's received profitability rating (i.e., $Q_1$) in Panel A and contact interest rating (i.e., $Q_3$) in Panel B. In each of Columns (1)–(10), the reported coefficient of "Has ESG Characteristics" stands for the effect of aiming for ESG on the $k$th conditional percentile ($k \in 5, 15, 25, ..., 95$) of the startup's received profitability rating (i.e., $Q_1$) in Panel A and contact interest rating (i.e., $Q_3$) in Panel B. In Column (11), the reported coefficients of "Has ESG Characteristics" using OLS regressions stand for the effects of aiming for ESG on the conditional mean of $Q_1$ in Panel A and $Q_3$ in Panel B. Standard errors in parentheses are clustered at the investor level. $*p < 0.10, **p < 0.05, ***p < 0.01$

Table 7: Quantile-Regression Estimates for Impact Investors' Evaluations on Startups' Profitability and Attractiveness

Panel A. Profitability (i.e., $Q_1$)

| | 5th (1) | 15th (2) | 25th (3) | 35th (4) | 45th (5) | 55th (6) | 65th (7) | 75th (8) | 85th (9) | 95th (10) | Mean (11) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Has ESG Characteristics | -2.00 | 0.00 | 5.00 | -0.00 | -5.00 | -7.00 | -11.00* | -13.00** | -11.00** | -5.00* | -4.44 |
| | (9.30) | (9.67) | (5.89) | (7.03) | (9.70) | (4.77) | (6.23) | (5.96) | (4.72) | (2.93) | (4.47) |
| Has IPO Plan | -1.00 | 0.00 | 4.00 | -2.00 | -4.00 | -2.00 | -17.00** | -16.00** | 6.00 | 8.00*** | -2.09 |
| | (5.59) | (7.29) | (3.75) | (4.58) | (9.16) | (6.54) | (7.16) | (7.61) | (9.88) | (2.15) | (0.43) |
| Quantile of Dep. Var. | 11 | 20 | 29 | 35 | 40 | 50 | 58 | 70 | 80 | 87 | 47.41 |
| Observations | 128 | 128 | 128 | 128 | 128 | 128 | 128 | 128 | 128 | 128 | 128 |

Panel B. Attractiveness (i.e., $Q_3$)

| | 5th (1) | 15th (2) | 25th (3) | 35th (4) | 45th (5) | 55th (6) | 65th (7) | 75th (8) | 85th (9) | 95th (10) | Mean (11) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Has ESG Characteristics | 0.00 | 16.00 | -4.00 | -8.00 | -7.00 | 6.00 | -9.00 | -3.00 | -0.00 | 0.00 | 0.28 |
| | (4.11) | (18.66) | (9.88) | (9.99) | (8.83) | (6.14) | (6.46) | (4.40) | (1.71) | (0.43) | (4.50) |
| Has IPO Plan | 0.00 | 17.00 | -10.00 | -16.00* | -17.00** | -10.00 | -16.00*** | -14.00* | -1.00 | 0.00 | -6.84 |
| | (3.69) | (20.20) | (7.76) | (8.21) | (7.98) | (7.68) | (5.22) | (7.76) | (18.15) | (2.03) | (4.16) |
| Quantile of Dep. Var. | 1 | 20 | 32 | 40 | 50 | 65 | 71 | 82 | 100 | 100 | 55.90 |
| Observations | 128 | 128 | 128 | 128 | 128 | 128 | 128 | 128 | 128 | 128 | 128 |

*Notes.* This table reports the effects of being an impact venture on different conditional quantiles and conditional mean of impact investors' profitability evaluations and attractiveness evaluations. The dependent variable is the startup's received profitability rating (i.e., $Q_1$) in Panel A and contact interest rating (i.e., $Q_3$) in Panel B. In each of Columns (1)–(10), the reported coefficient of "Has ESG Characteristics" stands for the effect of aiming for ESG on the $k$th conditional percentile ($k \in 5, 15, 25, ..., 95$) of the startup's received profitability rating (i.e., $Q_1$) in Panel A and contact interest rating (i.e., $Q_3$) in Panel B. In Column (11), the reported coefficients of "Has ESG Characteristics" using OLS regressions stand for the effects of aiming for ESG on the conditional mean of $Q_1$ in Panel A and $Q_3$ in Panel B. Standard errors in parentheses are clustered at the investor level. $*p < 0.10, **p < 0.05, ***p < 0.01$

Table 8: Effect of Startups' ESG Characteristics on Investors' Attention

| | Dependent Variable: Response Time (Unit: Seconds) | | | | | |
|---|---|---|---|---|---|---|
| | Full Sample | $Q_3 > 30$ | $Q_3 > 40$ | $Q_3 > 50$ | $Q_3 > 60$ | $Q_3 > 70$ |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Has ESG Characteristics | 4.10 | 8.41** | 10.17** | 8.26** | 10.15** | 8.87** |
| | (3.30) | (3.59) | (3.98) | (3.89) | (4.09) | (4.36) |
| Has IPO Plan | -1.56 | 1.95 | 4.06 | 3.33 | 3.04 | 2.05 |
| | (3.48) | (4.06) | (4.31) | (4.89) | (5.75) | (6.82) |
| Second Half of Study | -27.12*** | -27.00*** | -25.85*** | -27.49*** | -29.66*** | -30.77*** |
| | (2.46) | (3.22) | (3.39) | (4.09) | (4.78) | (5.64) |
| $Q_1$ | 0.01 | -0.04 | -0.03 | -0.02 | -0.09 | -0.16 |
| | (0.05) | (0.08) | (0.09) | (0.09) | (0.12) | (0.14) |
| $Q_2$ | 0.16* | 0.19 | 0.20 | 0.03 | -0.11 | 0.02 |
| | (0.09) | (0.15) | (0.14) | (0.20) | (0.25) | (0.31) |
| Investor FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 1184 | 817 | 726 | 618 | 519 | 410 |
| R-squared | 0.35 | 0.37 | 0.38 | 0.40 | 0.40 | 0.41 |

*Notes.* This table tests whether investors allocate more attention to ESG startups compared to similar profit-driven startups. The dependent variable is investors' response time, which is defined as the number of seconds before each page submission, winsorized at the 95th percentile (59.23 seconds on average). Column (1) tests all the evaluation results. Columns (2)-(6) focus on the high-stake situation where the investor indicates a higher likelihood of contacting the startup. I choose five thresholds to define high-stake situations (i.e., $Q_3 > 30$, $Q_3 > 40$, $Q_3 > 50$, $Q_3 > 60$, $Q_3 > 70$). Columns (2)-(6) stand for the situation where investors' likelihood of contacting the startup team is more than 30%, 40%, 50%, 60%, and 70%, respectively. "Second Half of Study" is an indicator variable for startup profiles shown among the last half of profiles evaluated by an investor. "Has ESG Characteristics" is an indicator that equals one if the startup has an ESG-related mission, and zero otherwise. "Has IPO Plan" is an indicator that equals one if the startup is profit-driven and considers IPO within five years, and zero otherwise. All the regressions add investor fixed effects. Standard errors in parentheses are clustered at the investor level. *** p<0.01, ** p<0.05, * p<0.1

Table 9: Investors' Implicit ESG Preferences and Potential Sorting

| Dependent Variable | Response Time (Unit: Second) (1) | Q1 Profitability (2) | Q2 Availability (3) | Q3 Contact (4) | Q4 Investment (5) |
|---|---|---|---|---|---|
| *Panel A: Impact Investors* | | | | | |
| Second Half of Study | -27.26** | -3.97 | 2.31 | -13.23 | -0.47 |
| | (11.49) | (8.19) | (3.68) | (8.01) | (2.05) |
| Has ESG Characteristics | 9.35 | -8.79* | 10.39** | -3.70 | -1.15 |
| | (8.02) | (5.43) | (3.48) | (6.79) | (1.63) |
| Has ESG Characteristics× | | 8.18 | -9.48 | 8.55 | 1.91 |
| Second Half of Study | | (10.46) | (6.41) | (12.65) | (2.41) |
| Has IPO Plan | 7.31 | -3.54 | -2.40 | -8.78* | -1.90 |
| | (12.42) | (4.16) | (3.68) | (4.54) | (1.61) |
| Has IPO Plan× | | 2.53 | 1.50 | 0.76 | 1.81 |
| Second Half of Study | | (8.30) | (3.00) | (9.68) | (2.41) |
| p-value of "Has ESG Characteristics" in the second half of study | | 0.96 | 0.93 | 0.64 | 0.59 |
| Investor FE | Yes | Yes | Yes | Yes | Yes |
| Observations | 128 | 128 | 128 | 128 | 128 |
| R-squared | 0.31 | 0.45 | 0.41 | 0.51 | 0.17 |
| *Panel B: Profit-driven Investors* | | | | | |
| Second Half of Study | -27.36*** | 1.98 | 5.31** | 0.49 | 0.34 |
| | (2.43) | (2.97) | (2.27) | (2.90) | (0.53) |
| Has ESG Characteristics | 2.14 | -2.67 | 1.52 | -4.50* | -0.65* |
| | (3.69) | (2.30) | (1.73) | (2.51) | (0.38) |
| Has ESG Characteristics× | | 0.29 | -5.89** | 2.82 | 0.49 |
| Second Half of Study | | (3.55) | (2.46) | (3.30) | (0.61) |
| Has IPO Plan | -3.20 | 3.85 | -0.69 | 1.57 | 0.65 |
| | (3.59) | (2.93) | (2.70) | (3.64) | (0.53) |
| Has IPO Plan× | | -6.97* | -2.38 | -8.08* | -0.79 |
| Second Half of Study | | (4.05) | (3.64) | (4.92) | (0.72) |
| p-value of "Has ESG Characteristics" in the second half of study | | 0.37 | 0.02 | 0.54 | 0.56 |
| Investor FE | Yes | Yes | Yes | Yes | Yes |
| Observations | 1,088 | 1,088 | 1,056 | 1,088 | 1,048 |
| R-squared | 0.34 | 0.30 | 0.54 | 0.48 | 0.36 |

*Notes.* This table reports regression results of impact investors' and profit-driven investors' implicit preferences on startups' ESG characteristics. Panel A focuses on impact investors. Panel B focuses on profit-driven investors. "Has ESG Characteristics" is a dummy variable that is equal to one if the startup has an ESG-related mission, and zero otherwise. "Has IPO Plan" is a dummy variable that is equal to one if the startup is profit-driven and considers IPO within five years, and zero otherwise. "Second Half of Study" is an indicator variable for startup profiles shown among the second half of the experiment. Fixed effects for subjects are included in all specifications. In column (1), the dependent variable is investors' response time, which is defined as the number of seconds before each page submission, winsorized at the 95th percentile (59.23 seconds on average). Columns (2)-(5) show the profitability evaluations, availability evaluations, contact interest ratings, and investment interest ratings, respectively. R-squared is indicated for each OLS regression. Standard errors in parentheses are clustered at the investor level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 10: Correlation Between Investors' Attitudes Towards ESG and Investors' Donation Behaviors

| Dependent Variable | Donate or Not | Donate or Not | Donate All or Not | Donate All or Not | Donation Amount | Donation Amount |
|---|---|---|---|---|---|---|
| | Probit | Probit | Probit | Probit | OLS | OLS |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| ESG Attitude ($\beta$) | 0.02** | 0.03** | 0.03** | 0.03** | 0.04** | 0.04** |
| | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) |
| Control | No | Yes | No | Yes | No | Yes |
| Observations | 70 | 70 | 70 | 70 | 70 | 70 |
| R-squared | 0.06 | 0.08 | 0.07 | 0.09 | 0.08 | 0.10 |

*Notes.* This table reports regression results for correlations between investors' attitudes towards startups' ESG characteristics and their anonymous donation behaviors in the donation game. In Columns (1) and (2), the dependent variable "Donate or Not" is an indicator that equals one if the investor donates any positive amount of money to startups and equals zero otherwise. In Columns (3) and (4), the dependent variable "Donate All or Not" is an indicator that equals one if the investor donated all \$15 to the startup and equals zero otherwise. In Columns (5) and (6), the dependent variable is the amount of money donated by the investor and the unit is dollars. "ESG Attitude" is calculated based on $Q_3$. It is the coefficient $\beta_i$ of the following regression, which uses each individual investor $i$'s contact interest ratings: $Q_{3ij} = \beta_{0i} + \beta_i \text{Has ESG Characteristics}_{ij} + \gamma_i \text{Has IPO Plan}_{ij} + \epsilon_{ij}$. It stands for the causal effect of "being an impact venture" on the investor's contact interest ratings (i.e., $Q_3$). Control variables include the investor's preferred industries and stages. Probit regressions are used in Columns (1) - (4), and OLS regressions are used in Columns (5) and (6). R-squared reports Pseudo R2 for Probit regressions and R-squared for OLS regressions. Standard errors in parentheses are robust standard errors. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Table 11: Compare the Performance of Impact Ventures and Profit-driven Ventures

| | Raised New Funding Short run 1 yr. | | Out of Business Short run 1 yr. | | Successful Exits Medium run 2.5 yr. | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| *Panel A. Global Startups* | | | | | | |
| Has ESG Characteristics | 0.044*** | 0.039*** | -0.020*** | -0.018*** | 0.009*** | 0.007** |
| | (0.008) | (0.007) | (0.005) | (0.005) | (0.003) | (0.003) |
| Observations | 50,646 | 50,646 | 50,646 | 50,646 | 50,646 | 50,646 |
| R-squared | 0.06 | 0.16 | 0.07 | 0.08 | 0.07 | 0.09 |
| Control | No | Yes | No | Yes | No | Yes |
| Location FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Stage FE | Yes | Yes | Yes | Yes | Yes | Yes |
| *Panel B. U.S. Startups* | | | | | | |
| Has ESG Characteristics | 0.042*** | 0.043*** | -0.023*** | -0.021*** | 0.007 | 0.005 |
| | (0.012) | (0.012) | (0.007) | (0.007) | (0.005) | (0.005) |
| Observations | 18,748 | 18,748 | 18,748 | 18,748 | 18,748 | 18,748 |
| R-squared | 0.05 | 0.19 | 0.05 | 0.07 | 0.06 | 0.10 |
| Control | No | Yes | No | Yes | No | Yes |
| Location FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Stage FE | Yes | Yes | Yes | Yes | Yes | Yes |
| *Panel C. Early-Stage Startups* | | | | | | |
| Has ESG Characteristics | 0.051*** | 0.041*** | -0.022*** | -0.017*** | 0.006* | 0.004 |
| | (0.010) | (0.010) | (0.006) | (0.006) | (0.003) | (0.003) |
| Observations | 36,572 | 36,572 | 36,574 | 36,574 | 36,571 | 36,571 |
| R-squared | 0.06 | 0.18 | 0.07 | 0.08 | 0.06 | 0.07 |
| Control | No | Yes | No | Yes | No | Yes |
| Location FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry FE | Yes | Yes | Yes | Yes | Yes | Yes |
| *Panel D. Startups Aiming for Environmental Impact* | | | | | | |
| Has ESG Characteristics | 0.057*** | 0.037*** | -0.024*** | -0.018*** | 0.014*** | 0.010** |
| | (0.011) | (0.011) | (0.006) | (0.004) | (0.005) | (0.005) |
| Observations | 49,000 | 49,000 | 49,000 | 49,000 | 49,000 | 49,000 |
| R-squared | 0.06 | 0.16 | 0.07 | 0.08 | 0.07 | 0.09 |
| Control | No | Yes | No | Yes | No | Yes |
| Location FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry FE | Yes | Yes | Yes | Yes | Yes | Yes |

*Notes.* This table tests whether impact ventures underperform profit-driven ventures in the short run (i.e., the 1-year period after the experiment) and in the medium run (the 2.5-year period after the experiment). Based on the Pitchbook data, the sample contains all the startups that have received funding between 01/01/2017 and 07/31/2020. Panel A examines the performance of global startups. Panel B focuses on the performance of U.S. startups, defined as startups whose headquarters are located in the U.S. Due to the existence of singleton observations among U.S. startups, the number of observations between different columns can be slightly different in Panel B. Panel C focuses on startups that just raised their early-stage funding. Panel D examines startups that aim for positive environmental impact. In Columns (1) and (2), the dependent variable is an indicator that equals one if the startup has successfully raised a new round of funding from the venture capital industry during 07/31/2020-07/31/2021, and zero otherwise. In Columns (3) and (4), the dependent variable is an indicator that equals one if the startup's business status is "out of business" in 10/2021. Ideally, I should use the business status on 07/31/2021. However, this information is not available to the researcher. "Out of Business" is defined as either "File Bankruptcy" or "Out of Business" in Pitchbook. Results are similar after including cases where startups' websites no longer function, such as reporting a 404 error. In Columns (5) and (6), the dependent variable is an indicator that equals one if the startup has experienced a successful exit during 07/31/2020-01/31/2023, and zero otherwise. "Successful Exit" includes both IPOs and an exit at a reported value at least twice the total capital invested. Columns (2), (4), and (6) include the following control variables that are last updated startup characteristics before 07/31/2020: number of deals, founding years, and log total raised amount of the latest deal. "Has ESG Characteristics" is an indicator that equals one if the startup is defined as an ESG startup based on the keyword method, and zero otherwise. Standard errors in parentheses are clustered at the headquarter location level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 12: Outcome Test for Recruited Investors' Portfolio Companies

| | Raised New Funding Short run 1 yr. | | Out of Business Short run 1 yr. | | Successful Exits Medium run 2.5 yr. | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| *Panel A. Global Startups* | | | | | | |
| Has ESG Characteristics | 0.126*** | 0.106** | -0.037** | -0.032* | 0.001 | -0.005 |
| | (0.047) | (0.042) | (0.018) | (0.018) | (0.017) | (0.016) |
| Observations | 2,595 | 2,595 | 2,595 | 2,595 | 2,595 | 2,541 |
| R-squared | 0.09 | 0.22 | 0.08 | 0.09 | 0.15 | 0.19 |
| Control | No | Yes | No | Yes | No | Yes |
| Location FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Stage FE | Yes | Yes | Yes | Yes | Yes | Yes |
| *Panel B. U.S. Startups* | | | | | | |
| Has ESG Characteristics | 0.137** | 0.106** | -0.045* | -0.037 | 0.009 | 0.000 |
| | (0.059) | (0.052) | (0.025) | (0.026) | (0.024) | (0.022) |
| Observations | 1,772 | 1,772 | 1,772 | 1,772 | 1,772 | 1,745 |
| R-squared | 0.07 | 0.21 | 0.06 | 0.08 | 0.12 | 0.17 |
| Control | No | Yes | No | Yes | No | Yes |
| Location FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Stage FE | Yes | Yes | Yes | Yes | Yes | Yes |
| *Panel C. Early-Stage Startups* | | | | | | |
| Has ESG Characteristics | 0.125** | 0.091* | -0.048** | -0.040* | 0.003 | -0.000 |
| | (0.059) | (0.054) | (0.023) | (0.023) | (0.015) | (0.014) |
| Observations | 2,001 | 2,001 | 2,001 | 2,001 | 2,001 | 1,954 |
| R-squared | 0.10 | 0.23 | 0.07 | 0.09 | 0.19 | 0.21 |
| Control | No | Yes | No | Yes | No | Yes |
| Location FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry FE | Yes | Yes | Yes | Yes | Yes | Yes |
| *Panel D. Startups Aiming for Environmental Impact* | | | | | | |
| Has ESG Characteristics | 0.159** | 0.124* | -0.057*** | -0.050*** | 0.033 | 0.021 |
| | (0.071) | (0.072) | (0.015) | (0.015) | (0.031) | (0.028) |
| Observations | 2,530 | 2,530 | 2,530 | 2,530 | 2,530 | 2,478 |
| R-squared | 0.09 | 0.22 | 0.08 | 0.09 | 0.16 | 0.20 |
| Control | No | Yes | No | Yes | No | Yes |
| Location FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry FE | Yes | Yes | Yes | Yes | Yes | Yes |

*Notes.* This table tests whether impact ventures underperform profit-driven ventures in the short run (i.e., the 1-year period after the experiment) and in the medium run (the 2.5-year period after the experiment). Based on the Pitchbook data, the sample contains all the startups that have received funding from *recruited investors*' affiliated VC companies between 01/01/2017 and 07/31/2020. Panel A examines the performance of global startups. Panel B focuses on the performance of U.S. startups, defined as startups whose headquarters are located in the U.S. Due to the existence of singleton observations among U.S. startups, the number of observations between different columns can be slightly different in Panel B. Panel C focuses on startups that just raised their early-stage funding. Panel D examines startups that aim for positive environmental impact. In Columns (1) and (2), the dependent variable is an indicator that equals one if the startup has successfully raised a new round of funding from the venture capital industry during 07/31/2020-07/31/2021, and zero otherwise. In Columns (3) and (4), the dependent variable is an indicator that equals one if the startup's business status is "out of business" in 10/2021. Ideally, I should use the business status on 07/31/2021. However, this information is not available. "Out of Business" is defined as either "File Bankruptcy" or "Out of Business" in Pitchbook. Results are similar after including cases where startups' websites no longer function, such as reporting a 404 error. In Columns (5) and (6), the dependent variable is an indicator that equals one if the startup has experienced a successful exit during 07/31/2020-01/31/2023, and zero otherwise. "Successful Exit" includes both IPOs and an exit at a reported value at least twice the total capital invested. Columns (2), (4), and (6) include the following control variables that are last updated startup characteristics before 07/31/2020: number of deals, founding years, and log total raised amount of the latest deal. "Has ESG Characteristics" is an indicator that equals one if the startup is defined as an ESG startup based on the keyword method, and zero otherwise. Standard errors in parentheses are clustered at the headquarter location level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

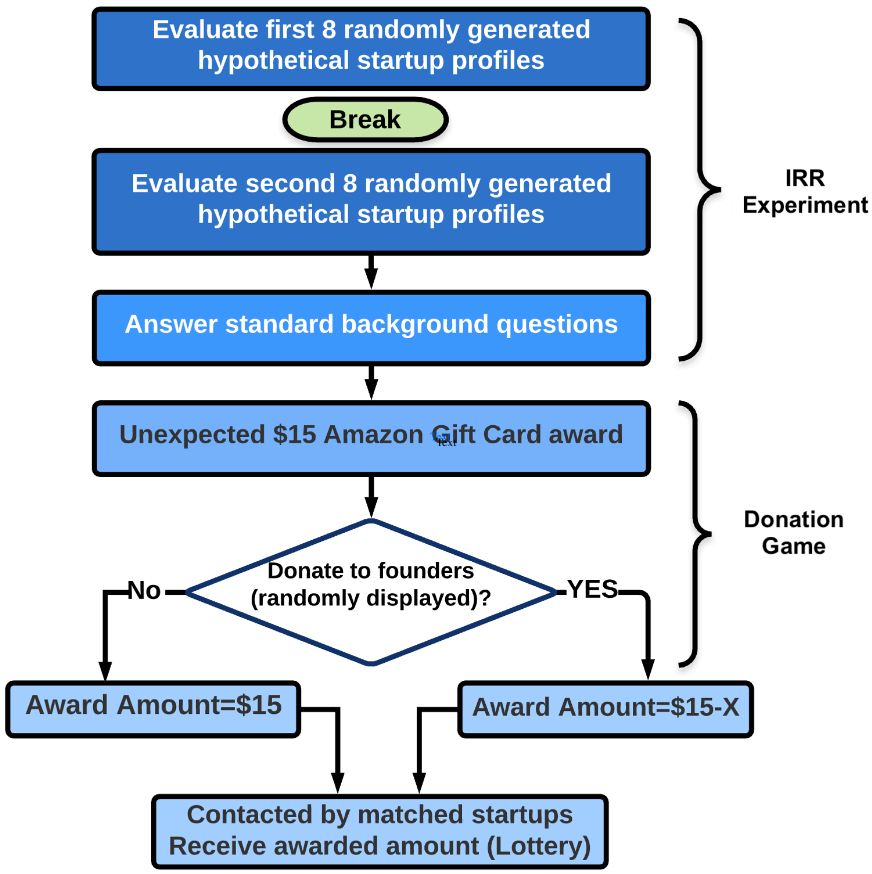



Figure 1: Flow Chart of the IRR Experiment

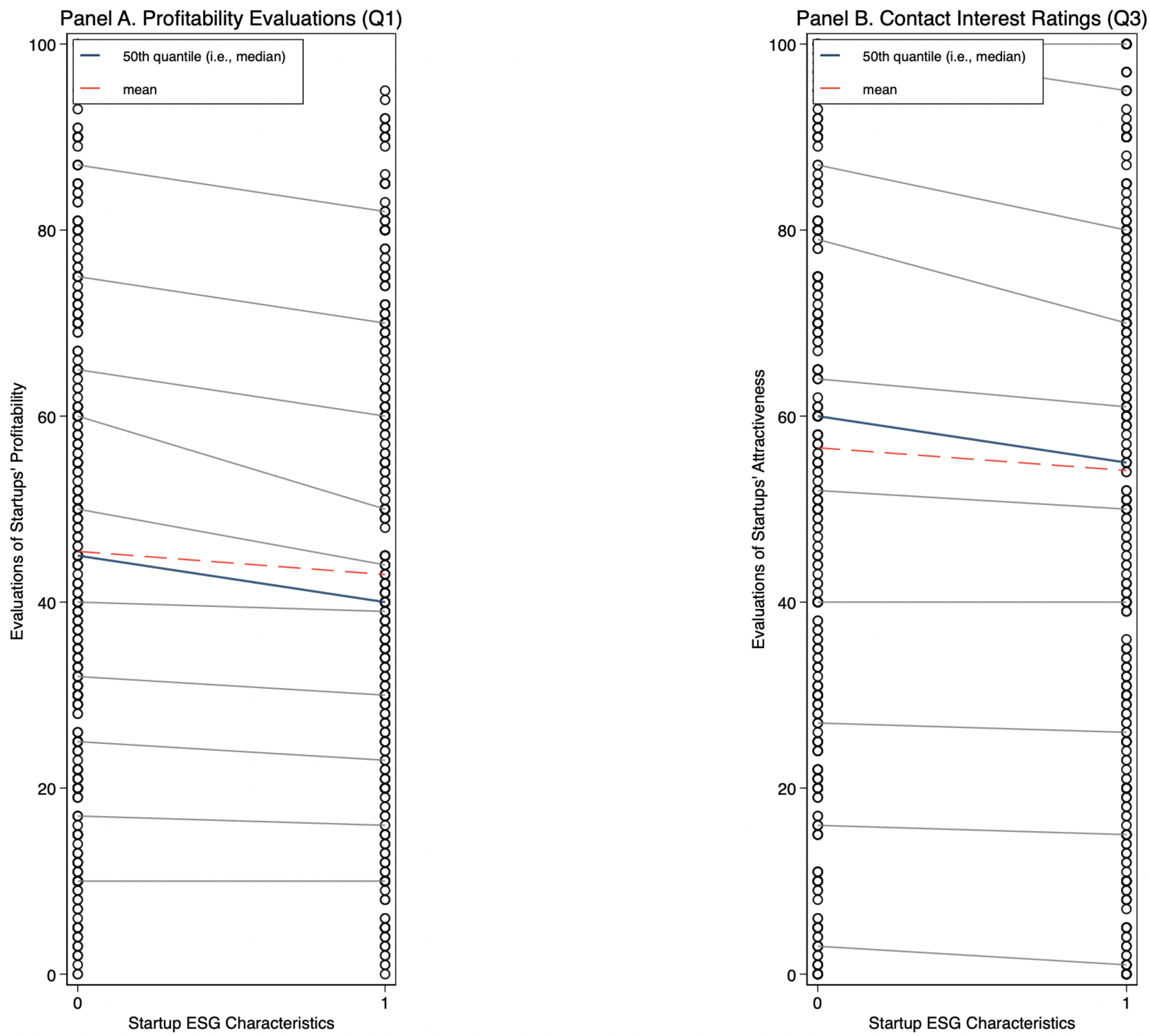



Figure 2: Effects of Startups' ESG Characteristics on Conditional Quantiles of Received Evaluations

*Notes*: This figure describes the effects of aiming for ESG on different conditional quantiles of startups' received evaluations. Panel A describes the effects on profitability evaluations (i.e., $Q_1$). Panel B describes the effects on contact interest ratings (i.e., $Q_3$). On the X-axis, "Startup ESG Characteristics" with value 0 stands for purely profit-driven startups and "Startup ESG Characteristics" with value 1 stands for impact ventures. The red dashed line stands for the effect of aiming for ESG on conditional *mean* of startups' received evaluations based on an OLS regression. The navy solid line stands for the effect of aiming for ESG on conditional *median* (i.e., the 50th conditional quantile) of startups' received evaluations based on an quantile regression. Other grey solid lines describe the effects of aiming for ESG on the $k$th conditional percentile ($k \in 5, 15, 25, ..., 95$) of the startup's received profitability rating (i.e., $Q_1$) in Panel A and contact interest rating (i.e., $Q_3$) in Panel B.

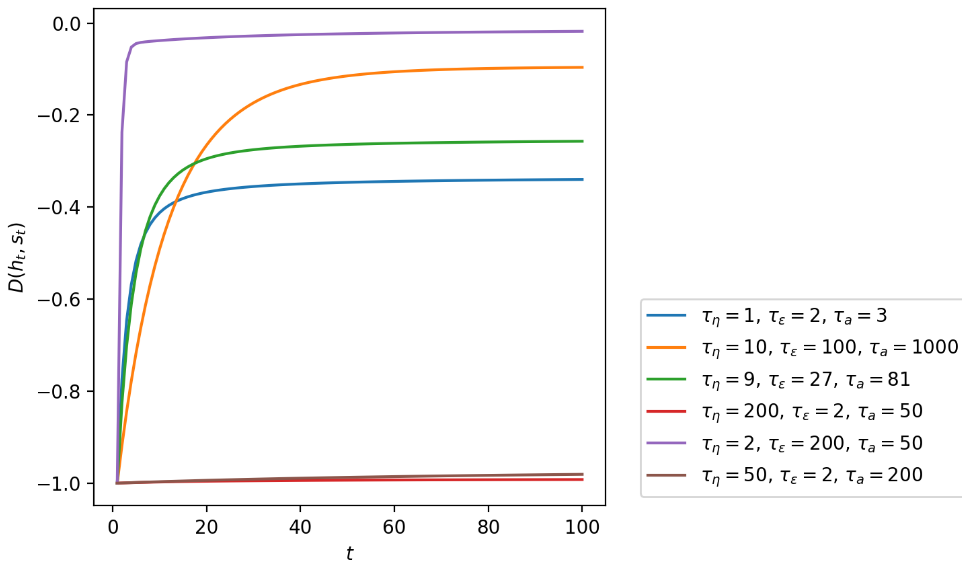



Figure 3: Simulation Results of the Model

*Notes*: This figure shows the simulation results of how impact investment will evolve in the dynamic setting with different initial parameters (i.e., $\tau_\eta, \tau_\epsilon, \tau_a, c = -1$) and zero initial belief-driven bias against impact ventures (i.e., $S(1) = 0$).

# Internet Appendix (Online Appendix)

## A IRR Experiment

Table A1: Full Names Populating Profile Tool

| Asian Female | White Female | Asian Male | White Male |
|---|---|---|---|
| Cynthia Huynh | Amber Morris | Evan Liu | Patrick Kelly |
| Jennifer Tang | Erica Carpenter | Alan Wu | Stephen Bennett |
| Amanda Cheung | Anna Hoffman | Bryan Liang | Steven Martin |
| Christina Chang | Amanada Gray | William Chung | Jeremy White |
| Linda Chung | Tiffany Roberts | Nicholas Wang | Jason Adams |
| Brittany Yi | Lisa Taylor | Charles Luu | Donald Schultz |
| Megan Ho | Karen Carroll | Zachary Ho | Jack Wright |
| Emily Xu | Danielle Collins | Marcus Yoon | Victor Becker |
| Jacqueline Lin | Megan Bennett | George Thao | Michael Hughes |
| Kayla Wang | Brenda Cox | Vincent Huynh | Keith Meyer |
| Cassandra Kwon | Kathleen Phillips | Luke Yang | Anthony Roberts |
| Julie Chan | Amber Sullivan | Justin Dinh | Justin Cooper |
| Monica Luong | Madeline Walsh | Matt Hoang | Benjamin Hill |
| Amber Hoang | Abigail Kelly | Jacob Xu | Mark Myers |
| Sara Truong | Alicia Cook | Donald Choi | Phillip Baker |
| Katrina Tsai | Amanda Jensen | Dennis Lin | Vincent Peterson |
| Abigail Zhao | Angela Larson | Victor Kwon | Dennis Reed |
| Vanessa Choi | Hayley Thompson | Jason Pham | Frank Phillips |
| Patricia Li | Christine Campbell | Eric Duong | Shane Taylor |
| Lisa Zhou | Caroline Parker | Stephen Hsu | William Welch |
| Caroline Lu | Kristy Baker | Kevin Jiang | Bryan Ward |
| Melissa Hwang | Tina Reed | Jeffrey Chen | Ian Russell |
| Mary Pham | Sara Burke | Erik Luong | Brian Wilson |
| Amy Hu | Victoria Snyder | Philip Zhao | Seth Schwartz |
| Jenna Nguyen | Molly Weaver | Jeremy Yu | Jared Walsh |
| Margaret Liang | Melissa Stone | Seth Truong | Zachary Parker |
| Danielle Liu | Melanie Wilson | Ian Zhou | John Carpenter |
| Megan Dinh | Rachael Ward | Matthew Chang | Jeffery Cook |
| Melanie Yang | Elizabeth Miller | Scott Lu | Nathan Nelson |
| Amanda Thao | Mary Hill | Sean Hwang | Matthew Rogers |
| Sarah Yu | Amy Moore | Patrick Hu | George Barker |
| Nichole Liu | Vanessa Smith | Mark Chan | Sean Beck |
| Christine Cho | Teresa Anderson | Jack Zhu | David Hall |
| Victoria Xiong | Catherine Schultz | Timothy Cheng | Andrew Miller |
| Teresa Wong | Heather Martin | Benjamin Nguyen | Peter Keller |
| Kara Yoon | Kathryn Myers | Steven Tang | Luke Jensen |

*Continued*

| Asian Female | White Female | Asian Male | White Male |
|---|---|---|---|
| Kathleen Cheng | Katie Meyer | Travis Wong | Kevin Hansen |
| Angela Wu | Valerie Price | David Zheng | Dustin Sullivan |
| Catherine Zheng | Melinda Evans | Paul Ngo | Philip Morris |
| Hayley Huang | Sandra Wright | Anthony Yi | Evan Moore |
| Karen Ngo | Christina Russell | Shane Huang | Paul Burke |
| Elizabeth Duong | Kayla Allen | Robert Zhang | Matt Price |
| Laura Luu | Jacqueline Schmidt | Kenneth Tsai | Marcus Collins |
| Rebecca Hsu | Jennifer Welch | Richard Xiong | Richard Thompson |
| Melinda Zhang | Michelle Nelson | Brian Cho | Thomas Snyder |
| Katherine Le | Sarah Fisher | Joel Le | Christopher Larson |
| Tara Jiang | Brittany Rogers | Michael Li | Travis Gray |
| Alicia Zhu | Grace Keller | Trevor Cheung | Charles Hoffman |
| Molly Huynh | Julie Beck | Adam Liu | Joel Stone |
| Samantha Tang | Monica Cooper | Peter Wu | Joseph Allen |

*Notes.* This table provides the name lists of hypothetical startup founders used in the survey tool. 50 names are selected to be highly indicative of each combination of race and gender. Considering that white and Asian startup founders account for most of the highly innovative startups, the experiment only contains four combinations listed above: Asian Female, White Female, Asian Male, and White Male. A name drawn from these lists is displayed at the beginning part of the startup profile and in the questions used to evaluate the resume. First and last names are linked every time as they appear, and the combinations of first and last names are randomly generated. Considering that Asian and white Americans have very similar naming patterns as documented by Fryer Jr and Levitt (2004), I choose their first names from the same name pool. After generating a list of potential full name candidates, the research team further check these names to make sure that there are no names owned by famous startup founders or CEOs.

Table A2: Educational Background and School List

| School Category | Universities | Percentage |
|---|---|---|
| (Top School) | Brown University | 50% |
| Example | Columbia University | |
| | Cornell University | |
| | Dartmouth College | |
| | Harvard University | |
| | Princeton University | |
| | University of Pennsylvania | |
| | Yale University | |
| | California Institute of Technology | |
| | MIT | |
| | Northwestern University | |
| | Stanford University | |
| | University of Chicago | |
| | | |
| (Common School) | Thomas Jefferson University | 50% |
| Example | University of Arkansas | |
| | Hofstra University | |
| | University of Mississippi | |
| | Virginia Commonwealth University | |
| | Adelphi University | |
| | University of Maryland-Baltimore County | |
| | University of Rhod Island | |
| | St.John's University | |
| | University of Detroit Mercy | |
| | University of Idaho | |
| | Biola University | |
| | Chatham University | |
| | Bellarmine University | |
| | Bethel University | |
| | Loyola University New Orleans | |
| | Robert Morris University | |
| | Regis University | |
| | Widener University | |
| | Laurentian University | |
| | Auburn University | |
| | Rochester Institute of Technology | |
| | University of Tulsa | |
| | DePaul University | |

*Notes.* This table provides the school list used to generate the educational background of each hypothetical startup founder. The percentage of top school and common school is 50% VS 50% to increase the experimental power. Top schools refer to the Ivy League schools (Brown University, Columbia University, Cornell University, Dartmouth College, Harvard University, Princeton University, University of Pennsylvania, and Yale University) as well as other top U.S. schools (California Institute of Technology, Duke University, MIT, Northwestern University, Stanford University, and University of Chicago). Considering that the collaborating incubators have more connections with Columbia University and Stanford University, I give more weights on these universities. Common Schools are those who are ranked lower than the 150th based on the U.S. News 2020 ranking results. I also add a Canadian common school since one of the incubators is from Canada.

Table A3: Company Comparative Advantage

| Advantage Category | Description |
|---|---|
| (Product) | trade secrets/patents registered |
| | celebrity endorsement |
| | exclusive partnerships |
| | accumulated many pilot consumers |
| | adoption of the latest technology |
| | pricing advantage |
| | great product design |
| | 1st mover |
| (Cost) | lower cost |
| | economies of scale |
| Total | 100% |

*Notes.* For each startup profile, a subset of comparative advantages is randomly drawn from the 10 advantages listed above.

Table A4: Covariate Balance Tables

| | Fraction of Evaluated Impact Ventures' Profiles (1) | Fraction of Evaluated Profit-driven Startup Profiles (2) | P-val of T-test (3) |
|---|---|---|---|
| Female Investor | 0.496 | 0.504 | 0.936 |
| Minority Investor | 0.498 | 0.502 | 0.985 |
| Impact Investor | 0.500 | 0.500 | 0.969 |
| STEM Industry | 0.497 | 0.503 | 0.932 |
| Top School | 0.500 | 0.500 | 0.911 |
| Has Entrepreneurial Experience | 0.498 | 0.502 | 0.978 |
| Accept Cold Emails | 0.499 | 0.501 | 0.943 |
| Also Invest Using Foreign Currency | 0.492 | 0.508 | 0.883 |

*Notes.* This table tests sample balance across randomized startup profiles and compares investor characteristics at the profile level. Column (3) shows the p-values associated with mean difference tests.

Table A5: Variance and Covariance of Orthogonally Randomized Startup Characteristics

| | ESG | IPO | Serial | Ivy | # of Founders | US | # Adv | Positive Revenue | # Employee [0-10] | # Employee [10-20] | # Employee [20-50] | Age | B2B | Domestic Market |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ESG | 1.0000 | | | | | | | | | | | | | |
| IPO | -0.5755 | 1.0000 | | | | | | | | | | | | |
| Serial | -0.0282 | 0.0295 | 1.0000 | | | | | | | | | | | |
| Ivy | 0.0327 | -0.0210 | 0.0643 | 1.0000 | | | | | | | | | | |
| # of Founders | -0.0065 | -0.0114 | 0.0123 | 0.0281 | 1.0000 | | | | | | | | | |
| US | -0.0200 | 0.0246 | 0.0038 | 0.0174 | -0.0302 | 1.0000 | | | | | | | | |
| # Adv | 0.0014 | 0.0286 | 0.0214 | -0.0334 | 0.0340 | -0.0487 | 1.0000 | | | | | | | |
| Positive Revenue | -0.0084 | -0.0295 | 0.0596 | 0.0747 | 0.0090 | 0.0167 | 0.0191 | 1.0000 | | | | | | |
| # Employee [0-10] | 0.0076 | 0.0559 | 0.0049 | 0.0690 | -0.0778 | 0.0136 | -0.0617 | 0.0220 | 1.0000 | | | | | |
| # Employee [10-20] | -0.0066 | 0.0382 | 0.0245 | -0.0016 | 0.0637 | 0.0357 | 0.0375 | -0.0186 | -0.2869 | 1.0000 | | | | |
| # Employee [20-50] | 0.0076 | -0.0581 | -0.0483 | -0.0648 | -0.0057 | -0.0519 | -0.0092 | -0.0160 | -0.3348 | -0.2869 | 1.0000 | | | |
| Age | 0.0162 | 0.0007 | 0.0021 | 0.0199 | 0.0007 | 0.0344 | 0.0252 | 0.0383 | 0.0013 | -0.0274 | 0.0352 | 1.0000 | | |
| B2B | -0.0148 | -0.0294 | 0.0164 | -0.0383 | -0.0510 | 0.0450 | -0.0135 | -0.0001 | 0.0028 | 0.0256 | -0.0465 | 0.0088 | 1.0000 | |
| Domestic Market | 0.0855 | -0.0760 | 0.0280 | 0.0762 | 0.0230 | -0.0177 | -0.0041 | -0.0214 | -0.0550 | -0.0124 | 0.0398 | 0.0375 | -0.0345 | 1.0000 |

*Notes.* This table reports variance and covariance of orthogonally randomized startup characteristics used in the IRR experiment.

Table A6: Incentive Structure Comparison

| | (1) Q1 | (2) Q2 | (3) Q3 | (4) Q4 |
|---|---|---|---|---|
| Has ESG Characteristics | -3.69* | -0.52 | -4.03 | -0.47 |
| | (1.99) | (1.52) | (2.47) | (0.35) |
| Has ESG Characteristics × Matching | 3.44 | -0.40 | 4.51 | 0.41 |
| | (3.40) | (2.59) | (3.28) | (0.56) |
| Has IPO Plan | -0.38 | -1.23 | -4.32* | 0.10 |
| | (2.27) | (1.70) | (2.57) | (0.46) |
| Has IPO Plan × Matching | 1.93 | -2.28 | 4.97 | 0.03 |
| | (3.96) | (2.93) | (4.65) | (0.68) |
| Matching | 16.08*** | 48.52*** | 30.63*** | 2.39*** |
| | (2.47) | (1.85) | (2.55) | (0.38) |
| Investor FEs | Yes | Yes | Yes | Yes |
| Observations | 1,216 | 1,184 | 1,216 | 1,176 |
| R-squared | 0.32 | 0.53 | 0.47 | 0.35 |

*Notes.* This table compares the evaluation results of startups' ESG characteristics from investors who are recruited by the following two incentive structures: "matching incentive + monetary incentive" and pure "matching incentive". "Matching" is an indicator that equals one when only the matching incentive is provided in the recruitment process, and zero if both the "matching incentive" and the "monetary incentive" are provided. The dependent variables in columns (1)-(4) are the profitability evaluations, availability evaluations, contact interest ratings, and investment interest ratings. All the regression specifications add investor fixed effects. Standard errors are clustered at the investor level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A7: Quantile-Regression Estimates for Investors' Evaluations (Remove First Few Profiles)

Panel A. Profitability (i.e., $Q_1$, Remove the First Two Profiles)

| | 5th (1) | 15th (2) | 25th (3) | 35th (4) | 45th (5) | 55th (6) | 65th (7) | 75th (8) | 85th (9) | 95th (10) | Mean (11) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Has ESG Characteristics | -2.00 | -5.00 | -1.00 | -4.00 | -1.00 | -6.00* | -7.00** | -8.00*** | -5.00** | -2.00 | -2.78 |
| | (2.79) | (3.26) | (2.51) | (2.51) | (2.64) | (3.44) | (3.21) | (2.55) | (2.45) | (2.43) | (1.76) |
| Has IPO Plan | 0.00 | -1.00 | 2.00 | 1.00 | -1.00 | 0.00 | -3.00 | -4.00 | -2.00 | 3.00 | 0.08 |
| | (3.45) | (4.01) | (3.15) | (2.77) | (3.20) | (3.53) | (3.69) | (3.20) | (2.57) | (2.92) | (1.98) |
| Quantile of Dep. Var. | 10 | 19 | 25 | 33 | 40 | 50 | 55 | 63 | 72 | 86 | 44.97 |
| Observations | 1,076 | 1,076 | 1,076 | 1,076 | 1,076 | 1,076 | 1,076 | 1,076 | 1,076 | 1,076 | 1,076 |

Panel B. Attractiveness (i.e., $Q_3$, Remove the First Two Profiles)

| | 5th (1) | 15th (2) | 25th (3) | 35th (4) | 45th (5) | 55th (6) | 65th (7) | 75th (8) | 85th (9) | 95th (10) | Mean (11) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Has ESG Characteristics | -3.00 | -4.00* | -2.00 | -2.00 | -7.00 | -9.00*** | -10.00*** | -10.00*** | -5.00 | 0.00 | -2.31 |
| | (2.95) | (2.37) | (3.04) | (4.06) | (4.27) | (3.16) | (3.73) | (2.09) | (3.44) | (0.19) | (1.93) |
| Has IPO Plan | -4.00 | -4.00 | -5.00 | -11.00** | -7.00* | -10.00*** | -9.00** | -10.00*** | -1.00 | 0.00 | -3.11 |
| | (4.08) | (3.07) | (3.82) | (4.43) | (4.03) | (3.41) | (4.12) | (2.46) | (4.04) | (0.21) | (2.21) |
| Quantile of Dep. Var. | 1 | 17 | 27 | 40 | 50 | 61 | 73 | 80 | 97 | 100 | 55.04 |
| Observations | 1,076 | 1,076 | 1,076 | 1,076 | 1,076 | 1,076 | 1,076 | 1,076 | 1,076 | 1,076 | 1,076 |

*Continued*

Panel C. Profitability (i.e., $Q_1$, Remove the First Three Profiles)

| | 5th (1) | 15th (2) | 25th (3) | 35th (4) | 45th (5) | 55th (6) | 65th (7) | 75th (8) | 85th (9) | 95th (10) | Mean (11) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Has ESG Characteristics | -2.00 | -3.00 | -1.00 | -4.00 | -1.00 | -6.00* | -6.00* | -5.00** | -4.00 | -5.00** | -2.60 |
| | (2.96) | (3.18) | (2.31) | (2.59) | (2.80) | (3.56) | (3.46) | (2.47) | (2.65) | (2.39) | (1.81) |
| Has IPO Plan | 0.00 | -1.00 | -1.00 | 1.00 | -1.00 | 0.00 | -3.00 | 1.00 | -2.00 | 0.00 | -0.17 |
| | (3.45) | (4.08) | (2.86) | (2.88) | (3.40) | (3.52) | (3.71) | (3.00) | (2.63) | (2.39) | (1.93) |
| Quantile of Dep. Var. | 10 | 19 | 25 | 33 | 40 | 50 | 56 | 63 | 73 | 87 | 45.09 |
| Observations | 1,006 | 1,006 | 1,006 | 1,006 | 1,006 | 1,006 | 1,006 | 1,006 | 1,006 | 1,006 | 1,006 |

Panel D. Attractiveness (i.e., $Q_3$, Remove the First Three Profiles)

| | 5th (1) | 15th (2) | 25th (3) | 35th (4) | 45th (5) | 55th (6) | 65th (7) | 75th (8) | 85th (9) | 95th (10) | Mean (11) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Has ESG Characteristics | -1.00 | -3.00 | -1.00 | -2.00 | -7.00* | -5.00 | -10.00** | -7.00*** | -5.00 | 0.00 | -2.17 |
| | (2.76) | (2.48) | (3.10) | (4.34) | (3.83) | (4.06) | (4.06) | (2.59) | (3.35) | (0.20) | (1.95) |
| Has IPO Plan | -3.00 | -8.00*** | -6.00 | -11.00** | -7.00* | -7.00* | -10.00** | -7.00** | -1.00 | 0.00 | -3.83* |
| | (4.10) | (2.77) | (4.27) | (4.65) | (3.83) | (4.23) | (4.36) | (3.25) | (3.90) | (0.23) | (2.11) |
| Quantile of Dep. Var. | 1 | 16 | 28 | 40 | 50 | 60 | 72 | 81 | 97 | 100 | 54.90 |
| Observations | 1,006 | 1,006 | 1,006 | 1,006 | 1,006 | 1,006 | 1,006 | 1,006 | 1,006 | 1,006 | 1,006 |

*Notes.* This table reports the effects of being an impact venture on different conditional quantiles and conditional mean of startups' received profitability evaluations and attractiveness evaluations after evaluations of the first two or three profiles are removed. The dependent variable is the startup's received profitability rating (i.e., $Q_1$) in Panel A and contact interest rating (i.e., $Q_3$) in Panel B. In each of Columns (1)–(10), the reported coefficient of "Has ESG Characteristics" stands for the effect of aiming for ESG on the $k$th conditional percentile ($k \in 5, 15, 25, ..., 95$) of the startup's received profitability rating (i.e., $Q_1$) in Panel A and contact interest rating (i.e., $Q_3$) in Panel B. In Column (11), the reported coefficients of "Has ESG Characteristics" using OLS regressions stand for the effects of aiming for ESG on the conditional mean of $Q_1$ in Panel A and $Q_3$ in Panel B. Standard errors in parentheses are clustered at the investor level. $*p < 0.10, **p < 0.05, ***p < 0.01$

Table A8: Quantile-Regression Estimates for Investors' Evaluations (Remove Subjects with Strongest ESG Attitudes)

Panel A. Profitability (i.e., $Q_1$)

| | 5th (1) | 15th (2) | 25th (3) | 35th (4) | 45th (5) | 55th (6) | 65th (7) | 75th (8) | 85th (9) | 95th (10) | Mean (11) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Has ESG Characteristics | 0.00 | -3.00 | -0.00 | -3.00 | 0.00 | -5.00* | -9.00*** | -4.00** | -2.00 | -3.00 | -2.04 |
| | (2.10) | (2.89) | (2.10) | (2.13) | (2.52) | (2.83) | (2.68) | (1.78) | (2.39) | (2.76) | (1.33) |
| Has IPO Plan | 0.00 | -1.00 | 3.00 | 2.00 | 0.00 | 0.00 | -5.00 | -3.00 | -1.00 | 4.00 | 0.43 |
| | (2.91) | (3.86) | (3.06) | (2.54) | (3.69) | (3.40) | (3.38) | (3.27) | (2.56) | (2.93) | (1.93) |
| Quantile of Dep. Var. | 10 | 19 | 25 | 32 | 40 | 50 | 55 | 61 | 71 | 85 | 44.45 |
| Observations | 1,168 | 1,168 | 1,168 | 1,168 | 1,168 | 1,168 | 1,168 | 1,168 | 1,168 | 1,168 | |

Panel B. Attractiveness (i.e., $Q_3$)

| | 5th (1) | 15th (2) | 25th (3) | 35th (4) | 45th (5) | 55th (6) | 65th (7) | 75th (8) | 85th (9) | 95th (10) | Mean (11) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Has ESG Characteristics | -1.00 | -4.00* | -0.00 | 0.00 | -2.00 | -3.00 | -7.00** | -7.00*** | -3.00 | 0.00 | -2.26 |
| | (2.39) | (2.24) | (2.33) | (3.26) | (2.57) | (3.03) | (3.26) | (2.18) | (3.36) | (0.12) | (1.50) |
| Has IPO Plan | -2.00 | -4.00 | -4.00 | -5.00 | -2.00 | -4.00 | -7.00* | -7.00** | -0.00 | 0.00 | -2.76 |
| | (3.56) | (3.04) | (3.73) | (4.27) | (3.34) | (3.80) | (3.73) | (2.94) | (0.32) | (0.10) | (2.24) |
| Quantile of Dep. Var. | 1 | 15 | 28 | 40 | 50 | 61 | 72 | 80 | 99 | 100 | 55.15 |
| Observations | 1,168 | 1,168 | 1,168 | 1,168 | 1,168 | 1,168 | 1,168 | 1,168 | 1,168 | 1,168 | 1,168 |

*Notes.* This table reports the effects of being an impact venture on different conditional quantiles and conditional mean of investors' profitability evaluations and attractiveness evaluations. The sample in this table has removed evaluations of experimental subjects with extreme ESG attitudes, which are identified in Online Appendix Figure A10. The dependent variable is the startup's received profitability rating (i.e., $Q_1$) in Panel A and contact interest rating (i.e., $Q_3$) in Panel B. In each of Columns (1)–(10), the reported coefficient of "Has ESG Characteristics" stands for the effect of aiming for ESG on the $k$th conditional percentile ($k \in 5, 15, 25, ..., 95$) of the startup's received profitability rating (i.e., $Q_1$) in Panel A and contact interest rating (i.e., $Q_3$) in Panel B. In Column (11), the reported coefficients of "Has ESG Characteristics" using OLS regressions stand for the effects of aiming for ESG on the conditional mean of $Q_1$ in Panel A and $Q_3$ in Panel B. Standard errors in parentheses are clustered at the investor level. $*p < 0.10, **p < 0.05, ***p < 0.01$

Table A9: Quantile-Regression Estimates for Investors' Profitability Evaluations (Controlling for Investors' Rating Levels)

Panel A. Profitability (i.e., $Q_1$, Controlling Median of Investor's Ratings)

| | 5th (1) | 15th (2) | 25th (3) | 35th (4) | 45th (5) | 55th (6) | 65th (7) | 75th (8) | 85th (9) | 95th (10) | Mean (11) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Has ESG Characteristics | 2.25 | 0.35 | -1.12 | -1.81 | -1.50 | -2.21 | -5.33*** | -5.00** | -4.63* | -3.67 | -2.65 |
| | (1.74) | (2.69) | (1.92) | (1.71) | (1.43) | (1.37) | (1.88) | (2.02) | (2.63) | (3.22) | (1.60) |
| Has IPO Plan | 3.50 | 0.39 | -1.12 | -1.62 | -1.00 | 0.05 | -0.67 | 1.81 | 0.04 | 2.00 | 0.20 |
| | (2.47) | (3.29) | (2.20) | (2.00) | (1.87) | (1.81) | (2.50) | (2.77) | (2.95) | (2.95) | (1.82) |
| Median of Investor's | 0.30*** | 0.61*** | 0.75*** | 0.87*** | 1.00*** | 0.99*** | 0.93*** | 0.81*** | 0.74*** | 0.44*** | 1.00*** |
| $Q_1$ Ratings | (0.08) | (0.09) | (0.06) | (0.04) | (0.03) | (0.03) | (0.05) | (0.07) | (0.12) | (0.13) | (0.036) |
| Quantile of Dep. Var. | 10 | 17 | 25 | 31 | 40 | 49 | 55 | 61 | 71 | 85 | 44.29 |
| Observations | 1,216 | 1,216 | 1,216 | 1,216 | 1,216 | 1,216 | 1,216 | 1,216 | 1,216 | 1,216 | 1,216 |

Panel B. Profitability (i.e., $Q_1$, Controlling Leave-one-out Median of Investor's Ratings)

| | 5th (1) | 15th (2) | 25th (3) | 35th (4) | 45th (5) | 55th (6) | 65th (7) | 75th (8) | 85th (9) | 95th (10) | Mean (11) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Has ESG Characteristics | 1.00 | -0.42 | -0.73 | -1.20 | -2.00 | -3.42* | -4.00** | -5.43*** | -5.00** | -1.64 | -2.80 |
| | (1.87) | (2.02) | (1.87) | (1.88) | (1.95) | (2.08) | (1.90) | (2.10) | (2.09) | (2.78) | (1.68) |
| Has IPO Plan | 3.00 | -0.16 | 0.00 | -0.20 | -0.60 | 0.79 | -1.00 | -0.46 | -0.50 | 3.00 | -0.04 |
| | (2.10) | (2.22) | (2.54) | (2.30) | (2.55) | (2.76) | (2.42) | (2.91) | (2.85) | (2.24) | (1.89) |
| Leave-one-out Median | 0.27*** | 0.53*** | 0.73*** | 0.77*** | 0.80*** | 0.84*** | 0.80*** | 0.66*** | 0.50*** | 0.27*** | 0.61*** |
| of Investor's $Q_1$ Ratings | (0.07) | (0.07) | (0.05) | (0.05) | (0.05) | (0.05) | (0.05) | (0.09) | (0.06) | (0.08) | (0.05) |
| Quantile of Dep. Var. | 10 | 17 | 25 | 31 | 40 | 49 | 55 | 61 | 71 | 85 | 44.29 |
| Observations | 1,216 | 1,216 | 1,216 | 1,216 | 1,216 | 1,216 | 1,216 | 1,216 | 1,216 | 1,216 | 1,216 |

*Notes.* This table reports the effects of being an impact venture on different conditional quantiles and conditional mean of startups' received profitability evaluations and attractiveness evaluations after controlling for investors' profitability rating levels. The dependent variable is the startup's received profitability rating (i.e., $Q_1$). In each of Columns (1)–(10), the reported coefficient of "Has ESG Characteristics" stands for the effect of aiming for ESG on the $k$th conditional percentile ($k \in 5, 15, 25, ..., 95$) of the startup's received profitability rating (i.e., $Q_1$). In Column (11), the reported coefficients of "Has ESG Characteristics" using OLS regressions (without fixed effects) stand for the effects of aiming for ESG on the conditional mean of $Q_1$. In Panel A, "Median of Investor's $Q_1$ Ratings" stands for each investor's median of $Q_1$. In Panel B, "Leave-one-out Median of Investor's $Q_1$ Ratings" is generated for each profile $j$ that is evaluated by each investor $i$. The median of $Q_1$ is calculated after dropping $Q_{1ij}$ for each profile $j$ evaluated by investor $i$. Standard errors in parentheses are clustered at the investor level. $*p < 0.10, **p < 0.05, ***p < 0.01$

Table A10: Quantile-Regression Estimates for Investors' Risk Ratings ($Q_5$)

| | 5th (1) | 15th (2) | 25th (3) | 35th (4) | 45th (5) | 55th (6) | 65th (7) | 75th (8) | 85t (9) | 95thh (10) | Mean (11) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Has ESG Characteristics | 11.00 | 5.00 | -5.00 | -4.00 | 3.00 | 0.00 | 0.00 | 3.00 | -2.00 | 6.00*** | 2.08 |
| | (6.71) | (12.04) | (6.49) | (6.33) | (5.14) | (4.17) | (5.09) | (5.16) | (4.57) | (0.31) | (4.25) |
| Has IPO Plan | 10.00 | -4.00 | -5.00 | -7.00 | -6.00 | -5.00 | 0.00 | 1.00 | -2.00 | -1.00 | -1.89 |
| | (8.07) | (8.25) | (5.00) | (5.39) | (6.27) | (6.86) | (7.32) | (5.92) | (5.09) | (1.89) | (3.98) |
| Quantile of Dep. Var. | 25 | 40 | 50 | 60 | 67 | 75 | 80 | 86 | 90 | 94 | 66.75 |
| Observations | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 |

*Notes.* This table reports the effects of being an impact venture on different conditional quantiles and the conditional mean of investors' risk ratings (i.e., $Q_5$) in the IRR experiment. The dependent variable is the startup's received risk ratings (i.e., $Q_5$). In each of Columns (1)–(10), the reported coefficient of "Has ESG Characteristics" stands for the effect of aiming for ESG on the $k$th conditional percentile ($k \in 5, 15, 25, ..., 95$) of the startup's received risk ratings (i.e., $Q_5$). In Column (11), the reported coefficients of "Has ESG Characteristics" using OLS regressions stand for the effects of aiming for ESG on the conditional mean of $Q_5$. Standard errors in parentheses are clustered at the investor level. $*p < 0.10, **p < 0.05, ***p < 0.01$

Table A11: Effects of Other Startup Characteristics on Investors' Evaluations

| Dependent Variable | Q1 Profitability (1) | Q2 Availability (2) | Q3 Contact (3) | Q4 Investment (4) | Q3 Contact (5) |
|---|---|---|---|---|---|
| Serial Founder | 5.23*** | -0.81 | 5.64*** | 0.76*** | 1.26 |
| | (1.35) | (0.91) | (1.50) | (0.21) | (1.13) |
| Ivy League Educational background | 5.36*** | -1.06 | 7.44*** | 0.87*** | 3.01** |
| | (1.06) | (1.01) | (1.37) | (0.20) | (0.91) |
| Number of Founders | 1.56 | -1.21 | 1.17 | 0.21 | -0.11 |
| | (0.96) | (0.79) | (1.21) | (0.18) | (1.02) |
| US Founder | 0.95 | 0.02 | 4.23* | 0.08 | 3.69** |
| | (1.20) | (1.05) | (2.16) | (0.27) | (1.73) |
| Number of Comparative Advantages | 3.10*** | -0.22 | 2.76*** | 0.55*** | 0.34 |
| | (0.53) | (0.53) | (0.61) | (0.11) | (0.44) |
| Has Positive Traction | 12.70*** | 1.75 | 13.35*** | 1.81*** | 1.91* |
| | (1.88) | (1.13) | (1.96) | (0.30) | (1.12) |
| Number of Employees [0-10] | 0.67 | 2.37** | -1.73 | -0.19 | -2.57** |
| | (1.43) | (1.06) | (1.65) | (0.28) | (1.02) |
| Number of Employees [10-20] | -1.08 | 0.94 | -3.26* | -0.46* | -2.08* |
| | (1.57) | (1.30) | (1.84) | (0.24) | (1.22) |
| Number of Employees [20-50] | -0.47 | -0.02 | -1.21 | -0.16 | -0.72 |
| | (1.47) | (1.17) | (1.84) | (0.26) | (1.40) |
| Company Age | -4.59* | -5.99** | -7.39** | -1.26** | -2.19 |
| | (2.71) | (2.46) | (3.15) | (0.49) | (2.57) |
| Company Age$^2$ | 0.75 | 1.12** | 1.27** | 0.23** | 0.42 |
| | (0.53) | (0.48) | (0.63) | (0.09) | (0.50) |
| B2B Startup | 3.90** | 3.73** | 6.10*** | 0.81** | 1.47 |
| | (1.45) | (1.22) | (1.72) | (0.26) | (1.00) |
| Domestic Market | -0.10 | -0.60 | 0.09 | 0.08 | 0.57 |
| | (0.98) | (0.97) | (1.37) | (0.22) | (1.17) |
| $Q_1$ | | | | | 0.88*** |
| | | | | | (0.05) |
| $Q_2$ | | | | | 0.18*** |
| | | | | | (0.04) |
| Investor FE | Yes | Yes | Yes | Yes | Yes |
| Observations | 1,216 | 1,184 | 1,216 | 1,176 | 1,216 |
| R-squared | 0.44 | 0.55 | 0.56 | 0.44 | 0.80 |

*Notes.* This table shows the effects of various startup team characteristics and startup project characteristics on investors' evaluations. Details are provided in Zhang and Ebrahimian (2020). In column (1), the dependent variable is the profitability evaluation, which indicates the percentile rank of each startup profile compared with investor's previous invested startups in terms of its potential financial return. In column (2), the dependent variable is the availability evaluation, which indicates how likely the investors feel the startup team will accept his/her investment rather than other investors. In column (3), the dependent variable is the contact interest rating, which describes the probability that the investor wants to contact this startup. In column (4), the dependent variable is the investment interest, which describes the relative investment amount compared with the investor's general investment amount. For example, if the investor's average investment amount is $1 million and $Q_4$ is equal to 0.5, then it means the investor only wants to invest $500,000 in this startup. "Serial Founder", "Ivy League Educational background", "US Founder", "Has Positive Traction", "B2B Startup" and "Domestic Market" are all indicative variables that equal to one if the founder is a serial entrepreneur, graduated from an Ivy League College, lives in the U.S., the project has positive traction, is a Business-to-Business startup, and focuses on the domestic market. These variables are equal to 0 if the startup does not match these characteristics. "Number of founders" is either 1 or 2; "Number of Comparative Advantages" and "Company Age" can be $\{1,2,3,4\}$; Company Age$^2$ is the square of the company's age. All the regressions add investor fixed effects. Standard errors in parentheses are clustered at the investor level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table A12: Correlations Between Investors' Evaluations and Real-world Investment Portfolios

| Dependent Variable | 1(*Prefer ESG*) | 1(*Prefer ESG*) | ESG Attitude |
|---|---|---|---|
| | OLS | Probit | OLS |
| | (1) | (2) | (3) |
| *Panel A: Evaluations of Attractive Startups ($\hat{Q}_3 \geq 50$)* | | | |
| Fraction of ESG Startups | 1.16*** | 4.33* | 19.95* |
| in Portfolio Companies | (0.39) | (2.54) | (10.77) |
| Observations | 61 | 61 | 61 |
| R-squared | 0.051 | 0.046 | 0.035 |
| *Panel B: Evaluations of All Startups* | | | |
| Fraction of ESG Startups | -0.06 | -0.16 | 25.77 |
| in Portfolio Companies | (0.65) | (1.63) | (23.57) |
| Observations | 68 | 68 | 68 |
| R-squared | 0.000 | 0.000 | 0.020 |

*Notes.* This table tests the correlations between investors' evaluations in the IRR experiment and their affiliated VC companies' real-world investment portfolios between 01/01/2017 and 07/31/2020. The dependent variable 1(*Prefer ESG*) in Columns (1) and (2) is a dummy variable that equals one if the investor's "ESG Attitude" is above the median of the distribution of all the recruited investors' "ESG Attitudes," and zero otherwise. "ESG Attitude" is the coefficient $\beta_i$ of the following regression, which uses each individual investor $i$'s contact interest ratings: $Q_{3ij} = \beta_0 + \beta_i \text{Has ESG Characteristics}_{ij} + \gamma_i \text{Has IPO Plan}_{ij} + \epsilon_{ij}$. It represents the causal effect of "Has ESG Characteristics" on the investor's contact interest ratings (i.e., $Q_3$). In Panel A, 1(*Prefer ESG*) and "ESG Attitude" are calculated based on investors' evaluations of attractive startups whose received "objective" attractiveness is above 50 (i.e., $\hat{Q}_3 \geq 50$). In Panel B, 1(*Prefer ESG*) and "ESG Attitude" are calculated based on investors' evaluations of all startups. $\beta_i$ is not identified in Panel A if less than three startups evaluated by investor $i$ are "objectively" attractive (i.e., $\hat{Q}_3 \geq 50$). That's why the number of observations in Panel A is slightly smaller than in Panel B. Columns (1) and (3) use OLS models. Column (2) uses Probit models. "Fraction of ESG startups in Portfolio Companies" is the fraction of ESG startups in the portfolio companies of each investor's affiliated VC firm. This fraction is calculated based on each investor's affiliated VC company's investments between 01/01/2017 and 07/31/2020, which are recorded in Pitchbook. R-squared reports R-squared for OLS regressions and Pseudo R-squared for Probit models. Standard errors in parentheses are robust standard errors. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table A13: Correlations Between Self-reported Information and Real World Investment Behaviors

| | Self-reported Impact Investors | | Self-reported Impact Investors |
|---|---|---|---|
| Fraction of Impact Investing | 1.34*** | Impact Funds | 0.36** |
| | (0.29) | | (0.15) |
| | | | |
| Observations | 64 | Observations | 65 |
| R-squared | 0.30 | R-squared | 0.18 |

*Notes.* This table examines the correlation between self-reported background information about investors' ESG characteristics in the experiment and investors' real-world investment decisions. "Self-reported Impact Investors" is an indicator that equals one if the investor claims to care about impact investing or work in ESG-related industries in the IRR experiment. "Fraction of Impact Investing" indicates the fraction of ESG-related deals in their VC companies' involved deals between 01/01/2017-10/31/2021. "Impact Funds" is an indicator that equals one if the investor worked in any impact funds between 01/01/2017-10/31/2021, and zero otherwise. Impact funds are defined by whether VC funds/companies emphasize their impact investing strategies on their websites.

Table A14: Effect of Startups' ESG Characteristics on Investors' Attention (Remove the First Two Profiles)

| | Dependent Variable: Response Time (Unit: Seconds) | | | | | |
|---|---|---|---|---|---|---|
| | Full Sample | $Q_3 > 30$ | $Q_3 > 40$ | $Q_3 > 50$ | $Q_3 > 60$ | $Q_3 > 70$ |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Has ESG Characteristics | 4.11 | 7.38** | 7.74** | 5.94* | 8.27** | 7.42* |
| | (2.78) | (2.92) | (3.28) | (3.30) | (3.39) | (3.96) |
| Has IPO Plan | 0.31 | 1.37 | 2.72 | 1.91 | 1.15 | 1.83 |
| | (3.25) | (3.78) | (4.15) | (4.92) | (5.69) | (7.22) |
| Second Half of Study | -12.71*** | -14.34*** | -14.93*** | -16.93*** | -17.97*** | -17.99** |
| | (2.50) | (3.22) | (3.49) | (4.23) | (5.04) | (6.14) |
| $Q_1$ | 0.16** | 0.12 | 0.11 | 0.09 | 0.06 | 0.05 |
| | (0.05) | (0.08) | (0.08) | (0.09) | (0.12) | (0.15) |
| $Q_2$ | 0.06 | 0.07 | 0.05 | -0.05 | -0.20 | -0.14 |
| | (0.08) | (0.15) | (0.17) | (0.21) | (0.24) | (0.30) |
| Investor FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 1046 | 726 | 646 | 548 | 457 | 363 |
| R-squared | 0.39 | 0.40 | 0.40 | 0.42 | 0.43 | 0.44 |

*Notes.* This table tests whether investors allocate more attention to ESG startups compared to similar profit-driven startups after evaluations of the first two profiles are removed. The dependent variable is investors' response time, which is defined as the number of seconds before each page submission, winsorized at the 95th percentile (59.23 seconds on average). Column (1) tests all the evaluation results. Columns (2)-(6) focus on the high-stake situation where the investor indicates higher likelihood of contacting the startup. I choose five thresholds to define high stake situations (i.e., $Q_3 > 30$, $Q_3 > 40$, $Q_3 > 50$, $Q_3 > 60$, $Q_3 > 70$). Columns (2)-(6) stand for the situation where investors' likelihood of contacting the startup team is more than 30%, 40%, 50%, 60%, and 70%, respectively. "Second Half of Study" is an indicator variable for startup profiles shown among the last half profiles evaluated by an investor. "Has ESG Characteristics" is an indicator that equals one if the startup has an ESG-related mission, and zero otherwise. "Has IPO Plan" is an indicator that equals one if the startup is profit-driven and considers IPO within five years, and zero otherwise. All the regressions add investor fixed effects. Standard errors in parentheses are clustered at the investor level. *** p<0.01, ** p<0.05, * p<0.1

Table A15: Effect of Startups' ESG Characteristics on Investors' Attention ("Objective Attractiveness")

| | Dependent Variable: Response Time (Unit: Seconds) | | | | | |
|---|---|---|---|---|---|---|
| | Full Sample | $\hat{Q}_3 > 30$ | $\hat{Q}_3 > 40$ | $\hat{Q}_3 > 50$ | $\hat{Q}_3 > 60$ | $\hat{Q}_3 > 70$ |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Has ESG Characteristics | 4.10 | 7.00* | 8.01** | 9.87** | 10.97*** | 9.86** |
| | (3.30) | (3.68) | (3.99) | (3.88) | (3.67) | (3.91) |
| Has IPO Plan | -1.56 | 2.09 | 2.30 | 3.76 | 5.02 | 3.37 |
| | (3.48) | (4.04) | (4.38) | (4.57) | (5.40) | (6.44) |
| Second Half of Study | -27.12*** | -26.54*** | -26.26*** | -26.93*** | -30.26*** | -29.58*** |
| | (2.46) | (3.08) | (3.33) | (3.88) | (4.74) | (5.86) |
| $Q_1$ | 0.01 | 0.01 | -0.05 | -0.01 | -0.09 | -0.23* |
| | (0.05) | (0.08) | (0.09) | (0.10) | (0.10) | (0.13) |
| $Q_2$ | 0.16* | 0.19 | 0.17 | 0.17 | 0.09 | 0.04 |
| | (0.09) | (0.14) | (0.16) | (0.18) | (0.24) | (0.33) |
| Investor FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 1184 | 869 | 750 | 639 | 528 | 404 |
| R-squared | 0.35 | 0.37 | 0.37 | 0.38 | 0.41 | 0.42 |

*Notes.* This table tests whether investors allocate more attention to ESG startups compared to similar profit-driven startups. The dependent variable is investors' response time, which is defined as the number of seconds before each page submission, winsorized at the 95th percentile (59.23 seconds on average). Column (1) tests all the evaluation results. Columns (2)-(6) focus on the high-stake situation where the investor evaluates relatively attractive startup profiles, whose received "objective" contact interest ratings (i.e., $\hat{Q}_3$) are above 50. $\hat{Q}_3$ are predicted using OLS models based on other orthogonally randomized startup characteristics used in Online Appendix Table A11. These startup characteristics include "Serial Founder", "Ivy League Educational background", "Number of founders", "US Founder", "Number of Comparative Advantages", "Has Positive Traction", number of employees, "Company Age", "Company Age$^2$", "B2B Startup", and "Domestic Market". I choose five thresholds to define high-stake situations (i.e., $\hat{Q}_3 > 30$, $\hat{Q}_3 > 40$, $\hat{Q}_3 > 50$, $\hat{Q}_3 > 60$, $\hat{Q}_3 > 70$). "Second Half of Study" is an indicator variable for startup profiles shown among the last half of profiles evaluated by an investor. "Has ESG Characteristics" is an indicator that equals one if the startup has an ESG-related mission, and zero otherwise. "Has IPO Plan" is an indicator that equals one if the startup is profit-driven and considers IPO within five years, and zero otherwise. All the regressions add investor fixed effects. Standard errors in parentheses are clustered at the investor level. *** p<0.01, ** p<0.05, * p<0.1

Table A16: Effect of Startups' ESG Characteristics on Different Types of Investors' Attention

| | Dependent Variable: Response Time (Unit: Seconds) | | | | | |
|---|---|---|---|---|---|---|
| | Full Sample | $Q_3 > 30$ | $Q_3 > 40$ | $Q_3 > 50$ | $Q_3 > 60$ | $Q_3 > 70$ |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Has ESG Characteristics | 3.57 | 7.92** | 9.91** | 8.40* | 11.59** | 10.76** |
| | (3.59) | (3.91) | (4.39) | (4.27) | (4.52) | (4.89) |
| Has ESG Characteristics × Impact Investor | 4.99 | 3.99 | 2.21 | -1.26 | -12.80 | -14.66 |
| | (7.95) | (9.65) | (9.58) | (9.62) | (10.35) | (11.19) |
| Has IPO Plan | -2.68 | 2.22 | 3.49 | 2.72 | 3.75 | 1.56 |
| | (3.63) | (4.10) | (4.48) | (5.07) | (5.82) | (6.74) |
| Has IPO Plan × Impact Investor | 10.38 | -2.58 | 5.40 | 6.46 | -5.90 | 10.70 |
| | (12.41) | (16.40) | (16.37) | (19.13) | (26.33) | (32.68) |
| Impact Investor | 62.77*** | 62.93*** | 68.39*** | 73.88*** | 84.54*** | 67.34*** |
| | (6.43) | (8.31) | (7.78) | (10.03) | (12.54) | (14.44) |
| Second Half of Study | -27.05*** | -27.05*** | -25.86*** | -27.44*** | -29.44*** | -30.24*** |
| | (2.46) | (3.22) | (3.42) | (4.11) | (4.82) | (5.77) |
| $Q_1$ | 0.01 | -0.04 | -0.03 | -0.02 | -0.09 | -0.17 |
| | (0.05) | (0.08) | (0.09) | (0.09) | (0.12) | (0.15) |
| $Q_2$ | 0.16* | 0.18 | 0.20 | 0.04 | -0.09 | 0.06 |
| | (0.09) | (0.14) | (0.14) | (0.20) | (0.25) | (0.30) |
| Investor FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 1184 | 817 | 726 | 618 | 519 | 410 |
| R-squared | 0.35 | 0.37 | 0.38 | 0.40 | 0.40 | 0.41 |

*Notes.* This table examines the effect of the startup's ESG characteristics on different types of investors' attention paid on evaluating each profile. The dependent variable is investors' response time, which is defined as the number of seconds before each page submission, winsorized at the 95th percentile (59.23 seconds on average). Column (1) tests all the evaluation results. Columns (2)-(6) focus on the high-stake situation where the investor indicates higher likelihood of contacting the startup. I choose five thresholds to define high stake situations (i.e., $Q_3 > 30$, $Q_3 > 40$, $Q_3 > 50$, $Q_3 > 60$, $Q_3 > 70$). Columns (2)-(6) stand for the situation where investors' likelihood of contacting the startup team is more than 30%, 40%, 50%, 60%, and 70%, respectively. "Second Half of Study" is an indicator variable for startup profiles shown among the last half resumes viewed by an investor. "Has ESG Characteristics" is an indicator that equals one if the startup has an ESG-related mission, and zero otherwise. "Has IPO Plan" is an indicator that equals one if the startup is profit-driven and considers IPO within five years, and zero otherwise. "Impact Investor" is an indicator that equals one if the investor is classified as an impact investor. "Has ESG Characteristics × Impact Investor" and "Has IPO Plan × Impact Investor" are interaction terms. All the regressions add investor fixed effects. Standard errors in parentheses are clustered at the investor level. *** p<0.01, ** p<0.05, * p<0.1

Table A17: Effect of Startups' Team and Project Characteristics on Investors' Attention

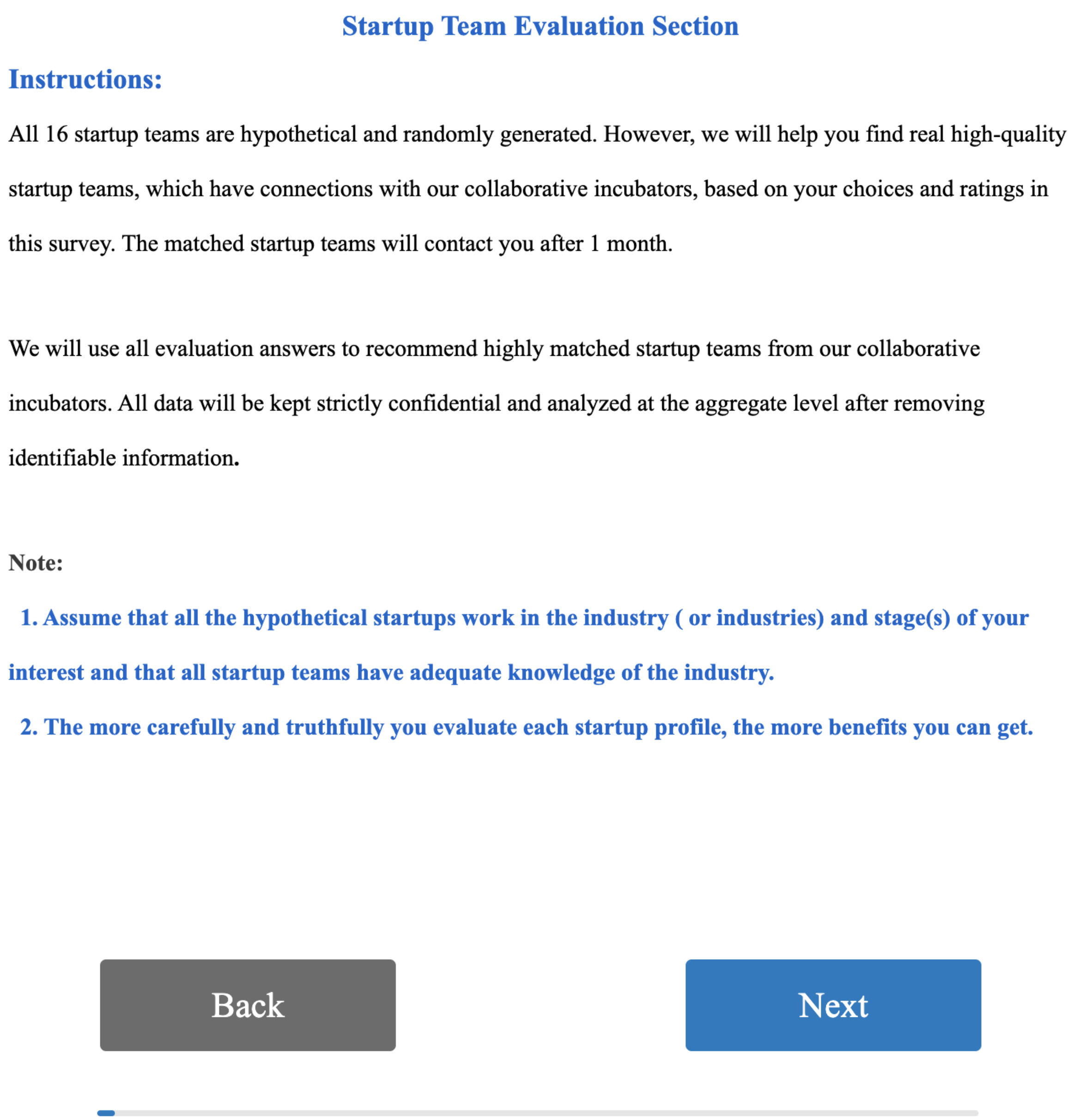
| | Dependent Variable: Response Time (Unit: Seconds) | | | | | |
|---|---|---|---|---|---|---|
| | Full Sample | $Q_3 > 30$ | $Q_3 > 40$ | $Q_3 > 50$ | $Q_3 > 60$ | $Q_3 > 70$ |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Serial Founder | 1.42 | 1.65 | 0.34 | -0.50 | -4.02 | -1.65 |
| | (2.49) | (3.43) | (3.39) | (3.75) | (4.29) | (5.20) |
| Ivy League Educational background | 0.42 | -0.01 | 0.01 | -1.66 | -1.14 | -2.16 |
| | (2.88) | (3.63) | (3.91) | (4.42) | (5.06) | (6.15) |
| Number of Founders | 5.19** | 4.49 | 5.76* | 6.71* | 7.63 | 9.20 |
| | (2.40) | (3.03) | (3.33) | (4.01) | (4.69) | (5.58) |
| US Founder | -2.61 | -0.13 | -1.57 | 0.71 | 0.25 | 4.86 |
| | (2.70) | (3.49) | (3.36) | (4.01) | (4.61) | (4.74) |
| Number of Comparative Advantages | 3.36** | 4.16** | 3.46** | 4.52** | 5.56** | 7.08** |
| | (1.24) | (1.64) | (1.71) | (2.10) | (2.52) | (3.16) |
| Has Positive Traction | 2.17 | 2.35 | 0.34 | -1.09 | -0.76 | 2.28 |
| | (2.61) | (3.21) | (3.39) | (3.72) | (4.03) | (4.64) |
| Number of Employees [0-10] | 4.01 | 5.04 | 3.44 | 2.47 | 5.88 | 2.71 |
| | (3.37) | (4.21) | (4.53) | (4.76) | (5.77) | (6.81) |
| Number of Employees [10-20] | 2.16 | 1.09 | -0.22 | -0.15 | 2.75 | -3.54 |
| | (3.84) | (5.01) | (5.07) | (5.83) | (7.32) | (8.69) |
| Number of Employees [20-50] | -1.55 | -3.16 | -2.49 | -1.94 | -0.19 | -9.08 |
| | (3.33) | (4.11) | (4.47) | (5.31) | (5.87) | (6.52) |
| Company Age | 3.48 | 3.77 | -3.36 | 5.30 | 4.82 | 7.50 |
| | (6.53) | (8.57) | (9.05) | (10.51) | (12.49) | (15.78) |
| Company Age$^2$ | -0.53 | -0.64 | 0.98 | -0.84 | -0.94 | -1.58 |
| | (1.31) | (1.70) | (1.84) | (2.12) | (2.49) | (3.10) |
| B2B Startup | -0.81 | -5.00 | -3.08 | -4.45 | -5.49 | -8.98* |
| | (2.58) | (3.15) | (3.25) | (3.48) | (4.05) | (5.10) |
| Domestic Market | 3.65 | 3.62 | 4.03 | 2.63 | 6.29 | 4.80 |
| | (2.34) | (2.99) | (3.22) | (3.66) | (4.16) | (5.33) |
| $Q_1$ | -0.06 | -0.17 | -0.12 | -0.09 | -0.19 | -0.25 |
| | (0.07) | (0.11) | (0.11) | (0.12) | (0.15) | (0.17) |
| $Q_2$ | 0.14 | 0.23 | 0.26 | 0.09 | -0.02 | 0.05 |
| | (0.10) | (0.16) | (0.16) | (0.20) | (0.24) | (0.30) |
| Investor FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 1184 | 817 | 726 | 618 | 519 | 410 |
| R-squared | 0.28 | 0.31 | 0.32 | 0.33 | 0.34 | 0.36 |

*Notes.* This table tests whether other startup team and project characteristics also affect investors' evaluation time. The dependent variable is investors' response time, which is defined as the number of seconds before each page submission, winsorized at the 95th percentile (59.23 seconds on average). Column (1) tests all the evaluation results. Columns (2)-(6) focus on the high-stake situation where the investor indicates a higher likelihood of contacting the startup. I choose five thresholds to define high-stake situations (i.e., $Q_3 > 30$, $Q_3 > 40$, $Q_3 > 50$, $Q_3 > 60$, $Q_3 > 70$). Columns (2)-(6) stand for the situation where investors' likelihood of contacting the startup team is more than 30%, 40%, 50%, 60%, and 70%, respectively. "Second Half of Study" is an indicator variable for startup profiles shown among the last half of profiles evaluated by an investor. "Serial Founder", "Ivy League Educational background", "US Founder", "Has Positive Traction", "B2B Startup" and "Domestic Market" are all indicative variables that equal to one if the founder is a serial entrepreneur, graduated from an Ivy League College, lives in the U.S., the project has positive traction, is a Business-to-Business startup, and focuses on the domestic market. These variables are equal to 0 if the startup does not match these characteristics. "Number of founders" is either 1 or 2; "Number of Comparative Advantages" and "Company Age" can be {1,2,3,4}; Company $\text{Age}^2$ is the square of the company's age. All the regressions add investor fixed effects. Standard errors in parentheses are clustered at the investor level. *** p<0.01, ** p<0.05, * p<0.1

Table A18: Correlation Between Extra Allocated Time on ESG and Investors' Donation Behaviors

| Dependent Variable | Donate or Not | Donate or Not | Donate All or Not | Donate All or Not | Donation Amount | Donation Amount |
|---|---|---|---|---|---|---|
| | Probit | Probit | Probit | Probit | OLS | OLS |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Extra Allocated Time on ESG Startups ($\beta$) | -0.002* | -0.002 | -0.004* | -0.004** | -0.003*** | -0.003*** |
| | (0.001) | (0.001) | (0.002) | (0.002) | (0.000) | (0.001) |
| Control | No | Yes | No | Yes | No | Yes |
| Observations | 68 | 68 | 68 | 68 | 68 | 68 |
| R-squared | 0.05 | 0.09 | 0.07 | 0.07 | 0.05 | 0.11 |

*Notes.* This table reports regression results for correlations between investors' extra allocated time on attractive ESG startups and their anonymous donation behaviors in the donation game. In Columns (1) and (2), the dependent variable "Donate or Not" is an indicator that equals one if the investor donates any positive amount of money to startups and equals zero otherwise. In Columns (3) and (4), the dependent variable "Donate All or Not" is an indicator that equals one if the investor donated all \$15 to the startup and equals zero otherwise. In Columns (5) and (6), the dependent variable is the amount of money donated by the investor and the unit is dollars. "Extra Allocated Time on ESG Startups ($\beta$)" is calculated based on investors' response time of attractive startup profiles (i.e., startups with $Q_3 > 30$). It is the coefficient $\beta_i$ of the following regression, which uses each individual investor $i$'s response time: Response Time$_{ij}$ = $\alpha_i + \beta_i$Has ESG Characteristics$_{ij} + \gamma_i$Has IPO Plan$_{ij} + \delta_i X_{ij} + \epsilon_{ij}$ where $X_{ij}$ includes "Second Half of the Study", "$Q_1$", and "$Q_2$". The same regression has been used in Table 8. Control variables include the investor's preferred industries and stages. Probit regressions are used in Columns (1) - (4), and OLS regressions are used in Columns (5) and (6). R-squared reports Pseudo R2 for Probit regressions and R-squared for OLS regressions. Since two investors did not provide all the availability evaluations (i.e., $Q_2$), the sample size is only 68. Standard errors in parentheses are robust standard errors. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$


**Startup Team Evaluation Section**

**Instructions:**

All 16 startup teams are hypothetical and randomly generated. However, we will help you find real high-quality startup teams, which have connections with our collaborative incubators, based on your choices and ratings in this survey. The matched startup teams will contact you after 1 month.

We will use all evaluation answers to recommend highly matched startup teams from our collaborative incubators. All data will be kept strictly confidential and analyzed at the aggregate level after removing identifiable information.

**Note:**

**1. Assume that all the hypothetical startups work in the industry ( or industries) and stage(s) of your interest and that all startup teams have adequate knowledge of the industry.**

**2. The more carefully and truthfully you evaluate each startup profile, the more benefits you can get.**

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Figure A1: Instruction Page (Version 2)

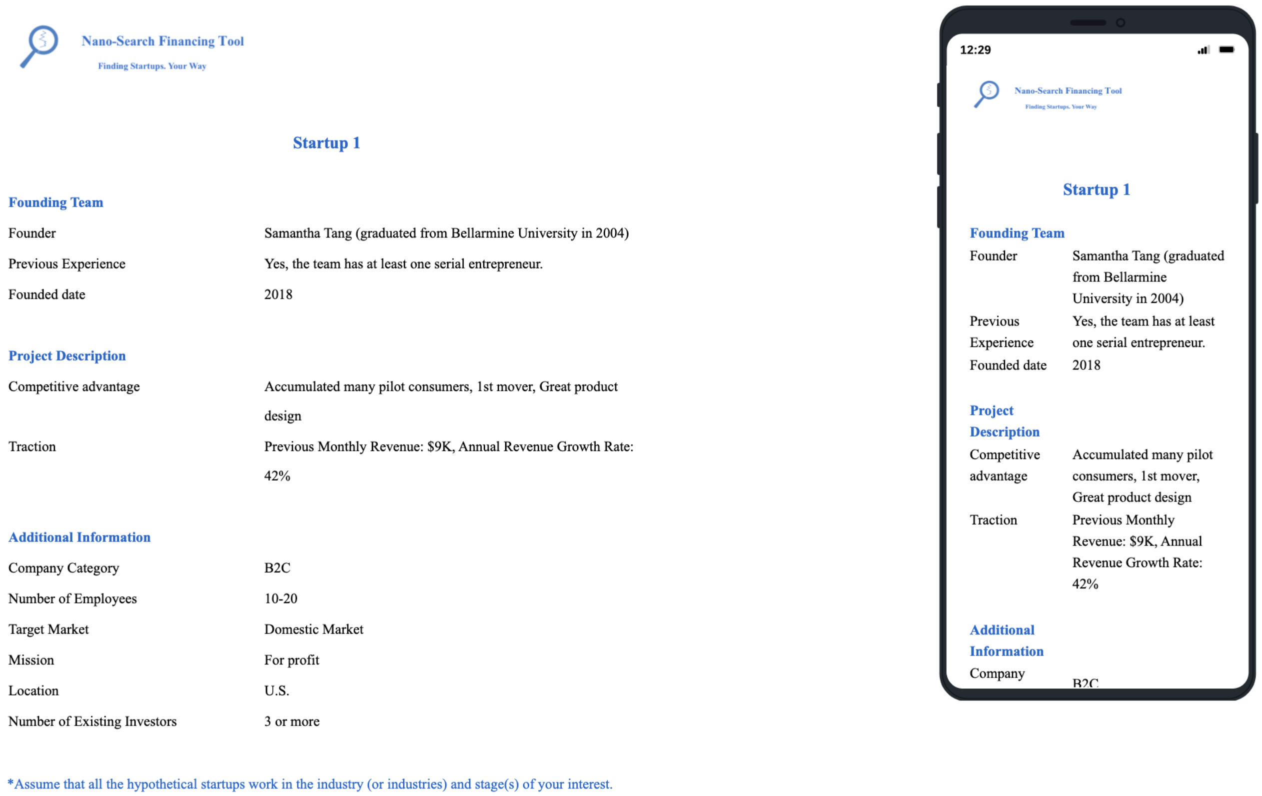



Figure A2: Randomly Generated Startup Profile

1. Imagine that Jeffrey Chen and David Zheng's team is guaranteed to accept your investment offer. Compared with firms you have previously invested in, which percentile do you feel this startup belongs to considering its quality?

| Extremely Low Quality | | | | | | | | | | Extremely High Quality |
|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 10 | 20 | 30 | 40 | 50 | 60 | 70 | 80 | 90 | 100 |

Probability of Generating Higher Return (**Drag the bar**)

2. Considering the potential network and negotiation power of Jeffrey Chen and David Zheng's startup team, what's the probability that this startup team will accept your investment offer rather than that of another investor (Angel, VC, Loans, etc)?

| Guaranteed Rejection | | | | | | | | | | Guaranteed Acceptance |
|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 10 | 20 | 30 | 40 | 50 | 60 | 70 | 80 | 90 | 100 |

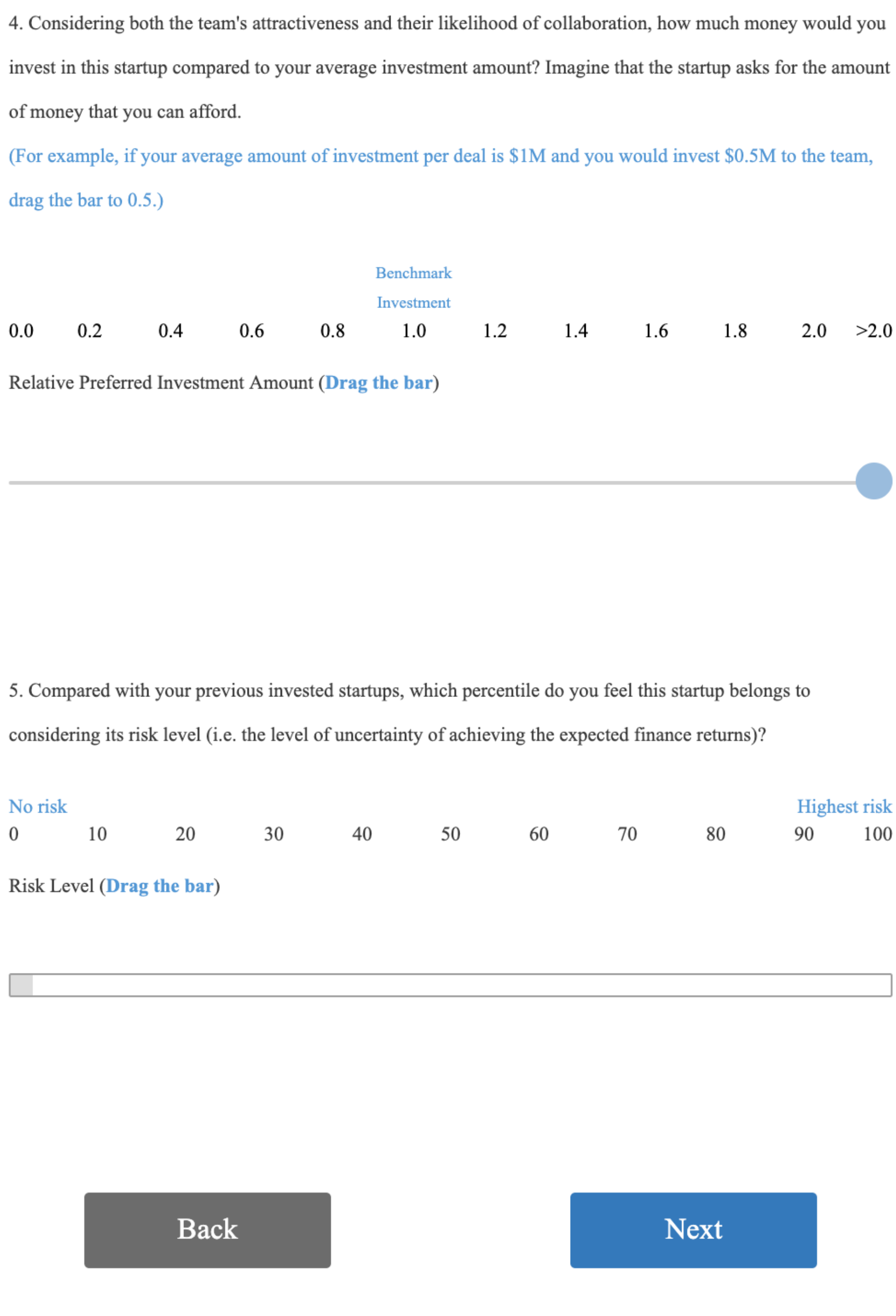
Probability of Accepting Your Offer (**Drag the bar**)

3. If you consider both the team's attractiveness and their likelihood of collaboration, how likely would you be to ask for their contact information or pitch deck?

| Will Not Ask | | | | | | | | | | Will Ask |
|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 10 | 20 | 30 | 40 | 50 | 60 | 70 | 80 | 90 | 100 |

Probability of Asking for More Information (**Drag the bar**)

Figure A3: Evaluation Questions (Part 1)



4. Considering both the team's attractiveness and their likelihood of collaboration, how much money would you invest in this startup compared to your average investment amount? Imagine that the startup asks for the amount of money that you can afford.

(For example, if your average amount of investment per deal is $1M and you would invest $0.5M to the team, drag the bar to 0.5.)

Benchmark Investment

0.0 0.2 0.4 0.6 0.8 1.0 1.2 1.4 1.6 1.8 2.0 >2.0

Relative Preferred Investment Amount (**Drag the bar**)

5. Compared with your previous invested startups, which percentile do you feel this startup belongs to considering its risk level (i.e. the level of uncertainty of achieving the expected finance returns)?

No risk / Highest risk

0 10 20 30 40 50 60 70 80 90 100

Risk Level (**Drag the bar**)

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Figure A4: Evaluation Questions (Part 2)

Dear [Investor Name],

Our research team learned about your startup investment experience from Pitchbook and would like to invite you to participate in a research project conducted by [redacted] Department. Given your expertise in the startup investment, your insight would be indispensable to our research, which we hope would shed light on the entrepreneurial financing process in the U.S. and help the recovery of entrepreneurial activities from recession.

The research project is supervised by [redacted] who is collaborating with Hash Outliers and the En Lab. The purpose of the project is to understand the current entrepreneurial financing process (for example, investors' preferences for future collaborative startups) and remove the frictions typically found in the fund-raising process using the matching algorithms we have developed. We have developed a matching tool (the "Nano-Search Financing Tool") that can match investors with the best fit startup teams.

Using the tool takes about 20 minutes and involves evaluating 16 hypothetical startup profiles in your invested industry. After evaluating these profiles, the tool uses a newly developed machine-learning algorithm to identify startups who could be a good fit for your investment portfolios from our collaborative incubators. The matched startup teams will try to contact you after 1 month.

**Besides the potential investment and collaboration opportunities, we will offer a lucky draw opportunity to thank you for your support of this research project.** At the end of July 2020, we will randomly pick 2 survey participants and inform them of the lucky draw results. These 2 participants will be paid in July 2021 according to the startup quality evaluation results they made in the financing tool (that is, the $500 and the extra return based on their quality evaluation results). Details are described on the instruction page and consent form in the matching tool.

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

Our research team will also use a completely anonymized version of your data to research broader trends in what investors value when investing in startups. We will be glad to share these insights with you when the research is complete.

If you have any questions or would like more detailed information about how the tool will enhance your portfolio construction process, please contact the tool developer and project investigator, [redacted]

Thank you very much and have a nice day!

Sincerely,

Figure A5: Recruitment Email (Version 1)

*Notes.* The recruitment email (Version 1) provides both matching incentive and monetary incentive to randomly selected 11183 U.S. venture capitalists.

Dear [Investor Name],

Our research team learned about your startup investment experience from Pitchbook and would like to invite you to participate in a research project conducted by the [redacted] Department. Given your expertise in the startup investment, your insight would be indispensable to our research, which we hope would shed light on the entrepreneurial financing process in the U.S. and help the recovery of entrepreneurial activities from recession.

The research project is supervised by [redacted] who is collaborating with Hash Outliers and the En Lab. The purpose of the project is to understand the current entrepreneurial financing process (for example, investors' preferences for future collaborative startups) and remove the frictions typically found in the fund-raising process using the matching algorithms we have developed. We have developed a matching tool (the "Nano-Search Financing Tool") that can match investors with the best fit startup teams.

Using the tool takes about 20 minutes and involves evaluating 16 hypothetical startup profiles in your invested industry. After evaluating these profiles, the tool uses a newly developed machine-learning algorithm to identify startups who could be a good fit for your investment portfolios from our collaborative incubators. The matched startup teams will try to contact you after 1 month.

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

Our research team will also use a completely anonymized version of your data to research broader trends in what investors value when investing in startups. We will be glad to share these insights with you when the research is complete.

If you have any questions or would like more detailed information about how the tool will enhance your portfolio construction process, please contact the tool developer and project investigator, [redacted]

Thank you very much and have a nice day!

Sincerely,

Figure A6: Recruitment Email (Version 2)

*Notes.* The recruitment email (Version 2) provides only matching incentive to randomly selected 4000 U.S. venture capitalists.


Figure A7: Recruitment Poster (Version 1)

*Notes.* The recruitment poster (Version 1) provides both matching incentive and monetary incentive to randomly selected 11183 U.S. venture capitalists.


Figure A8: Recruitment Poster (Version 2)

*Notes.* The recruitment poster (Version 2) provides only matching incentive to randomly selected 4000 U.S. venture capitalists.

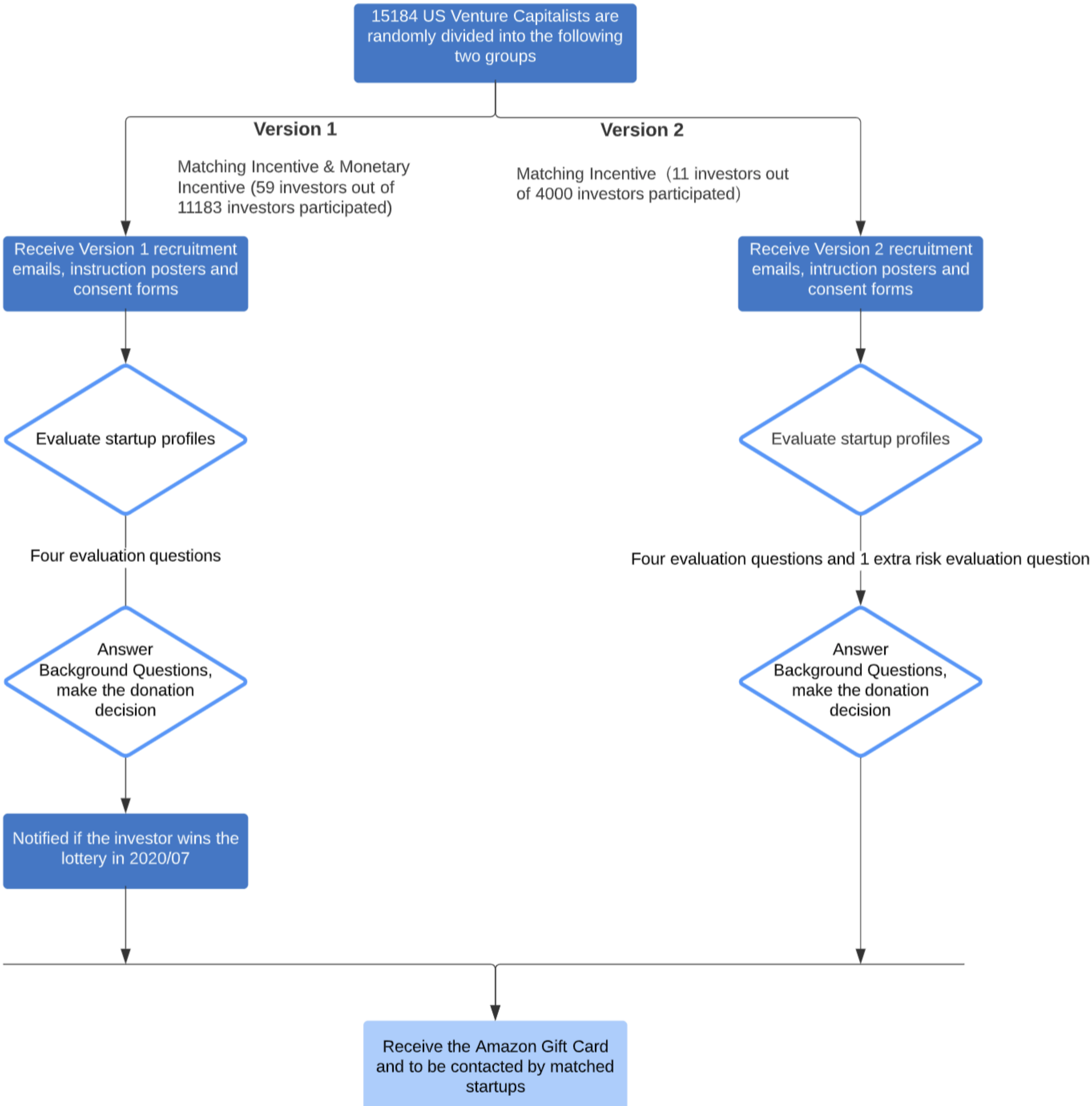


Figure A9: Incentive Structure of the IRR Experiment

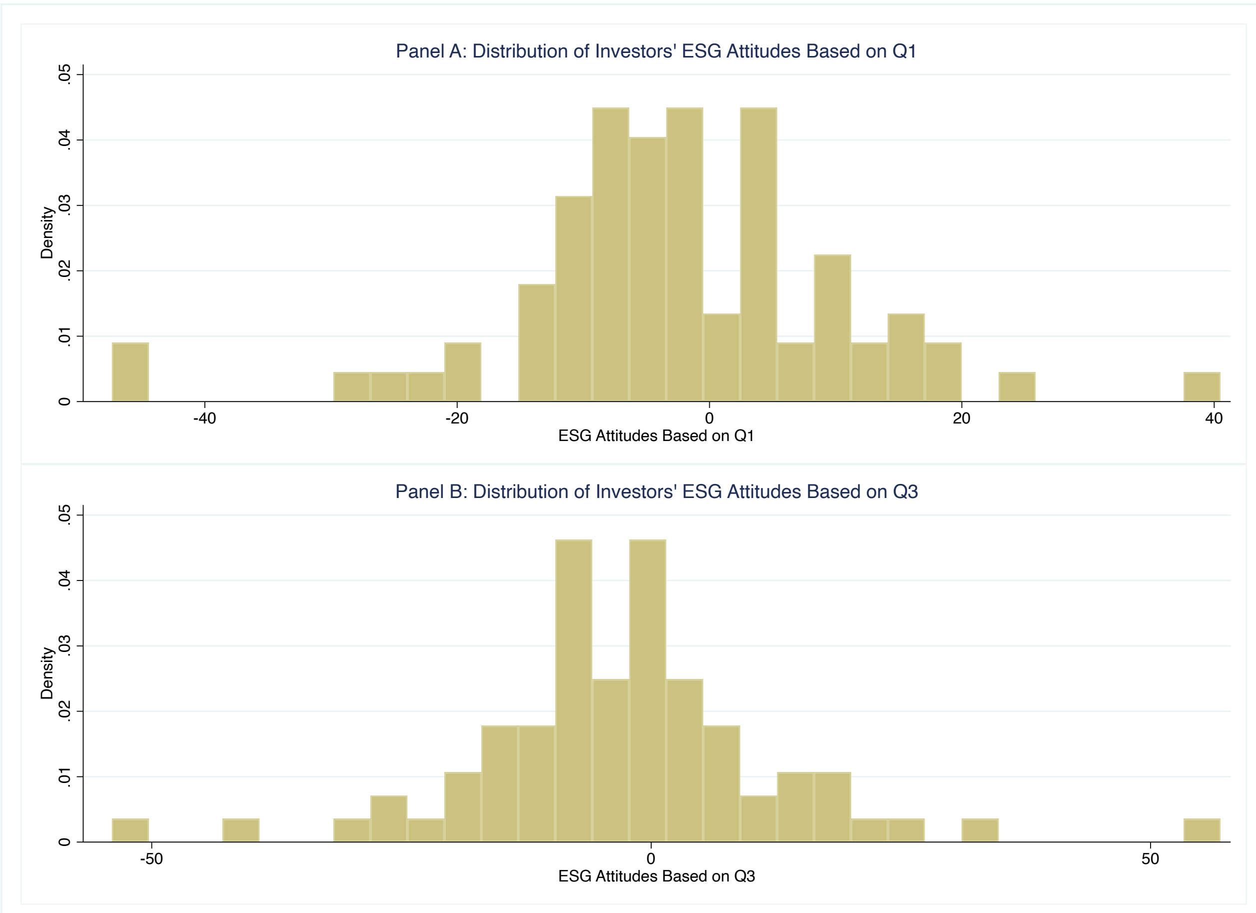


Figure A10: Distribution of Recruited Investors' ESG Attitudes

*Notes*: This figure plots the distribution of recruited investors' ESG attitudes. The ESG attitude of each investor is the coefficient $\beta_i$ of the following regression: $Y_i = \beta_i \text{Has ESG Characteristics} + \gamma_i \text{Has IPO Plan} + \epsilon_i$. In Panel A, $Y_i$ is $Q_{1i}$ and investors' ESG attitudes are calculated based on their profitability evaluations (i.e., $Q_1$). In Panel B, $Y_i$ is $Q_{3i}$ and investors' ESG attitudes are calculated based on their contact interest ratings (i.e., $Q_3$).

# B Outcome Test

***(Extrapolations)*** If impact ventures did not have impressive performances before COVID-19 and ESG-related assets are more resilient during the economic downturn (Albuquerque, Koskinen and Santioni, 2021), then simple extrapolation from recent information may cause investors to underestimate impact ventures' performances during the COVID-19 recession. To test this channel, I investigate impact ventures' historical performances before 2021.

Figure B1 compares the likelihood of raising new funding for impact ventures and conventional ventures by using Pitchbook data that cover all the deals starting from 01/01/2017-07/31/2021. The y-axis describes that conditional on successfully raising funding in the previous *one* year, how being an impact venture is associated with the likelihood of raising new funding in the next *one* year. The regression used in the figure is similar to that used in Column (2) of Table 11. The only difference is that this regression focuses on startups that successfully raised funding in the previous one year rather than three years. Then I repeat this regression by rolling the window from 2017 to 2020. Panel A shows that although global impact ventures' relative likelihood of raising new funding steadily increased between 2018 and 2021, the outperformance of ESG-related startups mainly happened during the COVID-19 pandemic. Before 2020, impact ventures were not associated with significantly better financing outcomes than conventional ventures. Assuming the existence of impact investors with preferences towards impact ventures, conventionally profit-driven startups need to generate more profits in order to perform equally well as impact ventures in terms of raising external funding. However, impact ventures might be more resilient during a time of economic hardship. Given that the experiment was implemented just after COVID-19 broke out, the extrapolation from historical information before COVID-19 may generate inaccurate expectations of impact ventures' performance. Panel C shows that similar patterns also apply to global early-stage startups. Panel B focuses on US startups, showing that the outperformance of ESG-related startups started after 2018. Similar patterns also exist in Panel D when I focus on US early-stage startups.

As I do not observe startups' fundraising information before 01/01/2017, it is hard to come to conclusions about impact ventures' relative performance before 2017. To mitigate this issue, I investigate the historical trend of impact ventures' IPOs in Figure B2 by using the SDC Platinum Database on venture-backed IPOs. Startups are labeled as impact ventures if 1) their business descriptions and product keywords contain the ESG-related keywords in Table B1, and 2) they are manually verified as correctly labeled ESG-related companies. Based on Figure B2, impact ventures' IPO performance suddenly increased during the 2008 financial crisis period, accounting for 23.1% of total IPO cases in that year. However, after 2008, their IPO performance gradually declined and only slightly rebounded after 2017. These plots suggest that investors may undervalue ESG-related startups during the pandemic due to extrapolations. However, these results do not rule out the coexistence of other explanations for investors' inaccurate beliefs.

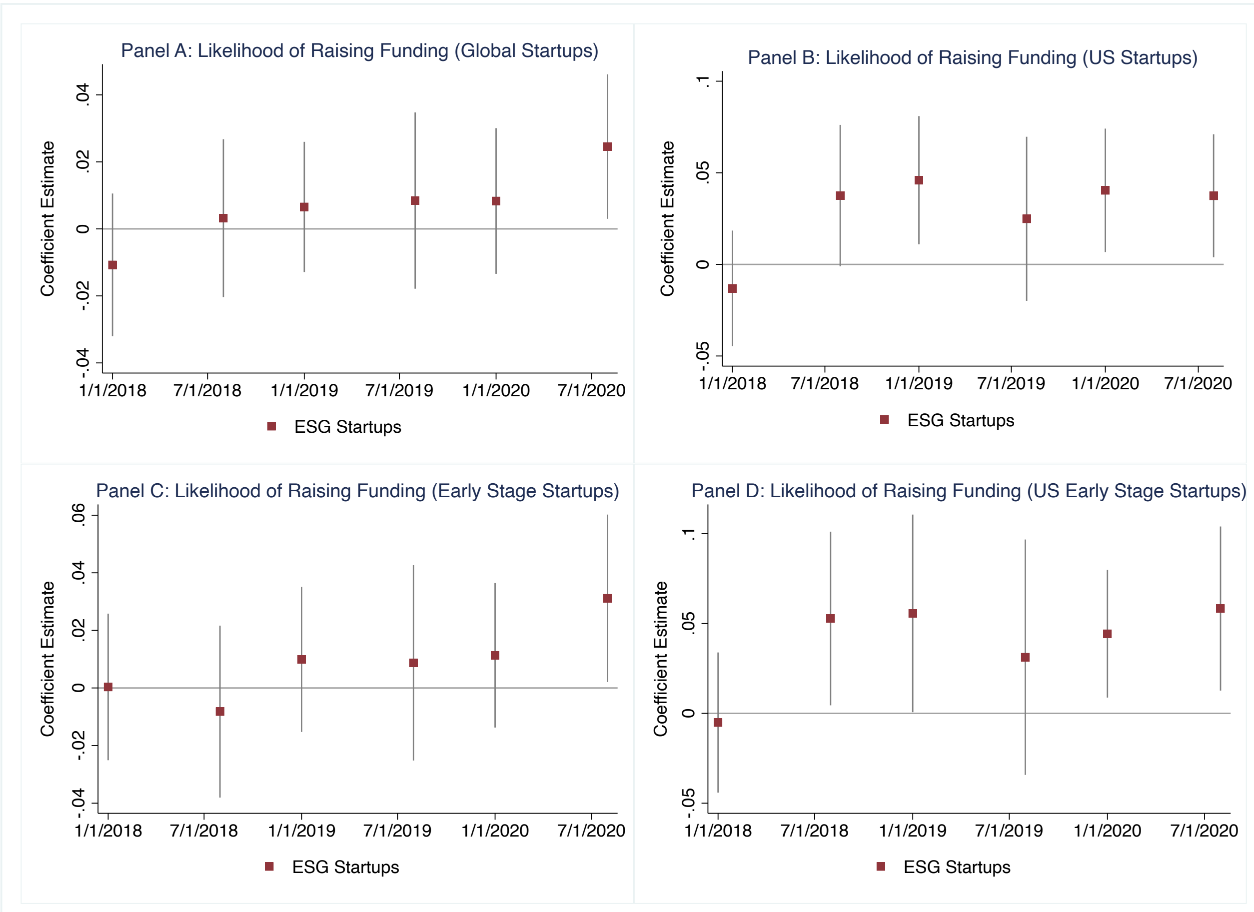


Figure B1: Impact Ventures' Relative Likelihood of Raising New Funding

*Notes*: This figure compares the likelihood of raising new funding for impact ventures and conventional ventures using Pitchbook data that covers all deals starting from 01/01/2017-07/31/2021. The y-axis describes that, conditional on successfully raising funding in the previous one year, how being an impact venture is associated with the likelihood of raising new funding in the next one year compared to being a conventional venture after controlling for number of previous deals, founding years, and log raised amount of the latest deal. The 95% confidence interval of each coefficient is also reported. Panel A tests global startups recorded by Pitchbook. Panel B examines the situation of US startups. Panel C focuses on early-stage startups. Panel D focuses on early-stage US startups.

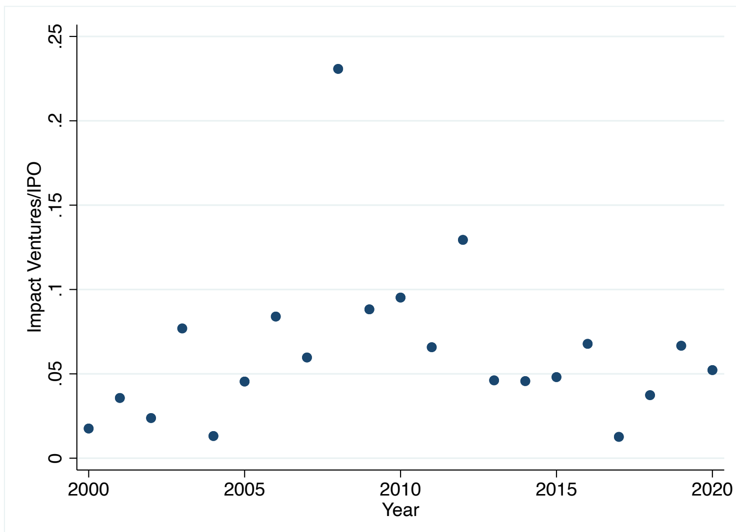


Figure B2: Percentage of Impact Ventures in Total IPOs between 1970 and 2020

*Notes*: This figure depicts how the percentage of impact ventures in total ventures with a successful IPO changes from 2000 to 2020 by using the SDC Platinum Database on venture-backed IPOs. The y-axis represents the ratio of the number of impact ventures with successful IPOs and total number of companies with successful IPOs in each specific year.

Table B1: Keywords Used for Identifying Impact Ventures

| | | | |
|---|---|---|---|
| affordable homes | agricultural sensors | air filtration | air pollution |
| alkaline | any else in the tribe | argi-tech | base of the pyramid |
| bio remediation | bio-remediation | bioenergy | biomass |
| charity | clean | clean air | clean energy |
| clean tech | clean water | clean-tech | climate |
| containment system | crop enhancement | crop yield optimization | disabilities |
| disadvantaged | donate | donation | driving hazards |
| e-waste | eco-friendly | elderly care | electric vehicle charging |
| electric vehicles | employee benefits | energy conservation | energy monitoring |
| environmental compliance | environmental impact | environmentally clean | environmentally conscious |
| environmentally sustainable | esg | ethically conscious | fight hunger |
| filtration | food waste | fossil fuel-free | fuel cells |
| gas sensor | gasification | green energy | greenhouse |
| human right | hydrogen | impact investing | impact investment |
| indigenous | invest ethical | leak detection | leather substitute |
| less waste | low carbon | low-carbon | low-income |
| lower-carbon | minerals | minority-owned | mission driven |
| mission investing | mission-driven | natural ingredients | nonprofit |
| nutritious food | ocean conditions | oil spill | organic |
| pollution control | poverty | pre-owned | purpose-driven |
| recycl | recycling technology | regulatory compliance tech | renewable |
| resale | social challenge | social finance | social good |
| social impact | socially conscious | socially responsible | soil cleanup |
| soil remediation | solar | surplus products | sustainable |
| sustainable agriculture | sustainable development | sustainable economic development | sustainable farming |
| sustainable forestry | sustainable investment | sustainable water | tidal power |
| tidal turbine | underrepresented | underserved | used items |
| waste recycling | waste services | wastewater | wastewater treatment |
| water analysis | water efficiency | water footprint | water management |
| water tracking | water waste | wind farms | women business |
| women owned | | | |

*Notes.* This table provides the list of keywords used to identify the impact ventures in the Pitchbook Database. The following keywords are removed from the list in Barber et al. (2020) as they never appear in the startups' descriptions: "bottom of the pyramid", "community invest", "double bottom line", "dual bottom-line", "environmental objective", "environmentally motivated", "ethical invest", "ethical objectives", "ethically motivated", "ethically-conscious", "impoverished", "investing ethical", "minority community", "missing middle", "mission driven", "mission related", "mission-related", "S.R.I.", "social objectives", "social responsible", "socially motivated", "socially-motivated", "SRI", "sustainable property", "tribe", "triple bottom line", and "triple bottom-line". I also add several new keywords to the list as impact ventures cover broader business descriptions compared to impact funds.