NBER WORKING PAPER SERIES

ESG AVERSION: EXPERIMENTAL EVIDENCE ON PERCEPTIONS AND PREFERENCES

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Working Paper 34048
http://www.nber.org/papers/w34048

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
July 2025, Revised November 2025

We thank Corinne Low, Colin Sullivan, and Judd Kessler for generously sharing the code for building resume-rating infrastructure. We thank Anders Anderson, Mark Dean, Emanuele Colonnelli, Michael Ewens, Stefano Giglio, Hanna Hottenrott, Harrison Hong, Torsten Jochem, Steven Kaplan, John List, Alexander Montag, Marcus Opp, Abhijeet Singh, Jan Starsman, Per Stromberg, Jack Willis, Jin Yu, Yifei Zhan, and participants at various conferences and seminars for helpful comments. Yuya Wang, Ziyue Zhu, and Xuzhi Yuan provided excellent research assistance. Funding for this project was provided by VINNOVA and Columbia University. This project is registered in the AEA RCT Registry (AEARCTR-0007973 for the startup experiment and AEARCTR-0004982 for the VC investor experiment). The detailed pre-registration plans are not publicly available but can be provided upon request. The experiments received approval from the Institutional Review Boards (IRBs) of Columbia University and the Stockholm School of Economics (SSE). All errors are our own. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

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NBER Working Paper No. 34048
July 2025, Revised November 2025
JEL No. C91, C93, G24, L26, M13, Q56

ABSTRACT

We develop an experimental framework to identify the belief-based and taste-based drivers of demand for Environmental, Social, and Governance (ESG) partnerships. Our study implements two symmetric experiments with real startup founders and venture capital (VC) investors, who evaluate hypothetical profiles under the understanding that their responses will inform an algorithm generating personalized real-world matches. We find a significant ESG penalty: profiles randomly labeled with ESG attributes receive lower interest from both founders and VCs. This penalty is primarily driven by negative performance beliefs—ESG-labeled profiles are perceived as less profitable and less accessible. To isolate taste-based preferences, we further implement a willingness-to-pay experiment in which participants may forgo part of a lottery reward to receive additional match recommendations of identical quality. Participants randomly offered ESG-oriented recommendations are significantly more likely to pay, revealing a latent preference for ESG once performance concerns are held constant. These findings highlight a tension between financial returns and personal values: in current market conditions, concerns about profitability obscure an underlying taste for ESG.

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1. Introduction

As Environmental, Social, and Governance (ESG) investing enters the financial mainstream, it has sparked both enthusiasm and skepticism. Proponents argue that ESG alignment fosters innovation and improves financial returns (Porter and Kramer, 2011; Friede, Busch, and Bassen, 2015), while critics see it as a costly constraint and a form of ideological signaling (Cutter and Glazer, 2024). At the heart of the debate lies a fundamental question: do markets really value ESG? And if so, is it because ESG enhances firm value, or because investors value sustainability for its own sake (i.e., the "value versus values" question)? As the ESG landscape becomes increasingly polarized and fast evolving, understanding what drives ESG demand has become urgent and still remains an open empirical question (Gillan, Koch, and Starks, 2021; Starks, 2023; Edmans, Gosling, Jenter, 2025)

We bring three new ideas to the evolving ESG debate. First, we propose an experimental approach that addresses the canonical identification challenges in this literature. Our framework allows us to causally identify the role of ESG in market participants' decisions and to disentangle financial motives from non-pecuniary motives underlying their ESG attitudes. Second, we apply this framework to a two-sided matching context—a market structure commonly observed in private markets. Since private firms can impose significant environmental impacts, we examine not only investors' ESG attitudes (the traditional focus on the capital *supply* side) but also whether businesses prefer ESG-oriented investors (the capital *demand* side). Third, we focus on a private market setting where ESG dynamics likely differ from those in public markets – the primary focus of prior research. In particular, we study the venture capital (VC) market, which is critical for innovation and growth but remains understudied due to data constraints.

Our experiment recruited 409 startup founders and 129 VC investors in the United States. Participants evaluated *hypothetical* profiles of potential collaborators on the other side of the market, with the understanding that their ratings would inform an algorithm to generate *real-world* match recommendations. We randomly assigned ESG attributes (e.g., an environmental focus) to some profiles, which allows us to identify the causal effect of an "ESG label" on matching interest. We also orthogonally varied other key profile features known to influence decisions. This design enables us to verify that participants respond credibly to well-known factors and to benchmark the magnitude of the ESG effect relative to those factors. Importantly, by embedding the experiment in an actual matchmaking process, we incentivized participants to provide sincere ratings. Startup founders knew their responses would help produce a tailored list of recommended VC investors, and VCs knew they would receive matches to promising startups from our partner incubators. If a matched startup and investor both showed interest in each other, we facilitated contact to encourage real-world collaboration.

Our experimental results point to a significant ESG penalty on both sides of the market: ESG features significantly reduce matching interest, particularly for environmental ("E") attributes. On the startup side, founders were about 5.7% less likely to express interest in an ESG-oriented investor compared to an otherwise identical profit-focused investor. On the investor side, VCs were similarly less inclined to pursue startups that emphasize ESG missions, with roughly a 5.1% lower interest in those profiles. These penalties are economically meaningful. For context, the penalty for an ESG-focused investor is comparable to the negative effect of a VC lacking prior entrepreneurial experience, and the penalty for an ESG-focused startup is about half the advantage conferred by a founder's top-tier education – both traits being among the most valued characteristics in this market (Bottazzi, Da Rin, and Hellmann, 2008; Gompers and Mukharlyamov, 2022).

What drives this apparent aversion to ESG? We consider two broad explanations. One is informational (i.e., belief-based): market participants may hold pessimistic beliefs about the profitability or reliability of ESG-focused startups or investors, akin to statistical discrimination based on a perceived signal of lower quality.[1] The other is preference-based: participants might simply reject ESG-related goals and perceive them as hoaxes (a taste-based animus). Distinguishing these explanations is important in practice. For example, if ESG is discounted due to misinformed beliefs, valuable projects with positive externalities could be starved of capital—a failure of market efficiency. Conversely, if the reluctance is driven purely by a lack of taste, the problem lies in investors' objectives rather than information, reflecting a gap between private and social returns.

[1] Firm beliefs matter. For example, in the climate finance context, Stroebel and Wurgler (2021) and Ramadorai and Zeni (2024) show how firms' beliefs about climate-related risks influence their sustainability performance.

We designed our experiment to separately measure belief-driven and taste-driven behavior toward ESG. In the profile-rating task, we directly test the belief-based mechanism by asking participants to rate each profile's perceived profitability (the financial potential of the counterparty) and perceived availability (the likelihood the counterparty would reciprocate interest). To prevent "sector mismatch" or "stage mismatch" problems, participants were told to treat all hypothetical profiles as belonging to their own industry and development stage. We find that ESG-labeled profiles are judged to be less profitable and less likely to engage in a match, with penalties similar in magnitude to the overall ESG interest gap. This suggests that performance- and availability-related concerns are a predominant force behind the ESG aversion. A complementary survey further indicates that many participants associate an ESG focus with weaker profitability or added constraints (e.g., having to meet additional environmental mandates).

To isolate the taste-driven channel, we conducted a follow-up willingness-to-pay (WTP) experiment with the same participants. We offered participants the opportunity to receive additional match recommendations in exchange for forfeiting a portion of a lottery prize, and we randomized whether these extra recommendations prioritized ESG profiles. Crucially, participants were explicitly told that the additional matches would be of identical matching quality to their original recommendations, eliminating any belief-driven, performance-related differences. We find that those in the ESG-weighted offer group were far more likely to pay for extra matches: startup founders were about 32% more likely to purchase additional ESG-oriented recommendations compared to a neutral list, and VCs were more than twice as likely. This behavior reveals latent pro-ESG preferences among both entrepreneurs and investors once profitability and availability concerns are neutralized.

Our experimental design also incorporates a rich set of validation checks to ensure internal validity and genuine responses. First, we confirmed the credibility of the responses by showing that participants reacted in expected ways to established signals, such as prior entrepreneurial experience or elite education. Second, as a robustness check, we excluded potentially unrealistic profiles (for example, a first-time fund manager claiming extensive ESG expertise or a small fund pursuing governance interventions). Third, we found no strong temporal or sequential dependencies in participants' ESG evaluations, suggesting stability of preferences over the course of the experiment. Fourth, in the startup-side experiment, where founders faced real cash-for-information trade-offs, we estimated their Willingness-to-Pay (WTP) for additional investor recommendations using a discrete choice model. The estimated WTP of about $77 closely aligns with the market price of similar matchmaking services. Fifth, we found strongly positive correlations between participants' experimentally elicited ESG preferences and their real-world decisions to engage ESG partners.

We also assess the external validity of our findings. One concern is the representativeness of our sample, given the private nature of the VC market and limited population data on both startups and investors. This issue is especially pronounced on the startup side, since most available datasets capture only *completed* deals, whereas our interest is in founders actively seeking VC funding. To address this concern, we conducted a separate recruitment targeting startups listed on the Crunchbase platform and found that the observable characteristics of the recruited sample closely resemble those of the broader Crunchbase population.[2] Although this does not conclusively prove our sample is fully representative, it suggests that our recruitment process did not introduce major selection bias. Moreover, our main results are successfully replicated in this independent sample—a strong test of external validity (List, 2020).

This paper offers several empirical and methodological contributions. First, we advance the value-versus-values debate amid growing polarization around ESG. As ESG investing becomes more widespread, critics argue that it compromises fiduciary duty by putting investors' personal sustainability values ahead of investment value (Garrett and Ivanov, 2023; Gormley, Jha, and Wang, 2024). A key challenge in this debate, as Starks (2023) emphasizes, is to disentangle pecuniary vs. non-pecuniary motivations and to carefully measure the financial and non-financial trade-offs of ESG engagement. While prior studies have documented that some investors exhibit ESG preferences (Riedl and Smeets, 2017; Brodback, Guenster, and Mezger, 2019; Bauer, Ruof, and Smeets, 2021; Houston and Shan, 2022; Heeb, Kölbel, Paetzold, and Zeisberger, 2023; Barber et al., 2021), few have causally identified both beliefs and preferences at the same time and quantified the strength of each channel. In the startup–VC context, we show that both founders and VCs have positive, non-pecuniary preferences for ESG. However, these preferences are often outweighed by stronger negative concerns about ESG's profitability and matching likelihood,

[2] The Crunchbase platform is widely used by startup founders and investors to seek potential collaboration partners and gather insights into the startup ecosystem and investment landscape.

resulting in an overall reluctance to engage in ESG partnerships. This aversion carries broader implications: when profit-focused firms shy away from ESG collaborations, investors who aim to promote sustainability through active governance may struggle to act as effective "washing machines" turning brown firms green (Gollier and Pouget, 2014; Bellon, 2020; Broccardo, Hart, and Zingales, 2022).[3] Similarly, when profit-driven mainstream investors avoid ESG startups, the broader mission to generate positive environmental and social impact loses a critical source of support.

Second, we contribute to the empirical literature on sustainable finance in private markets. Most existing research on impact-focused venture capital asks whether impact funds outperform traditional funds and documents their strategies (Kovner and Lerner, 2015; Starks, Venkat, and Zhu, 2017; Cole, Melecky, Mölders, and Reed, 2020; Barber et al., 2021; Jeffers, Lyu, and Posenau, 2024). While that literature centers on the capital supply side, we highlight that private markets are two-sided and show that ESG attributes matter on the capital demand side as well. Our findings reveal a dual ESG penalty from both investors and startups, suggesting that ESG aversion in private settings may be more pronounced than previously recognized. Viewing the issue through a matching lens also uncovers new drivers of this aversion: (1) matching concerns, where profit-driven agents doubt their likelihood to successfully partner with ESG-oriented counterparts; and (2) information gaps, where participants find it difficult to obtain reliable information about ESG-focused actors, complicating collaboration. In addition, our results provide a novel insight: the demand side can have a genuine taste for ESG. To our knowledge, this is among the first empirical validations of recent theories that relax the assumption of pure profit-maximization by allowing firms themselves to hold ESG preferences.[4]

Third, we add to the literature on the drivers of entrepreneurial finance. Prior studies have examined various factors influencing the startup–VC matching process (Hsu, 2004; Sørensen,

[3] Krueger, Sautner and Starks (2020) show that most institutional investors mitigate climate risks through engagement. If profit-driven firms reject ESG funding, these investors lose a crucial channel for exerting influence.

[4] Traditional sustainable finance models assume that firms only maximize market value (Heinkel, Kraus, and Zechner, 2001; Chowdhry, Davies, and Waters, 2019; Pastor, Stambaugh, and Taylor, 2020). More recent theories relax this assumption, allowing firms to incorporate ESG considerations and preferences into their decision-making (Geelen, Hajda, and Starmans, 2022; Gupta, Kopytov, and Starmans, 2022; Oehmke and Opp, 2022). Our findings provide empirical validation for these newer models, demonstrating that founders derive non-pecuniary utility from partnering with ESG-oriented investors.

2007; Ebrahimian and Zhang, 2020), but the role of ESG has remained largely unexamined. We provide the first experimental evidence that ESG attributes affect both VCs' deal selection and startups' fundraising behavior. Notably, we find that the weight placed on ESG is on par with that placed on factors traditionally viewed as paramount, such as a founder's experience or education. Furthermore, while earlier research shows that non-pecuniary motives—for example, founders' desire for control—can sway entrepreneurial decisions (Shane and Venkataraman, 2000), our results demonstrate that ESG preferences, as another form of non-pecuniary motivation, can similarly shape startups' fundraising decisions and matching outcomes.

Methodologically, we demonstrate that carefully structured field experiments—especially when paired with incentives and realism cues—can yield novel evidence beyond what surveys or observational studies typically offer, illuminating financial behavior in a controlled yet realistic setting (List, Sinha, and Taylor, 2006; He et al., 2023). Our design builds on Kessler, Low, and Sullivan (2019), who pioneered a profile-rating experiment to study discrimination, and we extend it by incorporating a new WTP component to further disentangle belief-based versus taste-based effects. Traditional approaches to elicit such non-pecuniary preferences often rely on lab experiments (Brodback, Guenster, Pouget, and Wang, 2021; Heeb, Kölbel, Paetzold, and Zeisberger, 2023; Riedl and Smeets, 2017). By contrast, our field-based WTP experiment captures non-pecuniary preferences in a context that closely mirrors real-world decision making—assessing participants' demand for an investor or startup recommendation service within the same entrepreneurial setting.

The rest of the paper is organized as follows. Section 2 outlines a simple conceptual model of ESG demand. Section 3 describes the empirical framework for the startup-side experiment. Section 4 presents the corresponding results. Section 5 describes the investor-side experiment. Section 6 presents its results. Section 7 discusses internal and external validity checks. Section 8 concludes the paper.

2. A Model of ESG Demand

We present a simple model that formalizes how an evaluator's demand for ESG can be decomposed into belief-driven and taste-driven components. We then discuss how this model guides our empirical strategy to identify these mechanisms. Our model builds on a standard discrimination framework that allows us to disentangle beliefs versus preferences channels (Bohren, Imas, and Rosenberg, 2019).

Set Up. Consider two groups of candidates: ESG candidates (E) and profit-driven candidates (P). From a startup's perspective, candidates refer to VCs evaluated by startup founders; from a VC's perspective, candidates refer to startups evaluated by VCs. A candidate has an observable type $g \in \{E, P\}$ and an unobservable potential a to help the evaluator achieve greater profits, where $a \sim N(\mu_g, 1/\tau_a)$, with mean μ_g and precision $\tau_a > 0$. Evaluators assess candidates but also need to consider whether they can be chosen by the candidates for a collaboration to take place. Let $a = \alpha + \beta$, where α represents the candidate's value-added to the evaluator's profits, and β represents the candidate's likelihood of collaborating with the evaluator.[5] Each candidate has a hidden quality $q = a + \epsilon$, where $\epsilon \sim N(0,1/\tau_\epsilon)$ is an independent random shock with precision τ_ϵ.

Each evaluator i reports her evaluation ν, such as contact interest ratings, in the experiment. She receives payoff $-\left(\nu - (q - c_g^i)\right)^2$ from reporting evaluation ν of a candidate with quality q and type g, where c_g^i is a type-specific taste parameter. Normalize $c_P^i = 0$. $c_E^i < 0$ if the evaluator has taste-based partiality toward ESG candidates.[6] The evaluator's subjective prior belief about the candidate's potential is expressed as $\hat{\mu}_g^i = \hat{\alpha}_g^i + \hat{\beta}_g^i$. When reading the candidate profile, each evaluator observes signal s of the hidden quality of each candidate, where $s = q + \eta$ and $\eta \sim N(0, 1/\tau_\eta)$ is also an independent random shock with precision $\tau_\eta > 0$. Lower signal precision (i.e., smaller τ_η) means that the candidate profile is less informative about the candidate's overall quality, hence reflecting greater uncertainty. Each evaluator chooses the

[5] Boston Consulting Group's 2023 report, *What Startup Founders Expect from Venture Capital Funds*, based on over 120 interviews with startup founders, confirms that founders pursue VC funding in part for the value-added contributions VCs provide. Similarly, Bernstein, Giroud, and Townsend (2016) demonstrate that VC monitoring significantly increases the likelihood of successful exits for portfolio companies, which also highlights the value VCs bring.

[6] c_E^i essentially captures all non-pecuniary utility gains from collaborating with ESG candidates. These include instances where evaluators integrate ESG into their collaboration decisions due to personal preferences or social pressure, or where ESG-related collaborations generate additional positive ESG impact from working with ESG candidates, even without obtaining extra financial benefits.

evaluation that maximizes her expected payoff with respect to her posterior belief and taste parameters. Let

$$\nu_i(s,g) \equiv \operatorname{argmax}_{\nu\in R}\widehat{E}_i\left[-\left(\nu-\left(q-c_g^i\right)\right)^2 \middle| s,g\right] \qquad (1)$$

denote her optimal evaluation, conditional on observing the signal s and candidate type g. Then, $\widehat{E}_i$ denotes the expectation with respect to her model of inference. Her optimal evaluation is

$$\nu_i(s,g) = \widehat{E}_i[q|s,g] - c_g^i \qquad (2)$$

Demand for ESG. Given that each evaluator's prior belief about quality is normally distributed with mean $\hat{\mu}_g$ and precision τ_q, i.e., $q \sim N(\hat{\mu}_g, 1/\tau_q)$, the initial signal s has conditional distribution $s|q \sim N(q, 1/\tau_\eta)$. Then, the evaluator's posterior belief about quality, conditional on observing s, is also normally distributed, i.e., $q|s \sim N(\frac{\tau_q\hat{\mu}_g+\tau_\eta s}{\tau_q+\tau_\eta}, \frac{1}{\tau_q+\tau_\eta})$. Based on equation (2), the evaluator's optimal evaluation is equal to

$$\nu(s,g) = \frac{\tau_q\hat{\mu}_g+\tau_\eta s}{\tau_q+\tau_\eta} - c_g = \frac{\tau_q(\hat{\alpha}_g+\hat{\beta}_g)+\tau_\eta s}{\tau_q+\tau_\eta} - c_g \quad (3)$$

The key insight of our model is that, conditional on observing the same signal (i.e., evaluating ESG candidates and profit-driven candidates with comparable characteristics), the evaluator's differential evaluation of profit-driven candidates relative to ESG candidates, defined as $D_i(s) \equiv \nu_i(s,P) - \nu_i(s,E)$, can be written as:

$$\begin{aligned}\underbrace{D_i(s)}_{\text{Demand for ESG}} &= \left(\frac{\tau_q}{\tau_q+\tau_\eta}\right)(\hat{\mu}_P - \hat{\mu}_E) + c_E \\ &= \underbrace{\left(\frac{\tau_q}{\tau_q+\tau_\eta}\right)(\hat{\alpha}_P - \hat{\alpha}_E) + \left(\frac{\tau_q}{\tau_q+\tau_\eta}\right)(\hat{\beta}_P - \hat{\beta}_E)}_{\text{Belief-driven mechanisms}} + \underbrace{c_E}_{\text{Taste-driven mechanisms}} \qquad (4)\end{aligned}$$

Equation (4) states that an evaluator's demand for ESG, $D_i(s)$, depends on both belief-driven mechanisms and taste-driven mechanisms, and its sign is *theoretically ambiguous*:

The belief-driven mechanisms are influenced by factors including the evaluator's subjective prior beliefs regarding the relative value-added of ESG candidates $(\hat{\alpha}_P - \hat{\alpha}_E)$, the relative likelihood of collaboration (i.e., $\hat{\beta}_P - \hat{\beta}_E$), and the precision of the signal (τ_η). Therefore, the sign of the belief-driven mechanism could be positive, null, or negative. For example, $(\hat{\alpha}_P -$

$\widehat{\alpha}_E$) can be positive if ESG mandate is extremely costly for firms, negative if the Porter hypothesis dominates, or null if ESG has little impact on firms profitability.

Similarly, the sign of the taste-driven mechanism c_E is also ambiguous. On one hand, standard sustainable finance theories typically assume that firms maximize profits (Chowdhry, Davies, and Waters, 2019; Heinkel et al., 2001), implying that taste-based considerations should not affect firm decisions (i.e., $c_E = 0$). On the other hand, recent sustainability models relax this assumption by allowing all agents to value ESG outcomes and hold ESG preferences (Geelen, Hajda, and Starmans, 2022; Gupta, Kopytov, and Starmans, 2022; Oehmke and Opp, 2022). Under this framework, founders may derive positive non-pecuniary utility from partnering with ESG-oriented VCs (i.e., $c_E < 0$). Conversely, amid the recent anti-ESG backlash, some founders may even exhibit aversion toward ESG investors (i.e., $c_E > 0$).[7]

The sign of $D_i(s)$ thus depends on the relative magnitude between the two types of mechanisms, which we will *empirically estimate* using the experiments.

Identification of Beliefs. In our profile rating experiment, we ask evaluators to rate candidate profiles both in terms of the candidates' value added and collaboration likelihood. Because the profiles are statistically identical, with some profiles randomly assigned an ESG status, evaluators' differential ratings of ESG and profit-driven candidates' value added and collaboration likelihood are thus empirically measured by $\left(\frac{\tau_q}{\tau_q+\tau_\eta}\right)(\widehat{\alpha}_P - \widehat{\alpha}_E)$ and $\left(\frac{\tau_q}{\tau_q+\tau_\eta}\right)(\hat{\beta}_P - \hat{\beta}_E)$, respectively. Since both τ_q and τ_η are positive, lower profitability ratings for ESG candidates (i.e., $\left(\frac{\tau_q}{\tau_q+\tau_\eta}\right)(\widehat{\alpha}_P - \widehat{\alpha}_E) > 0$) and lower availability ratings for ESG candidates (i.e., $\left(\frac{\tau_q}{\tau_q+\tau_\eta}\right)(\hat{\beta}_P - \hat{\beta}_E) > 0$) suggest that evaluators hold prior beliefs that ESG candidates are less likely to generate profits (i.e., $(\widehat{\alpha}_P - \widehat{\alpha}_E) > 0$) or collaborate with them (i.e., $(\hat{\beta}_P - \hat{\beta}_E) > 0$) compared to otherwise similar profit-driven candidates.

In addition to examining belief mechanisms, we experimentally assess the impact of a profile's ESG status on evaluators' overall intent to engage with the candidates, as well as their intended fundraising amount if engagement occurs. These are estimates of $D_i(s)$, the demand for

[7] See, for example, "Anti-ESG Takes a Leap Across the Pond" by Politico, published on 10/31/2023.

ESG. The sign and magnitude of $D_i(s)$ capture the combined influence of belief and taste mechanisms.

The taste mechanism c_E is not directly measured in the profile evaluation experiment. We could have asked evaluators about their pure preferences or tastes regarding ESG *itself*, but we consider this approach unnatural and could be prone to bias due to Hawthorne Effect. Instead, we estimate the taste mechanism using a revealed preference approach, as detailed next.

Identification of Taste. Our willingness-to-pay experiment is designed to identify c_E. Specifically, evaluators are asked to decide whether they are willing to pay for an ESG-inclined recommendation list of the same quality as the profit-driven one. This setup aims to minimize the impact of belief-driven mechanisms in equation (4), focusing instead on the taste channel as the primary driver of ESG demand. Importantly, the willingness-to-pay experiment does not need to *completely* freeze evaluators' prior beliefs. Given our findings from the profile evaluation experiment which revealed that evaluators stay away from ESG candidates, any reversal in ESG demand in the willingness-to-pay experiment would indicate a positive taste for ESG.[8]

Before proceeding, it is important to clarify two assumptions underlying our theoretical framework. First, following the discrimination literature, we assume linearity and separability in the effects of beliefs and tastes—that is, the belief-driven and taste-driven components of evaluation are independent and additively separable. This means we rule out the possibility that an evaluator's beliefs directly influence her tastes during the short course of the experiment (or vice versa). If, in reality, negative performance perceptions about ESG candidates were to exacerbate an evaluator's distaste for ESG (a form of interaction between the channels), our WTP experiment would tend to understate the true strength of any positive taste for ESG. Second, we assume that participants' preferences are stable over the duration of the experiment. In practice, this implies that each evaluator's beliefs and fundamental tastes regarding ESG do not change in the midst of our two-stage experimental procedure. These assumptions simplify the

[8] That is, as long as participants prefer ESG partners in the willingness-to-pay game (i.e., $D_i(s) < 0$) and the profile rating experiment indicates that their prior beliefs about ESG partners are negative (i.e., $\hat{\alpha}_P - \hat{\alpha}_E > 0$ and $\hat{\beta}_P - \hat{\beta}_E > 0$, then according to equation (4), participants' non-pecuniary preferences for ESG partners should be positive (i.e., $c_E < 0$).

interpretation of our results by ensuring that the belief and taste effects can be conceptually separated.

3. Startup Experiment: Framework

3.1 Experimental Platform

The entrepreneurial financing market is a classic two-sided matching environment: both startups and venture capital (VC) investors seek attractive counterparts and strive to be selected by the other side. The search process often requires significant amount of resources in private markets where far less information is available than in public markets. For example, both VCs and startups often rely on costly databases like PitchBook or Preqin, or on personal networks, to learn about potential partners. To facilitate our experiment, we developed an online platform—the NanoSearch Financing Tool—which uses a machine-learning-based matching algorithm to help startups identify suitable VC investors, and vice versa. Participants engage with this platform through a series of randomized, non-deceptive evaluation tasks that reveal their preferences regarding ESG and other counterparty characteristics. The platform's algorithm then uses these inputs to generate a personalized list of real-world recommended counterparts for each participant.

Our experiment provides tangible value to participants. Notably, there are commercial services (e.g., SuperWarm.AI and Dealroom) offering similar data-driven matching in the entrepreneurial finance context. Using our experimental data, we later show that participants value our matching tool at levels comparable to prevailing market prices for such services.

3.2 Experimental Design

Before the experiment begins, participants are required to provide key background information about their startups, including industry, stage, number of employees, and fundraising goals. This follows the standard procedure used in other investor recommendation services. Appendix Figure 1, panel A shows a sample screenshot of the experimental instructions. Towards the end of the instruction, we provided participants with two key reminders. First, to prevent issues related to "sector mismatch" or "stage mismatch" (where participants might feel that a profile belongs to a different sector or development stage of interest), participants are instructed to assume that all hypothetical VCs they evaluate would invest in *their* startup's specific industry and stage. Second, we emphasize that honest evaluations of all questions help improve the accuracy of the matching algorithm, so that they receive better investor recommendations. This matching incentive follows Kessler et al. (2019), which is designed to encourage participants to provide truthful evaluations to all questions.[9]

Figure 1A illustrates our startup-side experiment. The main experiment consists of two main modules executed sequentially, followed by an additional donation task. We describe each in turn.

Module 1. Profile Evaluation Experiment. In the first stage of the experiment, each startup founder evaluates 20 hypothetical VC investor profiles. Half of these profiles (10 out of 20, randomly assigned) are designated as profit-driven with no explicit ESG focus, and the other half are ESG-oriented. The ESG-oriented investors are further randomly divided into four categories: Funds targeting general ESG impact (20% of profiles), Environmental Funds focusing on environmental impact (10%), Social Funds focusing on social impact (10%), and Governance Funds emphasizing governance improvements (10%).[10] Each profile includes a brief description of the investor's stated investment philosophy corresponding to its category. For example, profit-driven funds emphasize helping startups grow faster and scale rapidly; Environmental funds highlight a mission to address global environmental challenges; Social funds stress creating positive social impact and reducing inequality; and Governance funds focus on backing high-growth companies led by women. These descriptions are adapted from real VC firms' websites. To ensure broad relevance, we removed any references to specific industries or stages in the descriptions. We also crafted multiple description variants for each category to avoid

[9] We collected additional data showing that startup founders on average believed the algorithm would generate satisfactory investor matches with a probability of 74.8%, suggesting that most participants found the incentive credible.

[10] To the best of our knowledge, there is no clear consensus on the proportion of ESG investors in the real-world startup market. For example, survey evidence from Botsari and Lang (2020) suggests that about 70% of VCs incorporate ESG criteria into their investment decision process. However, Barber et al. (2021), using a keyword analysis method, found that impact VC funds represented less than 5% of their sample. Given these contrasting findings, we opted for a 50-50 split between profit-driven and ESG profiles in our study to maximize statistical power.

idiosyncratic wording biases (Appendix Table 1 lists all descriptions). In addition to the ESG label, we orthogonally randomized several other profile attributes (see Table 1A) to mirror the types of information typically available about potential investors. Appendix Figure 2 provides an example investor profile used in the experiment.

We ask startup founders to evaluate each investor profile along five dimensions, presented in the following order during the experiment: (1) the investor's potential to enhance the startup's profitability; (2) the perceived likelihood that the investor would be interested in providing funding; (3) the informativeness of the investor's profile; (4) the proportion of their initial fundraising target they would now aim to raise from this investor;[11] and (5) the likelihood of reaching out to the investor, i.e., contact interest rating. For each question, founders respond using a sliding scale from 0 (least likely or lowest interest) to 100 (most likely or highest interest). The exact wording of the evaluation questions and experimental display are provided in Appendix Figure 3.

The primary outcome of interest is the contact interest rating (item 5). Zhang (2020) shows that in profile-rating experiments, this measure is highly informative of a candidate's overall appeal and strongly correlates with real-world behavior. We interpret item 4 (intended funding amount from the investor) as capturing the intensive margin of interest. Items 1–3 capture performance-related perceptions, which we use to explore mechanisms behind founders' attitudes toward ESG. Importantly, participants understand that their ratings will inform a real matchmaking algorithm. This design incentivizes truthful responses: founders expect that higher-rated investor profiles are more likely to appear in their future matches.

After completing Module 1, each startup founder proceeds to Module 2. Approximately two months after the entire experiment, participants received their personalized recommendation list of the ten best-matched real VCs with contact information, as generated by our algorithm in Appendix A.

Module 2. Willingness-to-Pay Experiment. The second stage aims to reveal participants' taste-based preferences (i.e., non-pecuniary preferences) for ESG, isolated from belief-driven performance concerns. In this module, founders face a lottery-based choice that measures their

[11] That is, if the founder initially planned to raise \$X, what percentage of \$X they would now request. This percentage could exceed 100%

willingness to sacrifice money for an ESG-focused matchmaking outcome (i.e., whether they want to purchase such service). Each founder is told that two participants will be randomly selected to win a $500 lottery prize. The founder must choose between two options: Option 1 – if selected in the lottery, receive the full $500; or Option 2 – if selected, receive a smaller prize in exchange for access to an expanded investor recommendation list. The expanded list includes the top 200 matched investors for that founder (in contrast to the basic top-10 list they would otherwise receive). We randomly assign each founder to one of three offer treatments for Option 2: (1) Standard List (i.e., the control group): The expanded list consists of the 200 best matches based purely on the founder's ratings from Module 1 with no preference applied; (2) Female-Preferred List: The founder is told the algorithm will prioritize female investors in compiling the 200 matches; and (3) ESG-Preferred List: The founder is told the algorithm will prioritize ESG-focused investors in the matches. In both the Female-Preferred and ESG-Preferred conditions, we explicitly clarify that the algorithm only favors the specified investor attribute when the match quality is otherwise equivalent. This ensures the founder knows that accepting the offer does not compromise the overall quality of recommended matches, aside from tilting toward the given preference.

Cross-cutting the above treatment, we also randomize the price of the expanded list (i.e. the prize reduction if Option 2 is chosen). This price is drawn uniformly between $20 and $80, reflecting the typical market cost for comparable matching services. By varying the price independently of the list type, we can estimate each founder's willingness-to-pay (WTP) for the expanded list under different conditions (in particular, an ESG-preferred list). Appendix Figure 4 provides the exact wording and interface of the WTP module.

Three design features of the WTP experiment are worth noting. <u>First</u>, because we cannot actually collect payment from participants, we frame the cost as a reduction in a potential prize. This mechanism elicits how much value a participant places on additional investor information without requiring an out-of-pocket payment. <u>Second</u>, we intentionally included the female-preference treatment as a control for framing or "nudge" effects. The female- and ESG-preference offers were presented with identical wording (simply substituting "female" versus "ESG"), allowing us to attribute any differential uptake specifically to an ESG preference rather than to any generic effect of offering a socially desirable specialized list. That is, if the preference for ESG investors is purely due to the observer/Hawthorne effect (and not genuine preference), then we might expect a similar preference for female investors. Third, our design does not require participants to believe that the matching quality is *exactly* the same between recommended ESG candidates and profit-driven candidates. As outlined in the theoretical framework, what matters is that the WTP experiment reduces the relative influence of belief-driven mechanisms in evaluators' decision-making. If, under this reduced role of beliefs, evaluators' preferences *flip* relative to the profile evaluation experiment—that is, if they initially view ESG counterparties negatively in the profile evaluation experiment but then begin to prefer them in the WTP experiment—this change provides strong evidence of a positive ESG taste.

In addition to the two main modules, we included a final donation task to measure participants' prosocial motives. Founders were informed of a separate lottery (with two winners of $1,000 each) and were asked, in the event they won, how much of their $1,000 prize they would donate to two causes: (1) an NGO supporting gender equality, and (2) an NGO promoting ESG outcomes in the entrepreneurial community. They made two donation pledges (one for each cause). They were told that one of the two donation decisions would be randomly selected and implemented if they won the lottery. This randomization of which donation counts was designed to encourage truthful reporting by reducing any incentive to overstate generosity toward a particular cause (since both pledges have an equal chance of being selected). Appendix Figure 5 shows the wording and interface of this donation module.

After completing all three experimental modules, participating startup founders were awarded $47 as monetary compensation.[12] Within about two months after the experiment, we emailed participants their personalized list of the top 10 matched VC investors (with contact details), generated by our NanoSearch algorithm. This delivered on the incentive for participants and provided a tangible benefit from their involvement.

3.3 Recruitment and Summary Statistics

Main Sample. We collaborated with Qualtrics Panel (a third-party recruitment service) to recruit U.S.-based startup founders and small business owners via email. Several screening

[12] The reward amount is set by the Qualtrics survey platform. Our replication experiment (Section 3.3) removes the monetary compensation and our results remain robust.

questions ensured that participants (1) were startup founders or business owners planning to seek VC funding, (2) understood the matchmaking incentive, and (3) passed attention checks (including minimum survey time, embedded check questions, and Qualtrics' bot-detection filter).[13] In the experimental consent form, we emphasized the general purpose of our startup–investor matching tool while avoiding any mention of a research focus on ESG, in order to minimize Hawthorne effects. Our final main sample consists of 409 real startup founders recruited between March 2021 and April 2022, corresponding to an approximate 6% response rate from our outreach.

Replication Sample. One limitation of using Qualtrics was that we could not collect identifying information, preventing us from linking participants' experimental behavior to their real-world outcomes. To address this, we ran a replication experiment with a separately recruited sample. We randomly selected 3,000 startups listed in the Crunchbase database (all with a contact email available) and directly invited their founders to participate. The recruitment emails were sent either to the founders' personal addresses (if available) or to generic company addresses likely to reach the founders or fundraising teams. In total, 65 founders participated in this replication between September and October 2023, collectively evaluating 1,300 profiles.

Summary Statistics. Appendix Table 2 reports summary statistics for both the main and replication samples. Our data include rich information on each startup's industry, the founder's background (e.g., age, gender, education), and firm characteristics (e.g., size, stage). We defer a detailed discussion of how representative our sample is to Section 7, when we address external validity.

Balancing Tests. In Table 2A, we present balance tests confirming that the profile randomization was successful. We regress each experimentally assigned profile attribute on the treatment indicators, as specified in Section 4.1, equation (5). Consistent with random assignment, we find no significant differences in any profile characteristics across the treatment groups.

Additional Survey Data. To further investigate the mechanisms driving the profitability concerns associated with the ESG penalty – especially the E penalty – observed in our experiment,

[13] If participants fail to meet any of the criteria, the Qualtrics system will automatically terminate their participation and notify them that they no longer qualify for the study. Disqualified participants are not allowed to join the study again.

we conducted a post-hoc survey of 281 startup founders (recruited independently from the main experiment). These respondents were asked about their views regarding why collaborating with ESG-focused investors might hurt startups' profitability – for example, whether E-oriented VCs tend to impose costly mandates, introducing additional operational costs to startups (i.e., the mandate hypothesis), whether the expertise and network of E-focused VCs might be more related to generating a positive E impact instead of maximizing profitability (i.e., the expertise hypothesis), and whether those VCs pursue E practices primarily to achieve environmental impact (versus to maximize profit, or both). The insights from this survey will be used to supplement our interpretation of the experimental results.

4. Startup Experiment: Results

4.1 Startups' ESG Demand

Estimation. Our experimental data from the main experiment contains evaluation of 8,180 unique profiles, with each of the 409 startup founders evaluating exactly 20 profiles. Let profiles be indexed by j and each startup founder indexed by i. Our workhorse estimation equation is as follows:

$$\text{Rating}_{ij} = \alpha + \beta^{ESG} \cdot 1(ESG)_j + \beta^{E} \cdot 1(E)_j + \beta^{S} \cdot 1(S)_j + \beta^{G} \cdot 1(G)_j + \eta_i + X_j \cdot \gamma + \varepsilon_{ij} \quad (5)$$

where Rating_{ij} is the startup i's rating on a given outcome (contact interest, funding amount, quality, mutual interest, or informativeness) of profile j. $1(ESG)_j$, $1(E)_j$, $1(S)_j$, and $1(G)_j$ are indicator variables for whether profile j is assigned to the corresponding treatment group. η_i are startup founder fixed effects dummies that absorb any cross individual differences in overall rating levels. This means our estimates examine how the *same* startup founder rates profiles with randomly assigned ESG statuses differently. X_j is the array of other experimentally-randomized profile characteristics as outlined in Table 1A. ε_{ij} is the regression error term. Our coefficients of interest are β^{ESG}, β^{E}, β^{S}, and β^{G}, which give us the average difference in the rating that an ESG/E/S/G profile receives relative to the control profiles (which are the omitted category in equation 5). Under random assignment, these coefficients identify the average causal effect of an ESG/E/S/G status. We report standard errors clustered at the startup founder level.

Note that because all profile characteristics are orthogonally randomized, the inclusion of the X_j controls should have little impact on our estimates of the ESG effects β^{ESG}, β^{E}, β^{S}, and β^{G}. But the γ coefficients are informative in the sense that they allow us to gauge the magnitude of the ESG effects against the importance of other characteristics. In our analysis below, we report both versions with and without these controls.

Results. Table 3A summarizes our main β^{ESG}, β^{E}, β^{S}, and β^{G} estimates across the five main outcomes (i.e., 20 coefficients in total). Begin with our primary outcome: startup's rated interest in contacting the investor (column 1). Our findings show that investor profiles with a (randomly assigned) ESG status leads to a 1.28 percentage points (pp) reduction in contact interest. We find a particularly strong penalty for profiles with an Environment (E) status, where founders assigning on average a statistically significant 3.47 pp lower contact interest, corresponding to about 5.7 percent relative to the mean contact interest rating in the control group. We find less conclusive evidence that the Social (S) and Governance (G) aspects of an investor profile matter for rating. If anything, we find a marginally significant positive effect for S. We find similar ESG penalty patterns for the startup's intended funding amount requested, shown in column 2.

Effect Sizes. In Figure 2A, we report regression coefficients on contact interest when we include other profile characteristics as covariates (X_j in equation 5). Recall that an advantage of our experimental design is that, because all characteristics are orthogonally randomized, the coefficients represent the causal effects of these other characteristics as well. This is useful in two ways. First, it serves as a sanity check for whether some *ex ante* important characteristics of the investor – such as investment performance – indeed emerge as significant predictors of contact interest in our experiment. Second, it allows us to gauge the relative magnitude of ESG effects by comparing them with these other factors that we know are important.

Our results indicate that an Environmental investor label is among the most influential determinants of founders' contact interest ratings. Notably, the magnitude of this environmental effect is comparable to that of an investor having prior entrepreneurial experience—a trait widely recognized as one of the most important dimensions of VC human capital (Bottazzi et al., 2008; Gompers and Mukharlyamov, 2022).

Heterogeneity. Figure 3 reports heterogeneous ESG penalty effects across four dimensions: whether the startup is self-reported to have an ESG focus or not, the startup founder's political party affiliation, the startup founder's gender, and whether the startup is large in size, defined by those with more than 50 employees. We estimate heterogenous effects by fully interacting the dimension dummy with the treatment dummies in equation 5.[14] The key takeaway is that ESG penalties vary considerably across groups. In particular, the penalty is concentrated among startups that do not have an ESG focus, founders who are not Democrats, male founders, and smaller startups.

We now discuss some nuances underlying these patterns. Starting with the top group of Figure 3, we find that the ESG investor penalty is driven primarily by founders who are solely profit-focused. Put differently, profit-driven founders evaluate ESG-oriented investors more negatively than ESG-oriented founders do. On its face, this could reflect an "ideological matching" effect, whereby environmentally minded founders are drawn to like-minded investors. However, this need not be the only explanation. Consider an ESG mandate requiring sustainable packaging: for an organic food startup, such a mandate might attract eco-conscious consumers and potentially increase profits, whereas for a BBQ-focused startup, the added cost of sustainable packaging might outweigh the benefits if its customers do not value sustainability. Consistent with this reasoning, we find that pecuniary factors—such as founders' perceptions of an investor's value-added and the likelihood of securing investment—help explain the heterogeneous ESG penalty patterns (see Figure 3). We further test for the presence of "pure" ESG preferences (beyond such pecuniary considerations) in Section 4.3.

The remaining heterogeneity results—by political affiliation, gender, and firm size—align with insights from prior literature. Political ideology is known to correlate with ESG investment decisions (Hong and Kostovetsky, 2012); smaller firms tend to be more adversely influenced by

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[14] For example, our precise estimation equation for the gender heterogeneity estimation is:

$$\begin{aligned}\text{Rating}_{ij} = \alpha &+ \beta^{\text{ESG}\times\text{Female}} \cdot 1(\text{ESG})_j \times 1(\text{Female founder}) + \beta^{\text{E}\times\text{Female}} \cdot 1(\text{E})_j \times 1(\text{Female founder}) \\ &+ \beta^{\text{S}\times\text{Female}} \cdot 1(\text{S})_j \times 1(\text{Female founder}) + \beta^{\text{G}\times\text{Female}} \cdot 1(\text{G})_j \times 1(\text{Female founder}) \\ &+ \beta^{\text{ESG}} \cdot 1(\text{ESG})_j + \beta^{\text{E}} \cdot 1(\text{E})_j + \beta^{\text{S}} \cdot 1(\text{S})_j + \beta^{\text{G}} \cdot 1(\text{G})_j \\ &+ \eta_i + X_j \cdot \gamma + \varepsilon_{ij}\end{aligned}$$

In Figure 3, we plot β^{ESG} and $\beta^{\text{ESG}} + \beta^{\text{ESG}\times\text{Female}}$ (as well as the other corresponding E/S/G coefficients), which represent the ESG penalties for the non-female and female group, respectively. We repeat this estimation for each heterogeneity dimension and for each outcome variable.

sustainability policies compared to larger firms (Ivanov, Kruttli, and Watugala, 2024), and women are more inclined to support ESG initiatives (Bosone, Bogliardi, and Giudici, 2022). Our findings reinforce these patterns, demonstrating that they also hold in the VC–startup matching context.

4.2 Startups' Beliefs about ESG

A natural question is what drives the ESG penalty among startups. To investigate this, we leverage additional rating outcomes from the experiment. In particular, founders also rated each profile on whether the investor would add value to the startup's profitability ("perceived quality") and whether the investor would reciprocate interest in the startup ("perceived interest"). These two measures capture key performance expectations in the VC context and provide an initial glimpse into the mechanisms behind the ESG aversion.[15] The estimated treatment effects for these belief outcomes are reported in Table 3A (columns 3–5). We find that ESG labels incur similar penalties on these perceived performance measures, especially for E. Relative to purely profit-driven investors (who receive an average profitability rating of 63.3 points), Environmental investors are rated 3.17 points lower—representing a 5.0% decrease in perceived likelihood of improving the startup's profits (Column 3). They are also rated 3.40 points lower in availability compared to a control group mean of 59.5 points, indicating a 5.7% lower perceived likelihood of being interested in investing in the startup (Column 4). In our main sample, we find little evidence that an ESG label affects the perceived informativeness of the profile (column 5).

We further examine what might underlie these performance concerns about ESG investor. First, working with an ESG-oriented investor could impose costly operational mandates on the startup (e.g., meeting additional environmental standards), thereby hurting profits—a "mandate cost" channel. Second, founders may suspect some ESG investors are primarily chasing profits while merely paying lip service to environmental or social goals. In the extreme, such insincere

[15] In our theory section (Section 2), we show that "perceived informativeness" – how informative the investor's profile is to the founder as a function of the presence of ESG characteristics – can be a third channel. while the main experiment does not detect significant negative effects, the replication experiment finds that environmental investors' profiles are also perceived to be significantly less informative than those of profit-driven investors. This suggests that ESG penalties may also be driven by this informativeness channel.

ESG funds have been shown to underperform genuine ones in financial terms and to face greater agency problems (Lyon and Maxwell, 2011; Liang, Sun and Teo, 2021).

We shed light on these issues using a follow-up survey of 281 independently recruited startup founders, summarized in Appendix Figure 6. Panel (a) of Appendix Figure 6 presents a binned scatter plot (by ventiles) relating founders' concern that an ESG investor would impose higher costs to their expectation that an ESG investor would boost the startup's profitability. The linear regression slope is –0.643 and statistically significant at the 1% level, indicating that mandate cost concerns strongly predict a founder's perception of an ESG investor being detrimental to profitability.

Panel (b) further compares founders' beliefs and intentions across four groups defined by their view of an ESG investor's motive: purely environmental ("ESG = Pure Green"), both environmental and profit-driven ("ESG = Green & Profit"), purely profit-driven ("ESG = Profit"), or uncertain ("IDK"). An interesting pattern emerges: founders who believe ESG investors are mostly profit-driven (as opposed to truly mission-driven) assign significantly lower collaboration intent and profitability ratings and significantly higher mandate cost ratings, compared to those who believe the ESG focus is genuine. This suggests that a portion of the ESG performance penalty may indeed stem from skepticism about the investor's true intent or quality.

4.3 Startups' Taste for ESG

Estimation. We analyze choice data from the Willingness-to-Pay (WTP) experiment, where each startup founder chose whether to forgo part of a lottery prize in exchange for an expanded list of the 200 best-matched VC investors (with contact information). We estimate the following equation:

$$\begin{aligned} 1(\text{Pay for recommendation})_i &= \alpha + \beta^{\text{Female}} \cdot 1(\text{Female preferred list})_i \\ &+ \beta^{\text{ESG}} \cdot 1(\text{ESG preferred list})_i + X_i \cdot \gamma + \varepsilon_i \qquad (6) \end{aligned}$$

where $1(\text{Pay for recommendation})_i$ is a dummy variable that indicates whether investor i chooses to pay for the recommendation list. Startups are randomized to receive a standard list (the control group which is the reference category in equation (6), a list with the same matching quality but with a preference for female investors indicated by the treatment dummy $1(\text{Female preferred list})_i$, and a list with the same matching quality but with a preference for ESG investors indicated by the treatment dummy $1(\text{ESG preferred list})_i$. As discussed earlier, although our objective is to estimate the preference for ESG, we purposefully include a gender treatment group to examine whether potential nudge effects or observer effects play a role in driving the findings.[16]

X_i is an array of startup characteristics, including startup's confidence in the algorithm's ability to recommend well-matched investors, the founder's background (entrepreneurial experience and education), the startup's background (stage, employee count, and industry), and the founding team composition. Because of random assignment of offers, the inclusion or exclusion of these controls does not affect our estimates of the causal effects of offers. ε_i is the error term, and we report robust standard errors. The main coefficient of interest is β^{ESG}, which is the average causal effect of being offered an ESG-preferred recommendation list with similar matching quality. A positive β^{ESG} would indicate a non-pecuniary preference for ESG investor given the same quality, and a negative β^{ESG} would indicate a distaste.

Results. Table 4A presents the results. In columns (1)–(2), a linear probability model shows that founders offered the ESG-preferred list are 14 percentage points more likely to purchase the list than those in the control group. This corresponds to a 31.8% increase over the control group's purchase rate of about 44%. Columns (3)–(4) yield similar results using probit specifications. By contrast, offering a female-preferred list has no significant effect on purchase rates in any specification, suggesting that the revealed ESG preference is not driven by a generic framing/nudge effect or social desirability bias.

[16] One potential concern is that our findings may be driven by a "feel-good nudge effect" stemming from the phrase "To promote the social responsibility campaign in the entrepreneurial community" shown in the Treatment 2 condition. However, a nearly identical clause is also presented in the Treatment 1 condition, which prioritizes female VCs—yet founders do not exhibit a comparable preference for female investors. This pattern suggests that the results are unlikely to be driven by nudging alone. Similarly, concerns about observer effects or social desirability bias—where participants might express pro-social preferences due to perceived scrutiny—are also mitigated by the null effect in the gender treatment. If such effects were driving behavior, we would expect participants to favor both ESG and gender-diverse profiles. The absence of a preference for female VCs indicates that the observed ESG preference is not merely an artifact of social signaling.

Recall that we also randomized the price of the expanded list via the lottery prize reduction. This allows us to estimate a discrete choice model in which each founder decides between taking the full $500 prize (not purchasing) and receiving the expanded list at a cost (forfeiting part of the prize). Appendix Table 3 reports logit estimates from this design, indicating that founders' implied WTP for the ESG-preferred list is roughly $77. Notably, this is close to the market cost of similar online investor-matching services (around $50 per month).[17]

What Explains a Taste for ESG? A non-pecuniary taste for ESG could stem from several intrinsic motivations. One potential source is altruism (a social preference)—individuals may derive personal satisfaction from actions that benefit others or society at large (e.g., environmental preservation or social equity). Such altruistic inclinations can lead founders to prioritize ESG characteristics even in the absence of direct financial incentives. Appendix Table 4 provides suggestive evidence for this mechanism: startup founders who gave higher ratings to ESG-focused profiles are indeed more likely to donate to ESG-related NGOs in the end-of-experiment donation task.

Additionally, cultural values, ethical considerations, and social norms may reinforce these preferences, which shapes individuals' willingness to support ESG initiatives as an expression of their principles or identity. Understanding these motivations can be useful steps in understanding the non-pecuniary drivers of ESG demand.

5. VC Investor Experiment: Framework

5.1 Experimental Design

Figure 1B illustrates the experimental design on the VC side. This design closely mirrors that of the startup-side experiment, with two simplifications introduced to maximize statistical power given the smaller sample size of VCs who are much harder to recruit. First, in the Profile Evaluation Experiment, we randomize a startup's ESG orientation into only two categories: startups aiming for ESG impact and startups that are solely profit-driven. That is, we do not separately estimate the effects of the E, S, and G components as we did in the startup-side

[17] See Appendix B for full details on the discrete choice estimation.

experiment. Second, in the Willingness-to-Pay Experiment, we remove the gender treatment arm (which served as a placebo in the startup-side experiment). As a result, investors are randomly assigned to either a standard recommendation group or an ESG-preferred recommendation group.

In the VC-side experiment, each participating investor evaluates 16 hypothetical startup profiles. Eight of these profiles are randomly assigned to be purely profit-driven, and the remaining eight are presented as ESG-oriented. All other profile characteristics are orthogonally randomized (see Table 1B for the list of characteristics). Similar to the startup experiment, participants are reminded that (a) they should assume all startup profiles they rate are in industries and stages of interest to them, and (b) providing honest and careful evaluations increases their chances of receiving better real-world startup matches. Appendix Figure 1, panel B provides an example of the instruction page.

Appendix Figure 7 provides an example of a startup profile. We ask VCs to evaluate each profile along five key dimensions presented in the following order during the experiment: (1) the startup's potential profitability; (2) the likelihood that the startup would be interested in a collaboration; (3) the likelihood that the investor would reach out to the startup; (4) the investor's intended investment amount (relative to the investor's average investment size); and (5) the informativeness of the startup's profile. The exact wording of these questions and the visual layout of the interface are provided in Appendix Figure 8. As outlined in Appendix A, we use a similar data-driven algorithm to identify actual startup matches from our collaborating incubators. If a matched startup's founding team is also interested in raising capital from that VC, we facilitate contact between the two parties. These interactions typically occur within one month after the study concludes.

In the Willingness-to-Pay module, investors are informed that one participant will be randomly selected to win a $1,000 lottery prize. Each investor is then offered a choice: (1) receive the full $1,000 if they win, or (2) receive a reduced prize in exchange for continued startup recommendations from our partner incubators. Half of the investors are randomly assigned to an ESG-preferred recommendation group, in which the algorithm prioritizes ESG-focused startups while holding matching quality constant. As in the startup-side experiment, we randomize the size of the prize reduction (i.e., the "price" for the additional matching service) across investors, with the price randomly drawn between $100 and $500. We use a higher price range than in the startup experiment to raise the stakes for the VC participants. Appendix Figure 9 shows the exact wording and visual display of this module. Finally, upon completing the experiment, participants received an unexpected $15 Amazon gift card as compensation.

The investor-side experimental setting also closely mirrors real-world venture investing practices. In the industry, it is common to use data-driven algorithms to sift through thousands of potential opportunities during the initial screening stage. For example, Techstars, Social+ Capital, and Citylight Capital have all developed machine learning tools to aid in deal sourcing.[18] Moreover, because certain founder attributes (such as a founder's personality) are difficult to quantify, these data-driven methods are typically employed before the face-to-face due diligence stage.

5.2 Recruitment and Summary Statistics

Study Sample. The VC experiment subjects are recruited by contacting investors using email information listed on Pitchbook. The first wave of recruitment took place between March and July 2020, during which 70 investors participated. At this early stage of the project, the willingness-to-pay (WTP) module had not yet been developed, so these participants completed only the resume-rating experiment. To test preference-driven mechanisms—parallel to those in the startup experiment—we conducted a second wave of recruitment between September and November 2024, adding 59 investors who completed both the resume-rating and WTP modules. In total, 129 investors participated, yielding 1,856 profile evaluations, with 59 of them included in follow-up WTP experimentation. 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 from our collaborating incubators.

Summary Statistics. Appendix Table 5 summarizes participating investors' characteristics in our study sample (column 1), and those in the Pitchbook database (column 2).

[18] See https://www.forbes.com/sites/cognitiveworld/2019/09/12/using-machine-learning-in-venturecapital/?sh=363f1c3f239b; https://medium.com/vcdium/venture-capital-due-diligence-the-screening-process-19f0e837cd71

Pitchbook is among the most commonly used databases on US-based VCs and serves as a good benchmark for assessing sample representativeness. Our sample investors cover a diverse range of sectors that VCs typically focus on (Bernstein et al., 2017). 86% of recruited investors are in senior positions, as their contact information is more readily available in existing databases. Roughly 12% 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.

Balancing Tests. Table 2B presents tests for the balance of profile characteristics. We perform these tests by regressing each characteristic on the ESG group dummy, as specified in equation (7) of Section 6.1. Consistent with successful random assignment, we find no significant differences in any profile characteristic between the ESG and control groups.

6. VC Investor Experiment: Results

6.1 Investors' ESG Demand

Estimation. Our experimental data comprises evaluations of 1,856 unique startup profiles by 129 VC investors indexed by i, with each profile indexed by j. Our estimation equation is as follows:

$$\text{Rating}_{ij} = \alpha + \beta^{ESG} \cdot 1(ESG)_j + \eta_i + X_j \cdot \gamma + \varepsilon_{ij} \qquad (7)$$

where Rating_{ij} is the investor i's ratings on a given outcome (contact interest, funding amount, profitability, mutual interest, or informativeness) of profile j. $1(ESG)_j$ is an indicator variable for whether profile j is assigned to be an ESG startup (i.e., the treatment profiles). η_i are investor fixed effects dummies that absorb any cross individual differences in overall rating levels. Thus, our estimates exploit within-investor variation, comparing how the same investor rates profiles with an ESG label versus profit-driven profiles. X_j is the vector of other randomized profile characteristics (see Table 1B). ε_{ij} is the regression error term. Our coefficient of interest is β^{ESG}, which captures the average difference in outcome ratings for an ESG-labeled profile relative to a control profile. Under random assignment, this coefficient identifies the average causal effect of an ESG label on investors' ratings. We cluster standard errors at the investor level and adjust significance levels for family-wise error (as in Section 3).

Results. Table 3B summarizes our main estimates for all five outcome measures. Focusing first on contact interest (column 1), ESG-labeled startup profiles receive ratings that are 3.12 pp lower than their profit-driven counterparts — a 5.1% relative decrease, significant at the 1% level. Similarly, investors assign a lower intended investment amount to ESG startups (column 2), indicating a comparable ESG penalty in funding interest.

Effect Sizes. In Figure 2B, we report regression coefficients on contact interest when we include other profile characteristics as covariates (X_j in equation 7). Reassuringly, as in the startup-side experiment, strong historical performance remains the most influential factor driving contact interest. The second most important factor is whether the startup's founder comes from a top university, a well-established predictor of fundraising success in venture capital (Bernstein et al., 2017). Notably, a startup's ESG status still emerges as a key (negative) determinant of contact interest; its impact is comparable to the startup losing one major competitive advantage, or roughly 40% of the effect associated with having founders from a top university.

6.2 Investors' Beliefs about ESG

For perceived profitability, expected mutual interest, and profile informativeness (Table 3B, columns 3–5), we find similarly negative ESG effects on investors' beliefs. Compared to their profit-driven counterparts, ESG-oriented startups are judged to be 8.8% less likely to achieve high profitability and 5.9% less likely to reciprocate the investor's interest in collaboration. These belief-based penalties closely mirror the results from the startup-side experiment. We also find that a startup's ESG label reduces the perceived informativeness of its profile by 2.93 pp (approximately 4.6% relative to control profiles).

6.3 Investors' Taste for ESG

Estimation. Our ESG preference estimation equation is:

$$1(\text{Pay for recommendation})_i = \alpha + \beta^{\text{ESG}} \cdot 1(\text{ESG preferred list})_i + X_i \cdot \gamma + \varepsilon_i \qquad (8)$$

where $1(\text{Pay for recommendation})_i$ is a dummy variable that indicates whether investor i chose to pay for the recommendation list. Investors are randomly assigned to either a standard recommendation list (control group) or an ESG-preferred list of startups with similar matching quality, indicated by the treatment dummy $1(\text{ESG preferred list})_i$. X_i denotes other investor characteristics (e.g., industry focus, fund size, demographics). We report specifications with and without these controls, though their inclusion has little impact given the randomized offer assignment. ε_i is the error term, and we report robust standard errors. The main coefficient of interest is β^{ESG}, representing the average causal effect of being offered an ESG-preferred recommendation list.

Results. Table 4B summarizes our findings. Columns (1) and (2) present linear probability model estimates. Investors offered an ESG-preferred startup list are 29 percentage points more likely to pay for the additional recommendations compared to those in the control group. This effect size corresponds to roughly a 120% increase over the 24% baseline purchase rate in the control group. Columns (3) and (4) show analogous results using probit specifications. A discrete choice estimation (Appendix Table 3B) further indicates that investors' implied willingness to pay for the ESG-oriented recommendation list is approximately $187.

7. Additional Checks of Experimental Validity

In this section, we report a number of additional tests that assess the validity of our experimental design and findings. Section 7.1 focuses on internal validity, i.e., whether the experimental results *per se* are robust, plausible, and indeed capture what we intend to measure. Section 7.2 addresses external validity, where we evaluate the extent to which our findings are likely to generalize beyond the specific context of our study.

7.1 Internal Validity

Given our experimental design, conventional endogeneity concerns do not pose a threat to the internal validity of the results. A more pertinent concern is whether the experiment participants, despite being aware that the profiles were randomly generated, regarded the experiment as credible, and engaged with it attentively enough to reveal their genuine preferences. In this section, we discuss several checks embedded in our study to address this issue.

First, we conduct sanity checks to verify that participants responded credibly to profile attributes where we have clear prior expectations. For example, in the startup experiment, investors' non-ESG characteristics like investment track record, and entrepreneurial experience should, in theory, positively influence founders' interest. Our design allows us to test this because *all* profile attributes—not just ESG labels—were randomly assigned. Indeed, as shown in Figure 2A, participants' evaluations of these non-ESG characteristics are directionally sensible. Moreover, Figure 3 shows that the ESG penalty varies in intuitive ways: it is weaker among founders who identify as Democrats, a group generally more supportive of ESG (Hong and Kostovetsky, 2012) and less pronounced among female founders, consistent with evidence that women often display greater prosocial tendencies (Andreoni and Vesterlund, 2001). Together, these results give us confidence that startup founders took the evaluation tasks seriously. Likewise, in the VC investor experiment, we observe that VC investors show preferences for attributes that are well-established predictors of fundraising success in venture capital, such as whether the startup founder had strong historical performance, and whether the founder comes from a top university (Section 6.1).

Second, we exclude potentially unrealistic profiles as a robustness check. Random assignment of profile attributes may sometimes produce implausible combinations: for example, a first-time fund manager claiming extensive ESG expertise, or a small fund pursuing governance interventions that typically require substantial resources. In Appendix Table 6, we report robustness checks excluding VC profiles that are first-time funds (about 20% of profiles) or those with small AUM (about 50% of profiles). The results remain robust. In Appendix Table 7, we report a corresponding check for the VC-side experiment, where we exclude startup profiles without prior entrepreneurial experience (about 50% of profiles) or without positive traction (about 50% of profiles). These checks also produce similar results.

Third, we examine potential temporal and sequential dependencies in the profile rating results (e.g., Kessler, Low, and Shan, 2024). Appendix Figure 10 presents dynamic specifications where we allow the effect of ESG profiles to vary with the order in which profiles were rated (e.g., in the startup experiment, "Profile ID = 1" denotes the first profile rated by a participant). As the figure shows, the estimated coefficients show no systematic temporal pattern and are generally statistically indistinguishable from one another, which suggests that participants' preferences remained stable throughout the experiment. Appendix Tables 8 and 9 report sequential-dependence tests in which we allow the impact of ESG profiles to depend on whether the immediately preceding profile was non-ESG. In both the startup and VC-investor experiments, none of the interaction terms are statistically significant, and the coefficient signs show no consistent pattern. Together, these results suggest little evidence of spillover effects across profiles.

Fourth, we compare participants' revealed preferences (from our experiment) with their real-world behaviors. Starting with startup founders, Appendix Table 10 examines our Crunchbase replication sample (see Section 3.3), where we observe actual fundraising outcomes. Consistent with the experimental data, we find that startup founders who expressed more favorable views toward ESG profiles in our experiment are significantly more likely to have raised capital from ESG-focused venture investors in the real world. A similar correlation is observed with VC investor participants. Appendix Table 11 reports that investors who were more favorable toward ESG profiles in the experiment are significantly more likely to be affiliated with a firm that has made investments in ESG-focused startups in real world according to the firm's records in Pitchbook data. Both pieces of evidence suggest that the ESG attitudes revealed in the experiment align with participants' true underlying preferences.

Fifth, recall that the primary incentive for truthful reporting was the prospect of receiving actual investor matches. Participants even had the option to purchase the expanded recommendation list in the WTP module at the cost of part of their lottery prize. Thus, an indirect test of sincerity is whether participants were willing to pay for the list—if they did not value the matches, they could simply keep the full prize and forego any recommendations. As shown in Table 4 (and Appendix Table 3), in the WTP experiment, participants exhibit substantial willingness to pay for the recommendation service, which implies that they value the matching incentive in the experiment. Moreover, the fact that the estimated WTP closely aligns with market prices for similar matching services further reinforces the credibility of our experimental measures.

Finally, we assess the robustness of our results with respect to statistical inference. In particular, our willingness-to-pay experiments on both the startup and investor sides involve relatively small sample sizes, as the analyses are done at the participant level (409 startup founders and 59 VC investors). To address potential concerns related to small-sample inference, we apply randomized inference in the spirit of Fisher's exact test, where the null distribution of the test statistics is empirically generated by fully permuting the treatment assignment (rather than assuming theoretical asymptotics which are typically valid only in large samples). Our randomized inference tests confirm the robustness of our findings. The exact *p*-value for the "**1**(ESG-preferred list)" coefficient in Table 4 is 0.080 in the startup experiment and 0.038 in the VC investor experiment, both of which are statistically significant at conventional levels.

Because we test multiple outcomes in our profile rating experiment, we also test robustness to controlling for family-wise error rate (FWER) – i.e., the probability of making at least one false rejection while testing multiple outcomes simultaneously – following the procedure by Westfall and Young (1993). We define families of hypotheses that encompass the five outcomes we primarily test in this paper, including Contact Interest, Funding Amount, Profitability, Availability, and Informativeness. We report FWER-adjusted *p*-values in brackets in Appendix Table 12, which shows that our inferences are robust to the adjustment.

Two additional aspects of our experimental context merit mention. First, participants were not informed that the study's focus was on ESG evaluations, which helps mitigate "framing" effects. Second, if our incentive mechanism had been too weak, one might expect founders to overstate their interest in ESG for reputational reasons (Levitt and List, 2007; Benz and Meier, 2008). Such bias would lead us to underestimate the true magnitude of the ESG penalty. The fact that we nonetheless observe a sizable ESG penalty suggests that our incentive was effective in eliciting preferences.

7.2 External Validity

Experimental findings are externally valid if they generalize beyond the specific study setting. In our case, external validity hinges on two key questions: (i) whether our study sample is representative of the broader startup population, and (ii) whether the preferences expressed in our experimental setup correspond to behavior in the real world.

Sample Representativeness. We first address potential selection issues in our sample. One concern is that startups recruited via the Qualtrics Panel might differ systematically from the broader population of U.S. startups seeking VC funding. Unfortunately, this is hard to evaluate directly, as the startup sector is largely private and rapidly evolving, and no comprehensive population data are available as a benchmark.[19]

Instead, we focus on a second potential selection bias: among the startups we contacted, were those who chose to participate somehow unusual? In other words, might our recruitment process itself have yielded a non-representative subset of founders? To examine this, we conducted a replication of our experiment by directly recruiting startups from the Crunchbase database, where we can compare the characteristics of participating startups to the larger population of Crunchbase firms. If our original recruitment introduced bias, we would expect to see differences between the recruited Crunchbase sample and the broader Crunchbase population. However, Appendix Table 2 shows that this is not the case. The industry distribution and founder demographics of our Crunchbase sample (Appendix Table 2, column 2) closely mirror those of the full Crunchbase startup population (column 3).

Appendix Table 2 also reports the characteristics of our main Qualtrics experimental sample (column 1). These are broadly similar to those of the Crunchbase replication sample, with two notable differences: the Crunchbase founders are disproportionately male, and fewer startups in that sample espouse an ESG-oriented business philosophy. As we discuss next, these differences manifest in even larger ESG penalty estimates in the Crunchbase replication, consistent with the fact that the replication sample is more male-dominated and less ESG-oriented.

Replication Study. Using the Crunchbase sample, we conduct a direct replication of our main startup experiment as a stringent test of external validity (List, 2020). Appendix Table 13 shows that the main ESG penalty results are indeed replicated. In fact, the ESG penalty is even stronger in the replication: significant negative effects appear for E, S, and G labels (with the E effect still the most pronounced). This is consistent with the replication sample's composition –

[19] While the census data has the company establishment data, it does not record whether these startups seek for VC funding or not.

predominantly male founders, who exhibited larger ESG penalties in our main sample, and fewer ESG-oriented startups.

Appendix Table 14 shows that the WTP experiment results are also successfully replicated. Startup founders in the Crunchbase sample are more likely to pay for the expanded list when it favors ESG investors (holding matching quality constant). These replication findings increase our confidence that our experimental results are not artifacts of a particular sample, but rather reflect a stable effect that holds across a broader population.

Link to Real-World Behavior. Finally, as discussed in Section 7.1, multiple pieces of evidence suggest that participants' responses in the experiment were sincere and reflective of their actual preferences. In particular, Appendix Table 12 shows that in the Crunchbase replication, founders' ESG inclinations revealed in the experiment are strongly correlated with their real-world fundraising partnerships with ESG-focused investors, and Appendix Table 13 shows a similar positive correlation between VC investor's experimentally-elicited ESG preference and their real-world investment in ESG-focused startups.

More broadly, our experimental setup was designed to mimic real-world decision-making. The profile evaluation task mirrors what founders naturally do during their fundraising process, lending a high degree of "naturalness" to our design (List, 2020). This realism increases the likelihood that our findings will generalize to actual business behavior.

8. Conclusion

Our field experiments reveal a robust "ESG penalty" on both sides of the entrepreneurial finance market. Through a series of incentivized matching exercises with real U.S. startup founders and venture capitalists, we found that ESG labels significantly dampen interest in prospective partners. Startup founders gave lower interest ratings to potential investors labeled as ESG-focused, primarily due to concerns about those investors' expected value added to their profitability and availability. Similarly, VCs were less inclined to pursue startups emphasizing ESG missions, citing doubts about such ventures' financial returns and the likelihood of a successful partnership.

However, our follow-up willingness-to-pay experiment uncovered a latent appetite for ESG once financial performance considerations were neutralized. When participants were offered the option to pay for additional match recommendations that prioritized ESG-oriented profiles (with match quality explicitly held constant), both founders and VCs became significantly more willing to make the purchase if their extra recommendations were ESG-focused. This behavior reveals an underlying non-pecuniary preference for ESG that is ordinarily masked by belief-driven concerns in baseline matching decisions.

Taken together, these dual findings shed new light on the broader "value versus values" debate in sustainable finance. They indicate that the tension between financial value and personal values arises not from an absence of preference for ESG, but from persistent skepticism about ESG's financial merits. In our setting, market participants do have genuine pro-ESG inclinations, yet their baseline decisions are dominated by concerns that engaging with ESG could compromise returns or matching success. In other words, the aversion to ESG we observe is not an outright rejection of environmental and social ideals; rather, it reflects doubt about whether ESG-focused partnerships can deliver financial returns comparable to those of more traditional investments. By disentangling belief-driven versus taste-driven motives, our study reconciles these perspectives and provides a clearer lens on how investors and entrepreneurs balance economic value with their social and environmental values.

Beyond its substantive insights, this study also contributes methodologically by demonstrating the value of incentivized field experiments to isolate belief-based and taste-based drivers of decision-making—an approach future research can extend to other settings. Looking ahead, our findings raise important questions for both research and policy. For example, if misperceptions about ESG performance are an important barrier, future experiments could test whether providing more transparent information about the financial track record of ESG-focused ventures would alleviate investor skepticism and narrow the ESG penalty. On the policy front, measures that better align private returns with social benefits—such as incentives for sustainable investment or mechanisms to internalize environmental externalities—may encourage the latent ESG demand we uncover to materialize. Ultimately, addressing the misalignment between ESG perceptions and preferences will be crucial for channeling capital toward socially and environmentally beneficial ventures without compromising financial performance.

References

Andreoni, James, and Lise Vesterlund. "Which is the fair sex? Gender differences in altruism." *The Quarterly Journal of Economics* 116, no. 1 (2001): 293-312.

Barber, Brad M., Adair Morse, and Ayako Yasuda. "Impact investing." *Journal of Financial Economics* 139, no. 1 (2021): 162-185.

Bauer, Rob, Tobias Ruof, and Paul Smeets. "Get real! Individuals prefer more sustainable investments." *The Review of Financial Studies* 34, no. 8 (2021): 3976-4043.

Bellon, Aymeric. "Does private equity ownership make firms cleaner? The role of environmental liability risks." *The Role Of Environmental Liability Risks (May 18, 2020). European Corporate Governance Institute–Finance Working Paper* 799 (2021).

Benz, Matthias, and Stephan Meier. "Do people behave in experiments as in the field?—evidence from donations." *Experimental Economics* 11 (2008): 268-281.

Bernstein, Shai, Arthur Korteweg, and Kevin Laws. "Attracting early-stage investors: Evidence from a randomized field experiment." *The Journal of Finance* 72, no. 2 (2017): 509-538.

Bernstein, Shai, Xavier Giroud, and Richard R. Townsend. "The impact of venture capital monitoring." *The Journal of Finance* 71, no. 4 (2016): 1591-1622.

Bohren, J. Aislinn, Alex Imas, and Michael Rosenberg. "The dynamics of discrimination: Theory and evidence." *American Economic Review* 109, no. 10 (2019): 3395-3436.

Bosone, Costanza, Stefania Maria Bogliardi, and Paolo Giudici. "Are ESG female? The hidden benefits of female presence on sustainable finance." *Review of Economic Analysis* 14, no. 2 (2022): 253-274.

Botsari, Antonia, and Frank Lang. *ESG considerations in venture capital and business angel investment decisions: Evidence from two pan-European surveys*. No. 2020/63. EIF Working Paper, 2020.

Bottazzi, Laura, Marco Da Rin, and Thomas Hellmann. "Who are the active investors?: Evidence from venture capital." *Journal of Financial Economics* 89, no. 3 (2008): 488-512.

Broccardo, Eleonora, Oliver Hart, and Luigi Zingales. "Exit versus voice." *Journal of Political Economy* 130, no. 12 (2022): 3101-3145.

Brodback, Daniel, Nadja Guenster, and David Mezger. "Altruism and egoism in investment decisions." *Review of Financial Economics* 37, no. 1 (2019): 118-148.

Brodback, Daniel, Nadja Katharina Guenster, Sébastien Pouget, and Ruichen Wang. *The valuation of corporate social responsibility: a willingness to pay experiment*. Netspar, Network for Studies on Pensions, Aging and Retirement, 2021.

Chowdhry, Bhagwan, Shaun William Davies, and Brian Waters. "Investing for impact." *The Review of Financial Studies* 32, no. 3 (2019): 864-904.

Cole, Shawn, Martin Melecky, Florian Mölders, and Tristan Reed. Long-run returns to impact investing in emerging markets and developing economies. No. w27870. National Bureau of Economic Research, 2020.

Cutter, Chip, and Emily Glazer. "The latest dirty word in corporate America: ESG." *The Wall Street Journal* (2024).

Ebrahimian, Mehran, and Ye Zhang. "Matching and Bargaining in Entrepreneurial Finance: Evidence From an Experimental System." *SSRN 3724424* (2024).

Edmans, Alex, Tom Gosling, and Dirk Jenter. "Sustainable Investing in Practice: Objectives, Constraints, and Limits to Impact." (2025). Working Paper.

Friede, Gunnar, Timo Busch, and Alexander Bassen. "ESG and financial performance: aggregated evidence from more than 2000 empirical studies." *Journal of Sustainable Finance & Investment* 5, no. 4 (2015): 210-233.

Garrett, Daniel G., and Ivan T. Ivanov. *Gas, Guns, and Governments: Financial Costs of Anti-ESG Policies*. No. WP 2023-07. Working paper, 2023.

Geelen, Thomas, Jakub Hajda, and Jan Starmans. "Sustainable organizations." *European Corporate Governance Institute–Finance Working Paper* 994 (2022).

Gillan, Stuart L., Andrew Koch, and Laura T. Starks. "Firms and social responsibility: A review of ESG and CSR research in corporate finance." *Journal of Corporate Finance* 66 (2021): 101889.

Gollier, Christian, and Sébastien Pouget. "The" washing machine": Investment strategies and corporate behavior with socially responsible investors." (2014).

Gompers, Paul A., and Vladimir Mukharlyamov. *Transferable skills? Founders as Venture Capitalists*. No. w29907. National Bureau of Economic Research, 2022.

Gormley, Todd A., Manish Jha, and Meng Wang. *The Politicization of Social Responsibility*. No. w32869. National Bureau of Economic Research, 2024.

Gupta, Deeksha, Alexandr Kopytov, and Jan Starmans. "The pace of change: Socially responsible investing in private markets." *SSRN* (2022).

He, Guojun, Yuhang Pan, Albert Park, Yasuyuki Sawada, and Elaine S. Tan. "Reducing single-use cutlery with green nudges: Evidence from China's food-delivery industry." *Science* 381, no. 6662 (2023): eadd9884.

Heeb, Florian, Julian F. Kölbel, Falko Paetzold, and Stefan Zeisberger. "Do investors care about impact?." *The Review of Financial Studies* 36, no. 5 (2023): 1737-1787.

Heinkel, Robert, Alan Kraus, and Josef Zechner. "The effect of green investment on corporate behavior." *Journal of financial and quantitative analysis* 36, no. 4 (2001): 431-449.

Hong, Harrison, and Leonard Kostovetsky. "Red and blue investing: Values and finance." *Journal of Financial Economics* 103, no. 1 (2012): 1-19.

Houston, Joel F., and Hongyu Shan. "Corporate ESG profiles and banking relationships." *The Review of Financial Studies* 35, no. 7 (2022): 3373-3417.

Hsu, David H. "What do entrepreneurs pay for venture capital affiliation?." *The Journal of Finance* 59, no. 4 (2004): 1805-1844.

Ivanov, Ivan T., Mathias S. Kruttli, and Sumudu W. Watugala. "Banking on carbon: Corporate lending and cap-and-trade policy." *The Review of Financial Studies* 37, no. 5 (2024): 1640-1684.

Jeffers, Jessica, Tianshu Lyu, and Kelly Posenau. "The risk and return of impact investing funds." *Journal of Financial Economics* 161 (2024): 103928.

Kessler, Judd B., Corinne Low, and Xiaoyue Shan. "Lowering the playing field: Discrimination through sequential spillover effects." *Review of Economics and Statistics* (2024): 1-28.

Kessler, Judd B., Corinne Low, and Colin D. Sullivan. "Incentivized resume rating: Eliciting employer preferences without deception." *American Economic Review* 109, no. 11 (2019): 3713-3744.

Kovner, Anna, and Josh Lerner. "Doing well by doing good? Community development venture capital." *Journal of Economics & Management Strategy* 24, no. 3 (2015): 643-663.

Krueger, Philipp, Zacharias Sautner, and Laura T. Starks. "The importance of climate risks for institutional investors." *The Review of Financial Studies* 33, no. 3 (2020): 1067-1111.

Levitt, Steven D., and John A. List. "What do laboratory experiments measuring social preferences reveal about the real world?." *Journal of Economic Perspectives* 21, no. 2 (2007): 153-174.

Liang, Hao, Lin Sun, and Melvyn Teo. "Greenwashing: Evidence from hedge funds." (2021): 1.

List, John A. Non est disputandum de generalizability? A glimpse into the external validity trial. No. w27535. National Bureau of Economic Research, 2020.

List, John A., Paramita Sinha, and Michael H. Taylor. "Using choice experiments to value non-market goods and services: evidence from field experiments." *The BE Journal of Economic Analysis & Policy* 6, no. 2 (2006).

Lyon, Thomas P., and John W. Maxwell. "Greenwash: Corporate environmental disclosure under threat of audit." *Journal of Economics & Management Strategy* 20, no. 1 (2011): 3-41.

Oehmke, Martin, and Marcus M. Opp. "Green capital requirements." *Swedish House of Finance Research Paper* 22-16 (2022).

Pástor, Ľuboš, Robert F. Stambaugh, and Lucian A. Taylor. "Fund tradeoffs." *Journal of Financial Economics* 138, no. 3 (2020): 614-634.

Porter, Michael E., and Mark R. Kramer. "The Big Idea: Creating Shared Value." *Harvard Business Review*, January–February 2011.

Ramadorai, Tarun, and Federica Zeni. "Climate regulation and emissions abatement: Theory and evidence from firms’ disclosures." *Management Science* 70, no. 12 (2024): 8366-8385.

Riedl, Arno, and Paul Smeets. "Why do investors hold socially responsible mutual funds?." *the Journal of Finance* 72, no. 6 (2017): 2505-2550.

Shane, Scott, and Sankaran Venkataraman. "The promise of entrepreneurship as a field of research." *Academy of Management Review* 25, no. 1 (2000): 217-226.

Sørensen, Morten. "How smart is smart money? A two-sided matching model of venture capital." *The Journal of Finance* 62, no. 6 (2007): 2725-2762.

Starks, Laura T. "Presidential address: Sustainable finance and ESG issues—value versus values." *The Journal of Finance* 78, no. 4 (2023): 1837-1872.

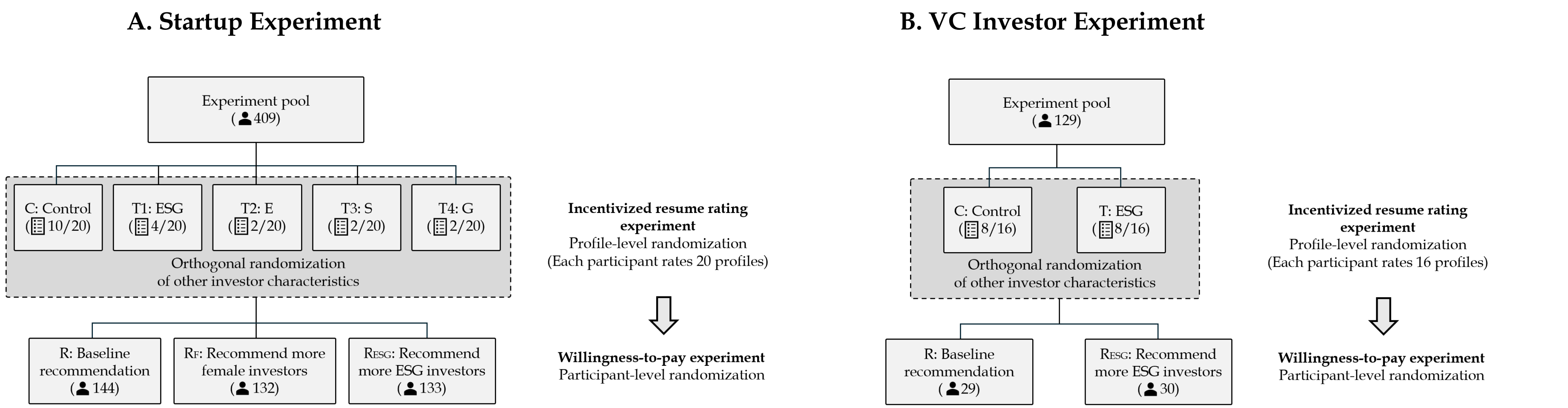
Starks, Laura T., Parth Venkat, and Qifei Zhu. "Corporate ESG profiles and investor horizons." *SSRN 3049943* (2017).

Stroebel, Johannes, and Jeffrey Wurgler. "What do you think about climate finance?." *Journal of Financial Economics* 142, no. 2 (2021): 487-498.

Westfall, Peter H., and S. Stanley Young. *Resampling-based multiple testing: Examples and methods for p-value adjustment.* John Wiley & Sons, 1993.

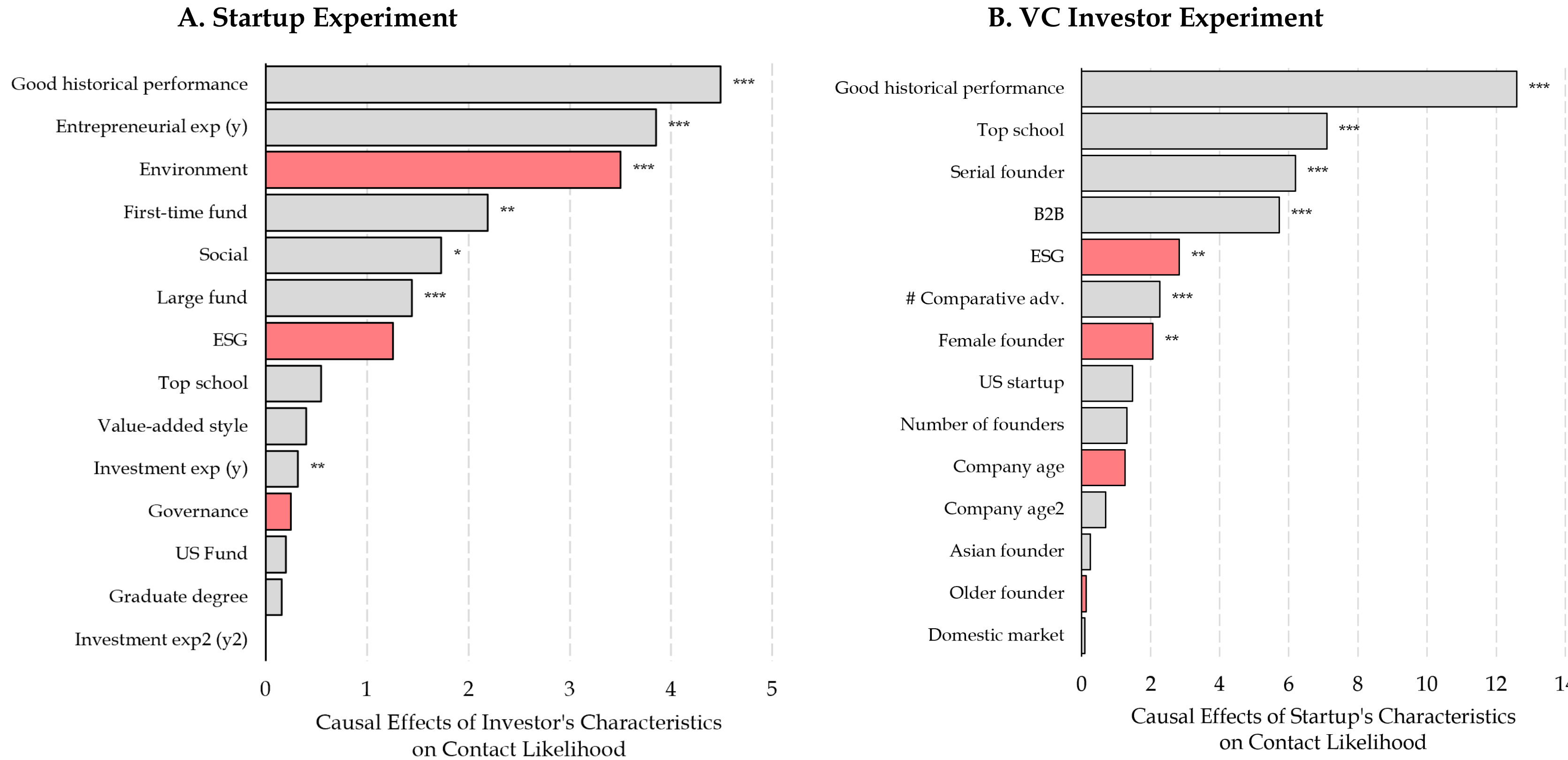
Zhang, Ye. "Discrimination in the venture capital industry: Evidence from two randomized controlled trials." *arXiv preprint arXiv:2010.16084* 1, no. 3.1 (2020).

Figure 1. Experimental Design



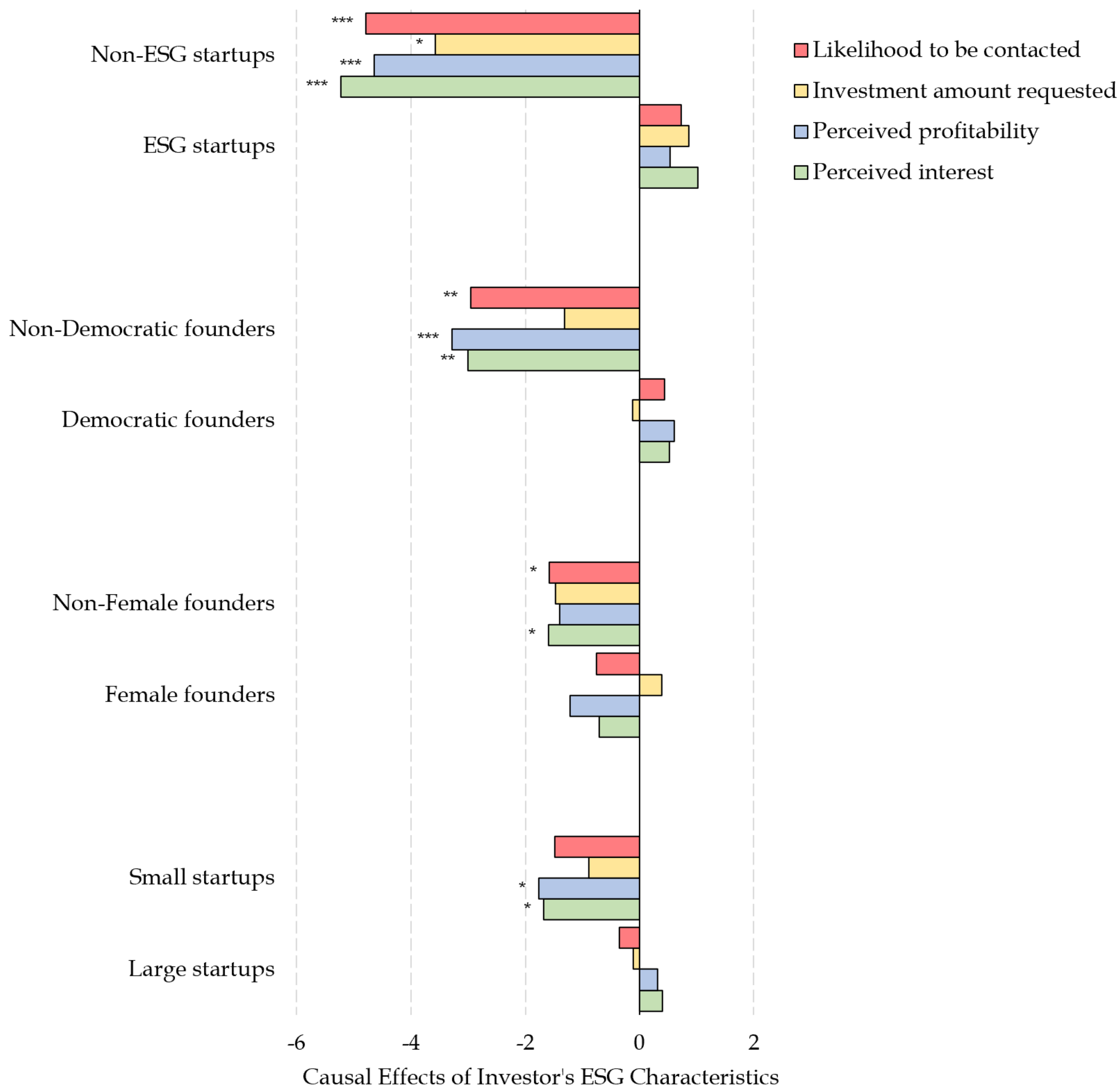
Notes: This figure outlines the startup-side experiment (Panel A) and the VC investor-side experiment (Panel B). Both begin with a profile-level randomization stage, where participants evaluate a fixed number of randomized profiles featuring various ESG types (e.g., control, ESG, E, S, G). This is followed by a willingness-to-pay experiment, where individuals are offered a choice to forgo part of the lottery award in exchange for additional recommendations of potential matches. Offers are randomized at the individual level: some participants expect to receive standard recommendations, while others expect to receive more ESG-aligned recommendations. In Panel B, the WTP module is implemented among 59 investors recruited in a later stage of the study. The remaining investors recruited earlier participated only in the resume rating task.

Figure 2. Causal Effects of Candidate Characteristics on Evaluators' Contact Interest



Notes: This figure reports regression coefficients for the effect of various candidate characteristics on evaluators' contact interest, ordered by effect size. Panel A shows results from the startup experiment, where startup founders evaluated VC investor profiles. Panel B shows results from the VC investor experiment, where investors evaluated startup profiles. Red bars represent negative coefficients, and gray bars indicate positive effects. $*$: $p < 0.10$, $**$: $p < 0.05$, $***$: $p < 0.01$.

Figure 3. Heterogeneity in ESG Penalties



Notes: This figure shows heterogeneity in the ESG penalties from the startup experiment across four groups: ESG vs. non-ESG startups, Democratic vs. non-Democratic founders, Female vs. Non-Female founders, and Small vs. Large startups. Results are presented for four outcomes: likelihood to be contacted (red), investment amount requested (yellow), perceived profitability (blue), and perceived interest (green). $*$: $p < 0.10$, $**$: $p < 0.05$, $***$: $p < 0.01$.

Table 1A. Startup Experiment: Randomization of Investor Profiles

Profile Characteristics	Randomization
A. ESG characteristics	
Investment philosophy	Profit-driven (10/20); ESG (4/20); Environment (2/20); Social (2/20); Governance (2/20)
B. Other characteristics	
Name	White female (25%); White male (25%); Asian female (25%); Asian male (25%)
Degree	Bachelor's degree (10/20); Graduate degree (10/20)
Top school	Top school (10/20); Non-top schools (10/20)
Investment experience	Years ~ Uniform[0,30]
Deals involved	3 x Investment experience + uniform[-2,2]
Entrepreneurial experience	Yes (10/20); No (10/20)
Fund type	First time VC (20%); Seasoned VCs with historical; performance (80%);
Historical performance	IRR ~ Normal(19.8%, 34%)
Fund size	Small AUM (10/20) ~ Uniform[1,130]; Large AUM (10/20) ~ Uniform[130,1500]
Investment style	Value-added (16/20); Spray and pray (4/20)
Location	USA (18/20); Foreign (2/20)

Notes: Weights of characteristics are shown as fractions when they are fixed across subjects (e.g., each subject observes exactly 10/20 profiles with profit-driven investors) and percentages when they represent a draw from a probability distribution.

Table 1B. VC Investor Experiment: Randomization of Startup Profiles

Profile Characteristics	Randomization
A. ESG characteristics	
Mission	For profit (8/16); ESG (8/16)
B. Other characteristics	
Names	White female (25%); White male (25%); Asian female (25%); Asian male (25%)
Number of founders	One founder (8/16); Two founders (8/16)
College graduation year	Junior (50%) ~ Uniform[2010, 2013]; Senior (50%) ~ Uniform[1984, 2009]
Top school	Top school (8/16); Non-top schools (8/16)
Entrepreneurial experience	Yes (8/16); No (8/16)
Founding date	2020 (25%); 2021 (25%); 2022 (25%); 2023 (25%)
Number of employees	≤ 10 (4/16); 11-20 (4/16); 21-50 (4/16); > 50 (4/16)
Company category	B2B (8/16); B2C (8/16)
Comparative advantages	1 advantage (4/16); 2 advantages (4/16) 3 advantages (4/16); 4 advantages (4/16)
Traction	No revenue (8/16); Positive traction (8/16)
Number of existing investors	0 (25%); 1 (25%); 2 (25%); 3+ (25%)
Target market	Domestic (8/16); International (8/16)
Location	USA (70%); Foreign (30%)

Notes: Weights of characteristics are shown as fractions when they are fixed across subjects (e.g., each subject observes exactly 8/16 profiles with profit-driven investors) and percentages when they represent a draw from a probability distribution.

Table 2. Balancing Tests

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
					A. Startup Experiment					
Dependent variable:	History perform.	Entrep. exp.	1st-time fund	Large fund	Top school	Value-add style	Yr. of exp.	Yr. of exp2.	US fund	Grad. degree
1(ESG investor)	-0.00	-0.01	0.01	0.01	0.01	0.00	-0.05	1.15	0.00	0.00
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.26)	(8.37)	(0.01)	(0.02)
1(E investor)	0.01	-0.01	0.00	-0.01	0.01	0.01	0.19	8.19	0.00	-0.00
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.33)	(10.58)	(0.01)	(0.02)
1(S investor)	-0.01	-0.02	0.01	-0.00	-0.00	-0.01	0.05	3.14	0.00	-0.00
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.34)	(10.78)	(0.01)	(0.02)
1(G investor)	0.02	-0.01	-0.01	0.03	-0.01	0.00	0.15	9.45	-0.01	0.05**
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.35)	(10.91)	(0.01)	(0.02)
Control group mean	0.41	0.51	0.20	0.49	0.50	0.80	15.5	313.5	0.90	0.49
Observations	8,180	8,180	8,180	8,180	8,180	8,180	8,180	8,180	8,180	8,180
					B. VC Investor Experiment					
Dependent variable:	History perform.	Top school	Serial founder	B2B startup	Num. of adv.	Female founder	US startup	Num. of founders	Age of company	Asian founder
1(ESG startup)	-0.03	0.00	0.01	-0.01	0.04	0.02	-0.01	-0.01	0.02	0.03
	(0.03)	(0.03)	(0.03)	(0.03)	(0.06)	(0.03)	(0.03)	(0.03)	(0.06)	(0.02)
Control group mean	0.50	0.48	0.49	0.51	2.17	0.48	0.69	1.52	2.49	0.48
Observations	1,856	1,856	1,856	1,856	1,856	1,856	1,856	1,856	1,856	1,856

Notes: This table presents balancing tests for the startup experiment (Panel A) and the VC investor experiment (Panel B). Each column corresponds to a separate regression of a randomized profile characteristic on treatment assignment dummies. All regressions include participant fixed effects (startup founders in Panel A and VC investors in Panel B), with standard errors clustered at the participant level. ∗: $p < 0.10$, ∗∗: $p < 0.05$, ∗∗∗: $p < 0.01$.

Table 3. Profile Evaluation Results: ESG Demand and Beliefs

Dependent variable:	(1) Contact Interest	(2) Funding Amount	(3) Profit-ability	(4) Avail-ability	(5) Informa-tiveness
	A. Startup Experiment				
1(ESG investor)	-1.28	-0.74	-1.35*	-1.26*	0.11
	(0.80)	(1.11)	(0.74)	(0.76)	(0.59)
1(E investor)	-3.47***	-2.80**	-3.17***	-3.40***	-0.90
	(0.98)	(1.34)	(0.94)	(0.90)	(0.70)
1(S investor)	1.64*	0.53	0.43	1.12	1.16*
	(0.89)	(1.16)	(0.82)	(0.79)	(0.64)
1(G investor)	-0.15	-1.09	-0.85	-0.70	0.52
	(0.95)	(1.37)	(0.87)	(0.89)	(0.71)
Control group mean	60.4	90.3	63.3	59.5	66.9
Observations	8,180	8,180	8,180	8,180	8,180
	B. VC Investor Experiment				
1(ESG startup)	-3.12**	-4.60**	-4.34***	-3.79***	-2.93***
	(1.45)	(0.19)	(1.07)	(0.86)	(0.88)
Control group mean	60.7	67.3	52.7	65.1	64.2
Observations	1,856	1,826	1,856	1,832	944

Notes: This table presents main estimation results for the startup experiment (Panel A) and the VC investor experiment (Panel B). Each column corresponds to a separate regression of an evaluation outcome on treatment assignment dummies. All regressions include participant fixed effects (startup founders in Panel A and VC investors in Panel B), with standard errors clustered at the participant level. ∗: $p < 0.10$, ∗∗: $p < 0.05$, ∗∗∗: $p < 0.01$.

Table 4. Willingness-to-Pay Experiment Results: Taste for ESG

	(1)	(2)	(3)	(4)
Dependent variable:	**1**(Pay for recommendation list)			
A. Startup Experiment				
1(Female-preferred list)	0.06	0.04	0.16	0.11
	(0.06)	(0.06)	(0.15)	(0.15)
1(ESG-preferred list)	0.14**	0.13**	0.36**	0.34**
	(0.06)	(0.06)	(0.15)	(0.16)
Specification	Linear	Linear	Probit	Probit
Control group mean	0.44	0.44	0.44	0.44
Other characteristics controls	No	Yes	No	Yes
Observations	409	409	409	409
B. VC Investor Experiment				
1(ESG-preferred list)	0.29**	0.25**	0.79**	0.79**
	(0.12)	(0.12)	(0.35)	(0.37)
Specification	Linear	Linear	Probit	Probit
Control group mean	0.24	0.24	0.24	0.24
Other characteristics controls	No	Yes	No	Yes
Observations	59	59	59	59

Notes: This table estimates whether startup founders and VCs are willing to pay for contact information for additional matched ESG investors and ESG startups. The dependent variable is an indicator that equals one if the experimental participant chooses to pay for a comprehensive list, and zero if the participant chooses to receive all the monetary award from the lottery rather than purchasing a comprehensive list. "**1**(Female-preferred list)" is a dummy variable that indicates if the participant's offer is to receive more female investors' contact information. "**1**(ESG-preferred list)" indicates offers that receive more ESG investors' contact information (in the startup experiment) and more ESG startups' recommendation (in the VC investor experiment). Robust standard errors are reported in parentheses. ∗: $p < 0.10$, ∗∗: $p < 0.05$, ∗∗∗: $p < 0.01$.

Online Appendix

Appendix A. Data-Driven Matching Algorithm

Here we describe the algorithm we use to match each startup founder with a list of investors based on the founders' response in Profile Evaluation Experiment. The recommendation algorithm used in the investor experiment is symmetric. We first select a subset of investors for each participant whose preferred industry and stage match the participant's background. We then run individual ridge regressions for the participants' responses to each of the five evaluation questions onto 10 matching variables, including management style, purpose, IRR, AUM, dry powder, location, investment experience, years of experience, and top school. This step provides us with five sets of slope coefficients for each participant. We then plug in the estimates to form out-of-sample forecasts for each participant using profiles of the real investors who are in the selected subset in the first step. Then, for each participant, we obtain five predicted scores corresponding to the five questions in the survey for each real investor in the subset. Aggregating the scores by taking simple averages, we recommend the top 10 investors with the highest scores to the participant.

We use ridge regression because each participant only evaluated 20 profiles, and the number of matching variables is large (10) in comparison. We pool all participants together and use cross-validation to find the optimal penalty coefficient for each question. Specifically, for each question, we randomly select two-thirds of the pooled data and run five-fold cross-validation to obtain the best penalty coefficient for this question and this subset of data. We repeat this process 1,000 times, take the average of the 1,000 best penalty coefficients, and treat it as the optimal penalty for this question. The chart below summarizes these steps.

```
Matching Algorithm

for each participant do
|  Find the subset of real investors that match industry and stage;
|  for each evaluation question do
|  |  Evaluation question ridge → matching variables (ridge regression + cross-validation);
|  |  Compute fitted value using the matching variables of the real investors in the subset;
|  end
|  Aggregate the 5 scores by simple average and obtain the top 10 investor profiles.
end
```

Appendix B. Discrete Choice Model Details

In Sections 4.3 and 6.3, we use a standard discrete choice model to quantify evaluators' WTP for ESG-preferred matched candidate recommendation list. Here we use the startup experiment as an example, and the estimation process for the investor experiment follows the same method.

Recall that each startup founder is presented with a binary choice between the full lottery ("Option 1") and purchasing the recommendation list at the cost of at the expense of part of their lottery award, where the expense is randomly assigned ("Option 2"). We model founder i's utility function as:

$$U_{i,j} = V_{i,j} + \epsilon_{i,j}$$

where $V_{i,j}$ stands for the utility from observable attributes of each option j, ($j = 1$ for Option 1 and $j = 2$ for Option 2). $\epsilon_{i,j}$ represents the utility from the unobservable attributes, which follows an i.i.d. extreme value type I distribution. The probability that a startup founder purchases an investor recommendation list is then given by:

$$P_{i,j=1} = \Pr\left(U_{i,j=2} > U_{i,j=1}\right) = \Pr\left(V_{i,j=2} + \epsilon_{i,j=2} > V_{i,j=1} + \epsilon_{i,j=1}\right) = \int_{\epsilon} 1\left(\epsilon_{i,j=1} - \epsilon_{i,j=2} < V_{i,j=2} - V_{i,j=1}\right) f(\epsilon_i) d\epsilon_i$$

From experimental assignment and using notations from equation (6),

$$V_{i,j=2} = \alpha + \beta^{Female} \cdot 1(\text{Female preferred list}) + \beta^{ESG} \cdot 1(\text{ESG preferred list}) + \delta \cdot \text{Price}$$

where $Price$ is the randomized price to be paid (via lottery rewards reduction) and $V_{i,j=1}$ is normalized to zero. Here, the α parameter denotes the utility of getting the standard investor recommendation list (i.e., the control group), β^{Female} is the additional utility from a list favoring female investors, β^{ESG} is the additional utility from a list favoring ESG investors, and δ is the utility of an extra dollar. The WTP for the ESG-preferred recommendation list is therefore given by the ratio β^{ESG}/δ. We estimate these parameters from the following relationship by the logit model:

$$P_{i,j=2} = \frac{e^{V_{i,j=2}}}{e^{V_{i,j=2}} + e^{V_{i,j=1}}} = \frac{e^{V_{i,j=2}}}{e^{V_{i,j=2}} + 1}.$$

Our parameter estimates are reported in Appendix Table 4A. We find the β^{ESG} coefficient is significantly positive, which echoes our reduced from findings in Table 4 that founders assigned with an ESG-preferred recommendation list offer are more likely to make purchases. Dividing β^{ESG} by δ, we estimate that the WTP for ESG-preferred recommendation list is roughly $77. Appendix Table 4B presents analogous results for the VC Investor Experiment, which shows similar findings.

Appendix Figures and Tables

Appendix Figure 1. Instrument Page of the Experiments

A. Startup Experiment Instruction Page

NANO-SEARCH FINANCING TOOL

Finding investors. Your Way

Investor Profile Rating Section (All the 20 investor profiles are hypothetical and randomly generated. However, the real investor recommendation list will be generated based on your choices and ratings in this study). In the following section, you will evaluate 20 investor profiles.

Note:

1. Assume that all the investors are active investors, investing in the industry (industries) and stage(s) of your interest.

2. All your answers will be used in our recommendation algorithm. Essentially, the more carefully and truthfully you evaluate each profile, the more benefits you can get from this study.

3. All the information you provide will be kept strictly confidential and analyzed at the aggregate level.

B. VC Investor Experiment Instruction Page

Nano-Search Financing Tool

Finding Startups. Your Way

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.

Notes: Example instruction page in the startup experiment (panel A) and in the VC investor experiment (panel B).

Appendix Figure 2. Startup Experiment: Example Investor Profile

3. Derek Roberts

Investment Experience:

Years of experience: 26

Number of deals involved: 76

Education:

BA, Harvard University

MBA, University of California, Berkeley (Haas)

Entrepreneurial Experience:

Yes. Derek Roberts was a successful entrepreneur earlier on in his career, cofounding 2 successful startups. Currently, he focuses on startup investment to promote more innovation in the world.

Fund Type:

Impact Fund

Investment Philosophy

We support companies from start-up to scale-up with a special focus on positive environmental impact.

Previous Fund Performance:

Internal rate of return: First-time venture-fund, no available historical information

Investment style:

(Value added strategy) concentrate towards startups with good prospects and add value to them

Fund Size (relatively large):

AUM: $647M; Dry Powder (also known as available capital): $175M

Location:

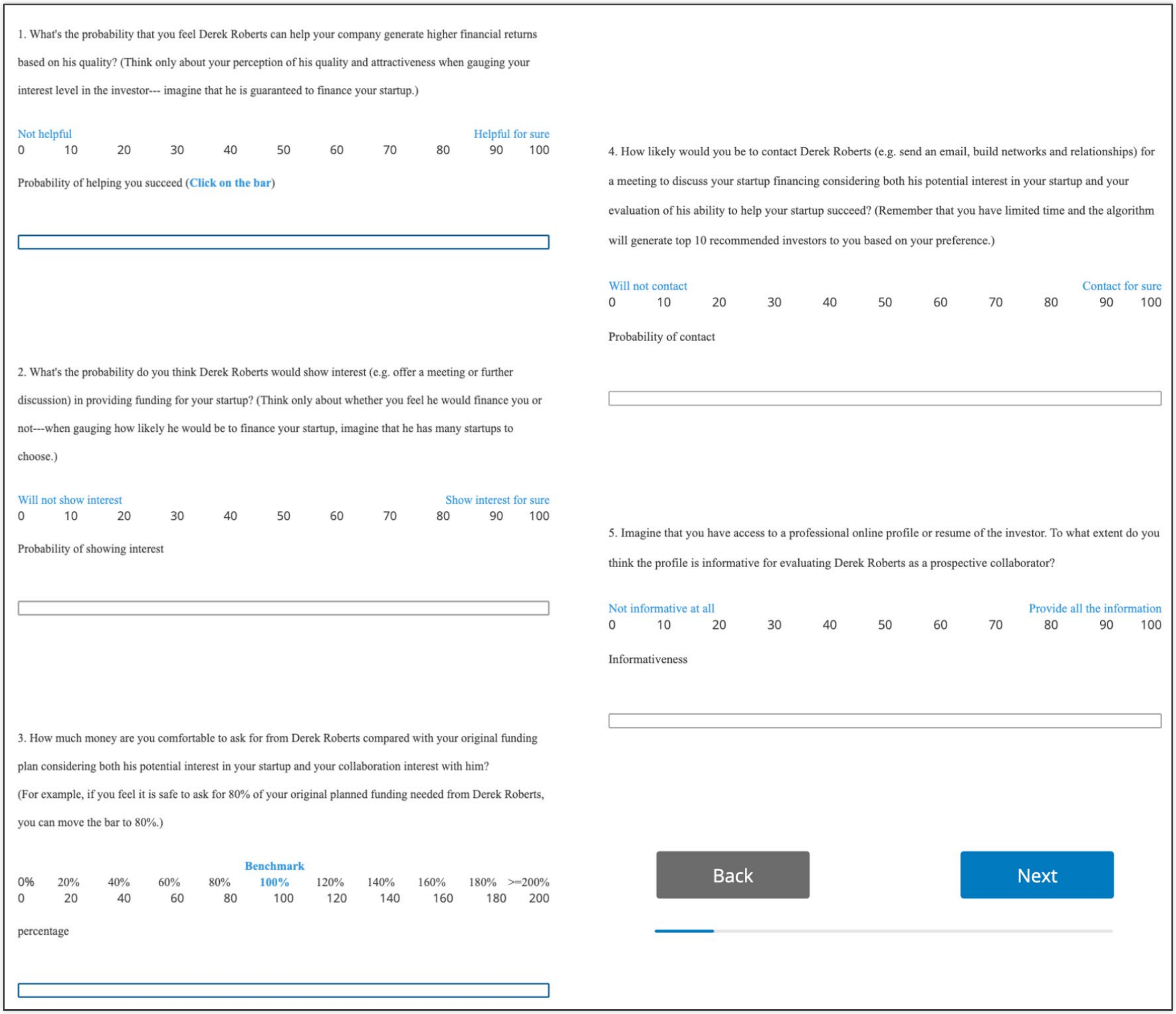
U.S.

Notes:

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

Notes: An example investor profile in the startup experiment.

Appendix Figure 3. Startup Experiment: Profile Evaluation Interface



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

Not helpful — Helpful for sure
0 10 20 30 40 50 60 70 80 90 100

Probability of helping you succeed (**Click on the bar**)

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

Will not show interest — Show interest for sure
0 10 20 30 40 50 60 70 80 90 100

Probability of showing interest

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

Benchmark
0% 20% 40% 60% 80% **100%** 120% 140% 160% 180% >=200%
0 20 40 60 80 100 120 140 160 180 200

percentage

4. How likely would you be to contact Derek Roberts (e.g. send an email, build networks and relationships) for a meeting to discuss your startup financing considering both his potential interest in your startup and your evaluation of his ability to help your startup succeed? (Remember that you have limited time and the algorithm will generate top 10 recommended investors to you based on your preference.)

Will not contact — Contact for sure
0 10 20 30 40 50 60 70 80 90 100

Probability of contact

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

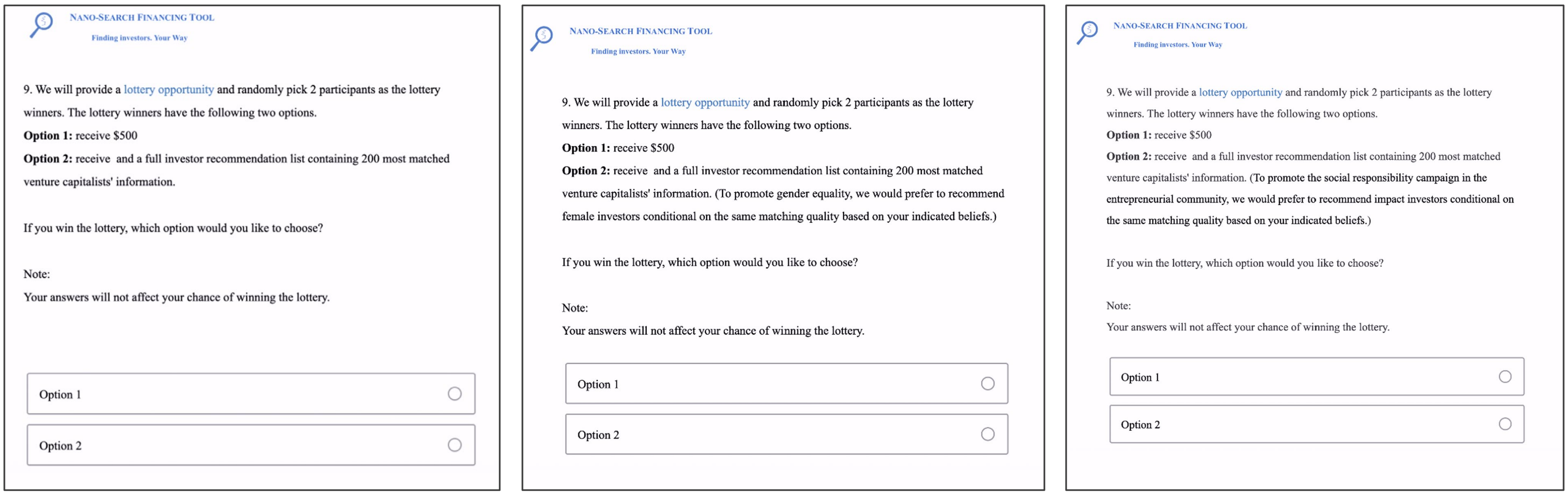
Not informative at all — Provide all the information
0 10 20 30 40 50 60 70 80 90 100

Informativeness

Back Next

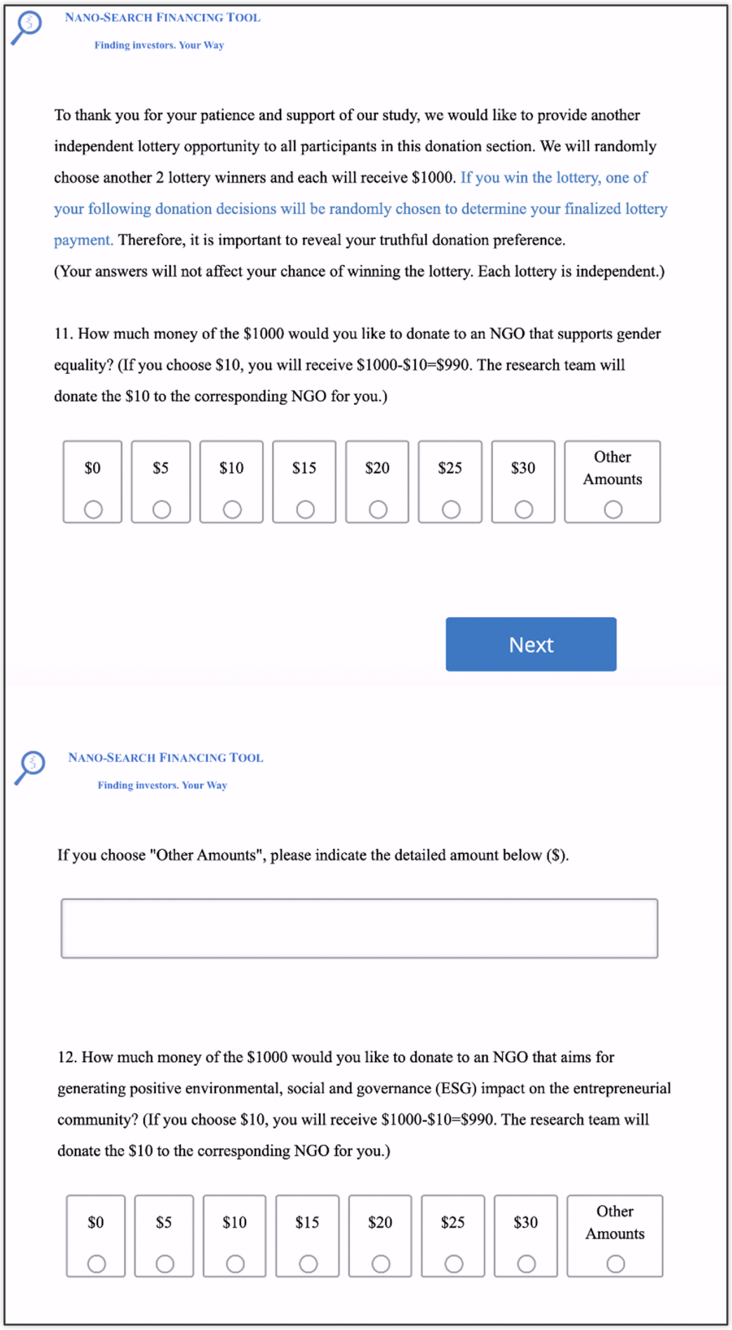
Notes: An example user interface from the profile evaluation module of the startup experiment.

Appendix Figure 4. Startup Experiment: Willingness-to-Pay Experiment Interface



Notes: An example user interface from the willingness-to-pay module of the startup experiment.

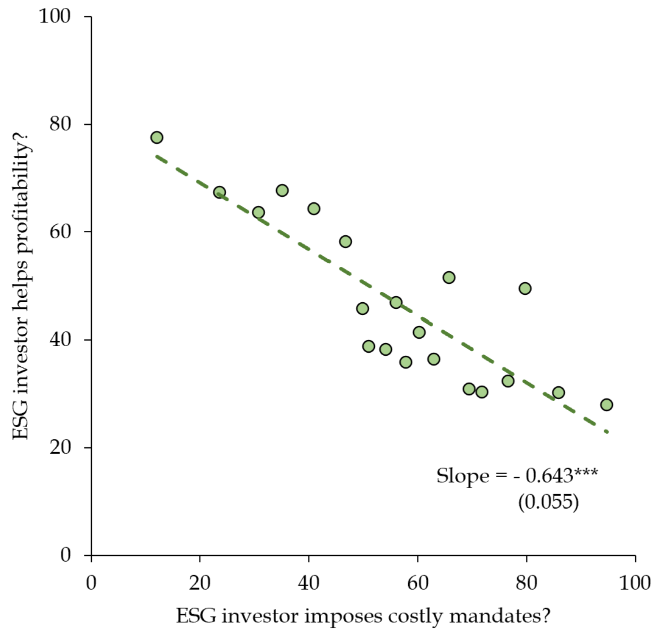
Appendix Figure 5. Startup Experiment: Donation Interface



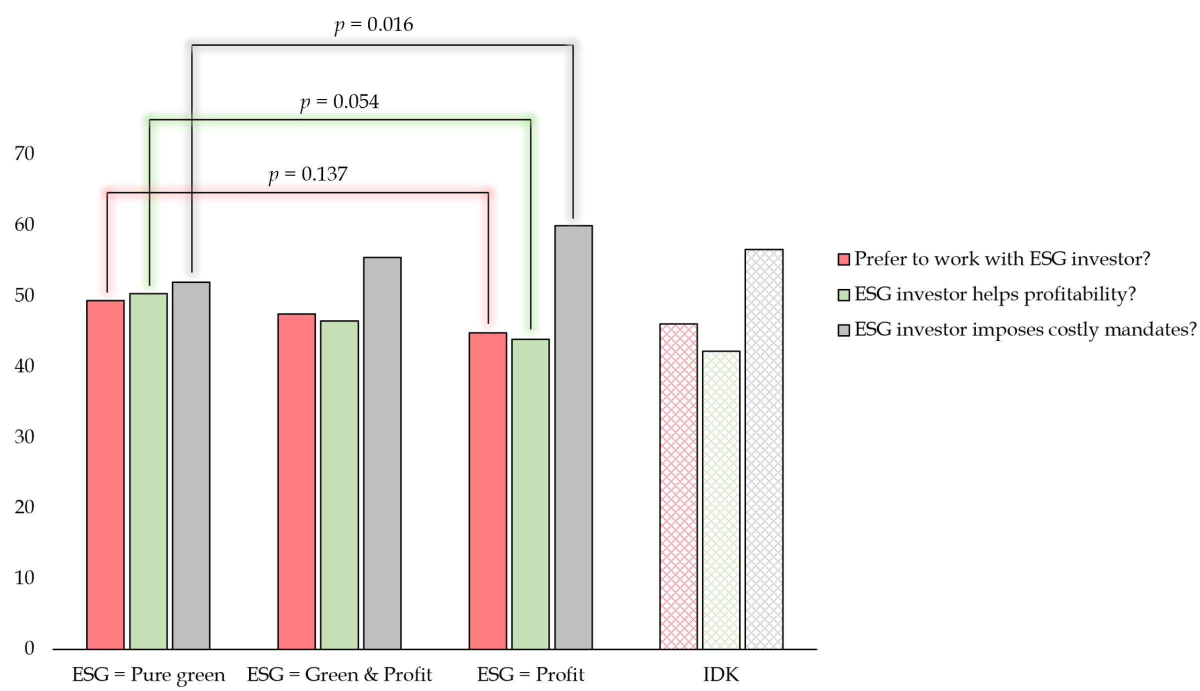
Notes: An example user interface from the donation module of the startup experiment.

Appendix Figure 6. Complementary Startup Survey:
What Drives Profitability Concerns towards ESG Investors?

(a) Association between Profitability Ratings vs Green Mandate Cost Ratings

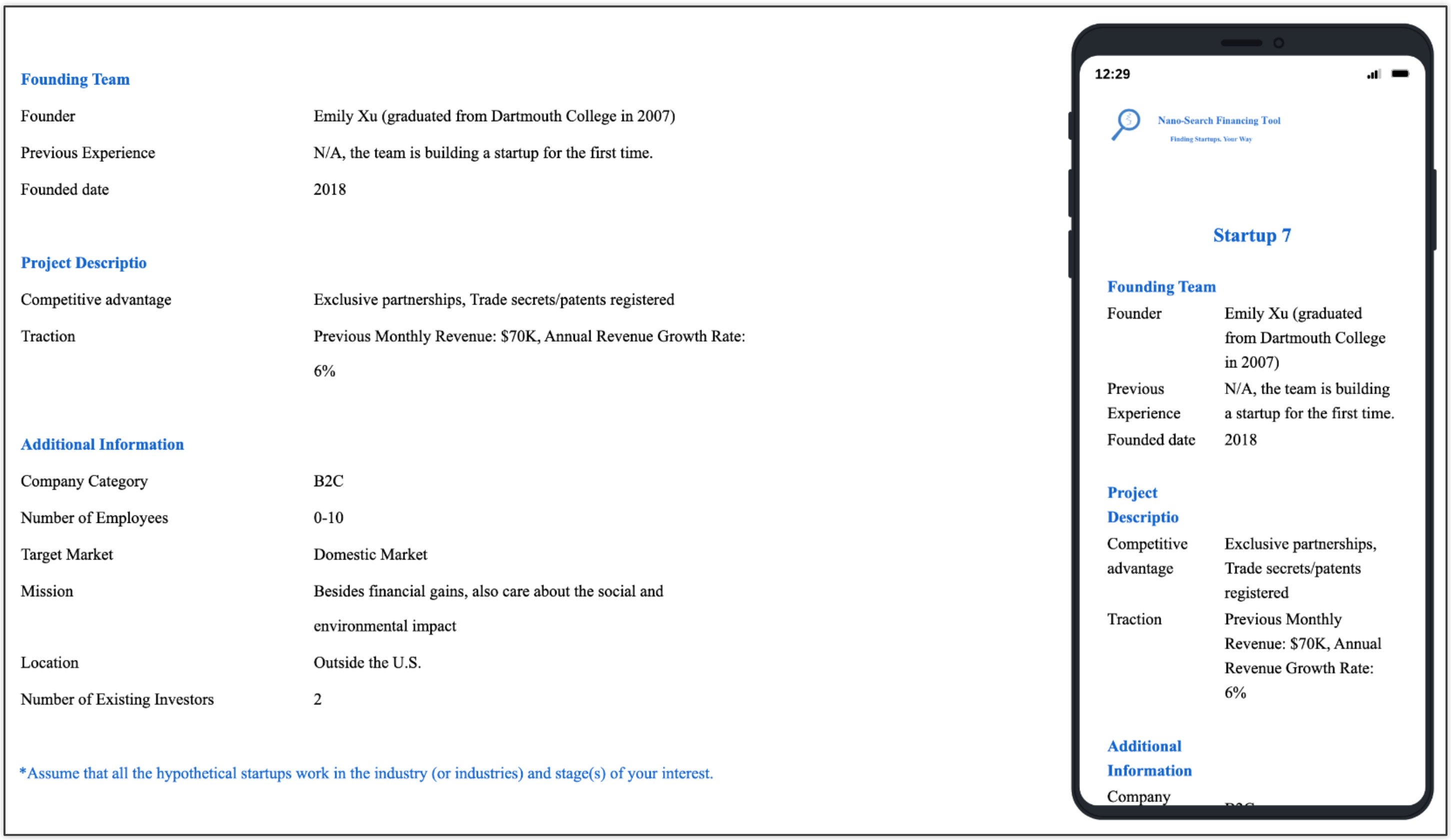


(b) Performance Ratings by ESG Motivation Beliefs



Notes: Panel (a) reports a ventile binscatter plot between startup respondents' rating of ESG investor profitability and mandate cost. "Slope" reports OLS regression coefficient with robust standard error. Panel (b) shows average collaboration intent, profitability, and cost ratings, grouped by respondents' beliefs about whether ESG investors are motivated by environmental goals ("Pure Green"), a combination of environmental goals and profit ("Green & Profit"), profit alone ("Profit"), or whether the respondent is uncertain ("IDK").. "*p*" values are two sample t-test significance levels.

Appendix Figure 7. VC Investor Experiment: Example Startup Profile



Founding Team

Founder	Emily Xu (graduated from Dartmouth College in 2007)
Previous Experience	N/A, the team is building a startup for the first time.
Founded date	2018

Project Descriptio

Competitive advantage	Exclusive partnerships, Trade secrets/patents registered
Traction	Previous Monthly Revenue: $70K, Annual Revenue Growth Rate: 6%

Additional Information

Company Category	B2C
Number of Employees	0-10
Target Market	Domestic Market
Mission	Besides financial gains, also care about the social and environmental impact
Location	Outside the U.S.
Number of Existing Investors	2

*Assume that all the hypothetical startups work in the industry (or industries) and stage(s) of your interest.

Notes: An example startup profile in the VC investor experiment.

Appendix Figure 8. VC Investor Experiment: Profile Evaluation Interface

Notes: An example user interface from the profile evaluation module of the VC investor experiment.

Appendix Figure 9. VC Investor Experiment: Willingness-to-Pay Experiment Interface

12. We will provide a lottery opportunity and randomly pick 1 participant as the lottery winners. The lottery winners have the following two options.

Option 1: receive $1000
Option 2: receive ${e://Field/residue} and a matching service that keeps recommending startups from partner incubators to your firm.

If you win the lottery, which option would you like to choose?

Note:
Your answers will not affect your chance of winning the lottery.

○ Option 1
○ Option 2

---

12. We will provide a lottery opportunity and randomly pick 1 participant as the lottery winners. The lottery winners have the following two options.

Option 1: receive $1000
Option 2: receive ${e://Field/residue} and a matching service that keeps recommending startups from partner incubators to your firm (However, we will prioritize recommending startups focused on environmental and social impact, provided that the matching quality is comparable.)

If you win the lottery, which option would you like to choose?

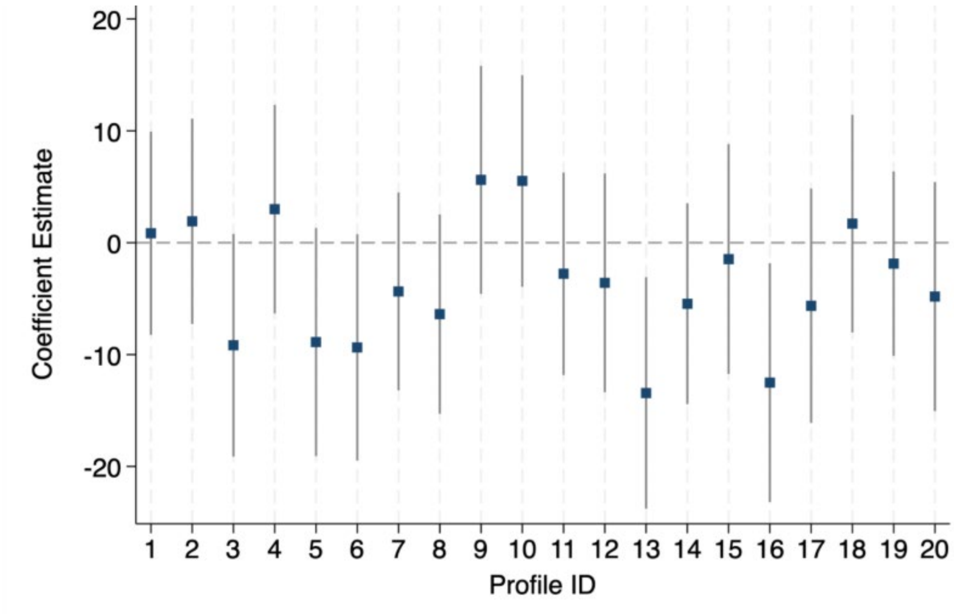
Note:
Your answers will not affect your chance of winning the lottery.

○ Option 1
○ Option 2

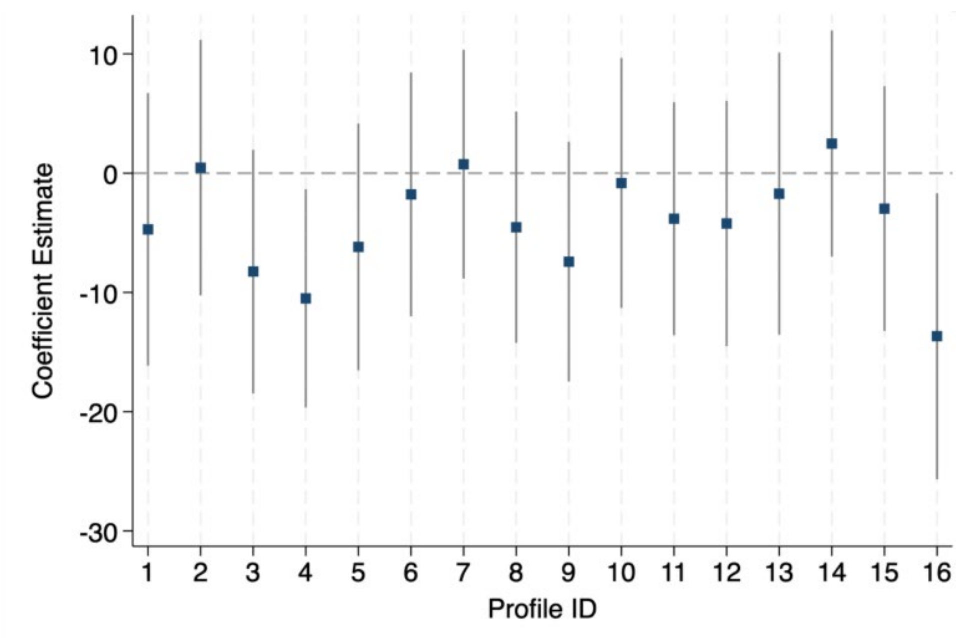
Notes: An example user interface from the willingness-to-pay experiment module of the VC investor experiment.

Appendix Figure 10. The Effect of ESG Profiles on Contact Interest across Profile Orders

(a) Startup Experiment: Impact of Environmental Investors



(b) VC Investor Experiment: : Impact of ESG Startups



Notes: Each panel plots the estimated effect of ESG attributes on contact interest by the order in which profiles were rated. In panel (a), "Profile ID = 1" corresponds to the first investor profile evaluated by each participant in the startup experiment; panel (b) presents the analogous specification for the VC investor experiment. Each dot represents the coefficient estimate of the Environmental indicator (panel a) and ESG indicator (panel b) for a given profile order, and vertical bars denote 95% confidence intervals.

Appendix Table 1. Descriptions of VCs' Investment Philosophies

Fund type	Description
Profit-driven investors	▪ We maximize our efforts and financial performances when we find extraordinary people, companies, and ideas. ▪ We have an established track record of success building strong companies. ▪ We believe our leadership makes us uniquely suited to deliver a better, fairer, and faster IPO. ▪ We exist to inspire business leaders and innovators to help them generate excellent financial performance. ▪ We have the ability to think strategically around how you position the business for further growth and fundraising rounds. ▪ We aim to support great entrepreneurs throughout different stages of faster growth. ▪ We partner with entrepreneurs to transform their ideas into world-changing companies and achieve great financial performance. ▪ We are a venture capital firm, enabling startups that grow faster and stronger. ▪ We are as ambitious as our founders and know winning requires passion. We aim to build iconic companies that make history. ▪ We remain committed to our existing portfolio companies as they work toward great success. ▪ We aim to preserve legacy and improve our portfolio companies' financial performance, making us a preferred partner for founders who are interested in faster growth. ▪ We help to build iconic companies with faster IPO speed. ▪ We are a VC firm helping companies and businesses grow faster. ▪ We help insightful companies build solid foundations for great success and faster growth. ▪ We help founders develop their businesses at every stage of growth and aim to achieve great success. ▪ We back ambitious founders and help their startups to thrive. ▪ We maximize our financial performance by building the next generation of transformative companies. ▪ We'll do everything we can to help you rapidly scale. ▪ We help our portfolio companies to be operationally excellent to drive faster growth and great success. ▪ We target startups with amazing products/services, and help them scale rapidly.

Notes: This table provides the selected wording that describes investment philosophies of different types of VCs. In our experiment, each part of a description is dynamically populated from a pool of options via Javascript.

Appendix Table 1 (cont.). Descriptions of VCs' Investment Philosophies

Fund type	Description
ESG investors	▪ We combine good financial performance with environmental and social targets, while taking into account the principles of good corporate governance. ▪ We have been investing to generate social and environmental impact alongside a healthy financial return. ▪ We are a leading impact investment fund. Our investments are guided by the conviction that creating positive, sustainable impact can go hand-in-hand with delivering market rate, risk-adjusted returns for our investors. ▪ As a pioneering impact investor, we are dedicated to generating lasting positive impact for communities and the environment. ▪ We support founders who innovate, considering social and environmental impact to be a foundation of the company, a part of its DNA, to deliver scalable social and environmental impact. ▪ We provide startups access to essential capital and services to achieve positive environmental and social impact. ▪ We support sustainable economic growth, regional development, secure employment and aim for positive social and environmental impact. ▪ Through the use of tailored financing alternatives, we support exceptional impact-driven entrepreneurs who are able to create innovative, self-sustaining, and scalable business models to address the most pressing social and environmental challenges. ▪ We invest in transformational companies that address key problems in environmental and social issues. ▪ We are a fund manager that specializes in sustainable and impact investing. We aim to generate attractive risk-adjusted financial returns for our investors alongside measurable positive social and/or environmental impact.

Notes: This table provides the selected wording that describes investment philosophies of different types of VCs. In our experiment, each part of a description is dynamically populated from a pool of options via Javascript.

Appendix Table 1 (cont.). Descriptions of VCs' Investment Philosophies

Fund type	Description
Environmental investors	▪ We invest in breakthrough venture companies developing solutions addressing our global environmental challenges. ▪ We are a venture capital fund that invests in start-ups that generate positive environmental impact. ▪ Our fund was founded with the recognition that sustainability is becoming central to consumer and business decision-making. For over a decade, we have partnered with high quality management teams building a more environmentally sound, resource-efficient future. ▪ At our fund, we're enabling the mitigation of climate change and environmental crisis through groundbreaking innovations. ▪ We exist for more than returns, and our mission is to develop the world's most environment-friendly, sustainable, inclusive, and mission-driven ecosystem. ▪ We support companies from start-up to scale-up with a special focus on positive environmental impact. ▪ We provide tailored equity and mezzanine impact financing to environment-friendly startups that also deliver solid financial returns to investors. ▪ We are a team of impact venture builders dedicated to supporting the people and ideas that turn existing environmental challenges into de-carbonized solutions. ▪ We are an impact VC fund supporting impact ventures that also deliver decent risk adjusted financial returns. ▪ We're forward-thinking industry leaders dedicated to making a global impact by providing innovative financial solutions to solve climate change and other environmental challenges.

Notes: This table provides the selected wording that describes investment philosophies of different types of VCs. In our experiment, each part of a description is dynamically populated from a pool of options via Javascript.

Appendix Table 1 (cont.). Descriptions of VCs' Investment Philosophies

Fund type	Description
Social investors	▪ We work to address social and economic inequity through new financial solutions that help empower people, build sustainable communities, and inspire systemic change. ▪ We are committed to making communities work for all people. We bring financial and analytical tools to partnerships that work to ensure that everyone has access to essential opportunities. ▪ We are a pioneering VC firm that delivers positive social and financial value. Our mission is to deliver attractive social and financial returns to our investors by investing in companies improving livelihood. ▪ We are a proven market leader in the global impact investing industry that invests to connect capital with the communities that need it most. ▪ We provide critical growth capital to innovative, high-impact, scalable businesses that are addressing the challenges faced by low-income communities, creating an opportunity to achieve significant impact while achieving risk-adjusted financial returns for investors. ▪ We invest in growing social innovation startups and deliver capacity-building support; efforts that support our work to build a foundation of equity, inclusiveness, and cooperation for communities. ▪ We invest in overlooked startups in sectors, industries, and communities that can transform the future value we seek. We envision a world with decreased gender-based violence and sexism, racial prejudice and xenophobia, class and status segregation, and exploitative business practices. ▪ We are an impact investment firm. Our mission is to mobilize massive amounts of capital that will build a foundation of equity, inclusiveness, and cooperation for communities. ▪ We are a pioneer and leading impact-investing manager, delivering competitive returns alongside positive social impact. ▪ We are an institutional impact investment manager that provides capital to demonstrate and scale responsible innovation in lending for underserved communities.

Notes: This table provides the selected wording that describes investment philosophies of different types of VCs. In our experiment, each part of a description is dynamically populated from a pool of options via Javascript.

Appendix Table 1 (cont.). Descriptions of VCs’ Investment Philosophies

Fund type	Description
Governance investors	▪ We are a fund manager in support of driving capital to high-growth companies with women leaders. ▪ We are an impact investment platform that uses technology to unlock diversified and proven community investments that generate economic mobility and financial inclusion. ▪ We implement gender programmes to bring women into C-Suite and ownership during our investment in startups. ▪ We are a pioneer and leading impact-investing manager, delivering competitive returns alongside positive social impact. ▪ We are an institutional impact investment manager that provides capital to demonstrate and scale responsible innovation in lending for underserved communities.

Notes: This table provides the selected wording that describes investment philosophies of different types of VCs. In our experiment, each part of a description is dynamically populated from a pool of options via Javascript.

Appendix Table 2. Startup Experiment: Participating Startups' Background

	(1) Main experiment sample	(2) Crunchbase replication sample	(3) Crunchbase startup universe
Industry			
Information technology	0.220	0.615	0.439
Healthcare	0.061	0.200	0.143
Consumers	0.286	0.154	0.153
Finance	0.130	0.139	0.115
Education	0.039	0.062	0.063
Manufacture & construction	0.167	0.031	0.052
Transportation & logistics	0.056	0.031	0.042
Clean technology	0.054	0.031	0.026
Media	0.054	0.015	0.163
Life sciences	0.020	0.015	0.046
Energy	0.039	0.015	0.024
Others	0.227	-	-
Founder			
Male founder	0.592	0.892	0.847
Minority founder	0.223	0.400	0.373
Serial founder	0.411	0.723	-
Bachelor's degree	0.333	0.477	-
Democratic party	0.504	0.369	-
Republican party	0.240	0.108	-
Stage			
Seed (developing products)	0.223	0.169	-
Seed (mature products, no revenue)	0.284	0.369	-
Seed (mature products, revenue)	0.386	0.385	-
Series A	0.042	0.046	-
Series B	0.029	0.031	-
Size			
≤ 5 employees	0.467	0.554	-
6-20 employees	0.154	0.339	-
21-50 employees	0.164	0.108	-
51-100 employees	0.120	-	-
>100 employees	0.095	-	-
Philosophy			
Financial gains	0.880	0.923	-
Promote diversity	0.592	0.592	-
ESG criteria	0.638	0.246	-
Observations	409	65	3,000

Notes: This table summarizes startup characteristics across the main experiment sample (Column 1), the Crunchbase replication sample (Column 2), and the broader Crunchbase startup universe (Column 3). Numbers represent fraction.

Appendix Table 3. Willingness-to-Pay Experiment Results: WTP for ESG Recommendation

	(1)	(2)
Dependent variable:	**1**(Pay for recommendation list)	
A. Startup Experiment		
1(Female-preferred list)	0.257	0.172
	(0.243)	(0.264)
1(ESG-preferred list)	0.571**	0.629**
	(0.243)	(0.272)
Price	-0.0051	-0.0101*
	(0.0056)	(0.0060)
Control group mean	0.44	0.44
Other characteristics controls	No	Yes
Observations	409	409
B. Investor Experiment		
1(ESG-preferred list)	1.008*	1.126*
	(0.593)	(0.655)
Price	-0.0054*	-0.0043
	(0.0029)	(0.0035)
Control group mean	0.24	0.24
Other characteristics controls	No	Yes
Observations	59	59

Notes: This table estimates startup founders and VC investors' willingness to pay for contact information for additional matched ESG collaborators based on a discrete choice model. The dependent variable is an indicator that equals one if the experimental participant chooses to pay for a comprehensive list, and zero if the participant chooses to receive all the monetary award from the lottery rather than purchasing a comprehensive list. "**1**(Female-preferred list)" is a dummy variable that indicates if the participant's offer is to receive more female investors' contact information. "**1**(ESG-preferred list)" indicates offers that receive more ESG investors' contact information (in the startup experiment) and more ESG startups' recommendations (in the VC investor experiment). "Price" is randomly generated. Robust standard errors are reported in parentheses. ∗: $p < 0.10$, ∗∗: $p < 0.05$, ∗∗∗: $p < 0.01$.

Appendix Table 4. Correlation between Startup Founder's Donation Behavior and Experimentally Elicited ESG Attitude

	(1)	(2)	(3)	(4)
Dependent variable:	**1**(Donation)			
Contact interest-ESG elasticity	0.002**	0.010**		
	(0.001)	(0.005)		
1(>Median contact interest-ESG elasticity)			0.084***	0.407***
			(0.031)	(0.150)
Specification	OLS	Probit	OLS	Probit
Observations	474	474	474	474

Notes: This table presents the relationship between startup founders' attitudes toward VCs' ESG characteristics and their anonymous donation behaviors in the donation module. The sample includes participants from both the main experiment and the replication experiment. The dependent variable is a binary indicator equal to one if founders choose to donate their experiment reward. For each founder, "Contact interest-ESG elasticity" is the β^{ESG} coefficient from equation (5), estimated individually for that founder. "1(>Median contact interest-ESG elasticity)" indicates founders with above median β^{ESG} estimates.

Appendix Table 5. VC Investor Experiment: Participating Investors' Background

	(1) Experiment sample	(2) Pitchbook universe
Industry		
Information technology	0.597	0.583
Healthcare	0.302	0.221
Consumers	0.256	0.284
Finance	0.194	0.097
B2B	0.155	0.085
Energy	0.101	0.159
Life sciences	0.085	0.099
Media	0.070	0.080
Transportation & logistics	0.054	0.057
Education	0.047	0.022
Others	0.163	0.128
Investor		
Male founder	0.79	0.76
Minority founder	0.36	0.43
Serial investor	0.83	0.80
Stage		
Seed	0.729	0.419
Series A	0.690	0.318
Series B	0.279	0.150
Financial Information		
Total active portfolio	41.72	21.16
	[46.22]	[47.71]
Total exits	35.87	22.75
	[54.46]	[57.07]
AUM (million $)	5,766.0	2,419.2
	[40,236]	[30,574]
Dry powder (million $)	168.22	137.54
	[349.70]	[615.08]
Observations	129	5,015

Notes: This table summarizes VC investor characteristics across the recruited experiment sample (Column 1), and the Pitchbook universe (Column 2). Numbers in Industry, Investor, and Stage panels represent fractions. Numbers in Financial Information panel shows mean and standard deviation in brackets.

Appendix Table 6. Startup Experiment Profile Evaluation Results: Robustness

	(1)	(2)	(3)	(4)	(5)
Dependent variable:	Contact Interest	Funding Amount	Profit-ability	Avail-ability	Informa-tiveness
			A. Exclude First-Time VCs		
1(ESG investor)	-1.64*	-0.72	-1.46*	-1.47*	0.03
	(0.92)	(1.21)	(0.85)	(0.86)	(0.68)
1(E investor)	-4.44***	-3.76**	-3.43**	-3.91***	-1.10
	(1.13)	(1.52)	(1.07)	(1.03)	(0.80)
1(S investor)	1.49	0.46	0.09	0.81	1.26*
	(0.95)	(1.29)	(0.93)	(0.86)	(0.70)
1(G investor)	-0.56	-1.44	-1.11	-1.01	-0.20
	(1.03)	(1.44)	(0.95)	(0.95)	(0.81)
Control group mean	60.5	90.4	63.3	59.7	66.9
Observations	6,544	6,544	6,544	6,544	6,544
			B. Exclude Small VC Funds		
1(ESG investor)	-1.41	-1.16	-1.71	-0.92	0.94
	(1.14)	(1.65)	(1.05)	(1.04)	(0.82)
1(E investor)	-3.25**	-2.75	-3.35**	-3.53**	-1.46
	(1.28)	(1.96)	(1.26)	(1.18)	(1.04)
1(S investor)	0.39	-1.06	-1.22	0.22	0.71
	(1.26)	(1.77)	(1.14)	(1.15)	(0.96)
1(G investor)	0.31	-1.26	-1.63	-1.01	0.51
	(1.30)	(1.92)	(1.16)	(1.18)	(0.98)
Control group mean	61.0	91.2	64.3	60.1	67.2
Observations	4,069	4,069	4,069	4,069	4,069

Notes: This table presents estimation results for the startup experiment excluding profiles that feature first-time VCs (Panel A) and small VC funds (Panel B). Each column corresponds to a separate regression of an evaluation outcome on treatment assignment dummies. All regressions include participant fixed effects, with standard errors clustered at the participant level. $*$: $p < 0.10$, $**$: $p < 0.05$, $***$: $p < 0.01$.

Appendix Table 7. VC Investor Experiment Profile Evaluation Results: Robustness

	(1)	(2)	(3)	(4)	(5)
Dependent variable:	Contact Interest	Funding Amount	Profit-ability	Avail-ability	Informa-tiveness
A. Exclude Startup Founders without Prior Entrepreneurial Experience					
1(ESG startup)	-5.30**	-9.55***	-5.59***	-4.65***	-4.05***
	(2.12)	(3.03)	(1.69)	(1.18)	(1.34)
Control group mean	65.4	73.3	56.6	64.3	67.1
Observations	899	885	889	889	477
B. Exclude Startups without Revenue					
1(ESG startup)	-3.87**	-4.35	-3.02**	-4.35***	-3.39***
	(1.79)	(3.03)	(1.48)	(1.16)	(0.90)
Control group mean	67.9	75.8	58.7	65.7	71.9
Observations	908	895	908	896	469

Notes: This table presents estimation results for the VC investor experiment excluding profiles that feature startup founders with no prior entrepreneurial experience (Panel A) and those without revenue (Panel B). Each column corresponds to a separate regression of an evaluation outcome on treatment assignment dummy. All regressions include participant fixed effects, with standard errors clustered at the participant level. $*$: $p < 0.10$, $**$: $p < 0.05$, $***$: $p < 0.01$.

Appendix Table 8. Startup Experiment Profile Evaluation Results: Sequential Dependence

	(1)	(2)	(3)	(4)	(5)
Dependent variable:	Contact Interest	Funding Amount	Profit-ability	Avail-ability	Informa-tiveness
1(ESG investor)	-1.16	-0.64	-1.16	-1.52	-0.58
	(1.06)	(1.51)	(0.94)	(0.94)	(0.79)
1(E investor)	-2.45*	-0.96	-3.07**	-2.03	-1.47
	(1.41)	(1.90)	(1.30)	(1.27)	(1.04)
1(S investor)	1.65	-0.65	0.40	0.85	0.51
	(1.26)	(1.79)	(1.23)	(1.17)	(1.03)
1(G investor)	0.01	-0.77	-1.37	-1.53	0.24
	(1.40)	(1.92)	(1.29)	(1.33)	(1.02)
1(ESG investor) × After non-ESG profile	-0.40	-0.14	-0.43	0.55	1.44
	(1.26)	(1.91)	(1.21)	(1.15)	(1.06)
1(E investor) × After non-ESG profile	-1.86	-3.81	-0.13	-2.74	1.32
	(1.91)	(2.48)	(1.78)	(1.77)	(1.57)
1(S investor) × After non-ESG profile	-0.60	2.04	0.05	0.19	1.16
	(1.68)	(2.49)	(1.62)	(1.56)	(1.41)
1(G investor) × After non-ESG profile	0.07	0.88	1.29	1.54	0.72
	(1.77)	(2.51)	(1.73)	(1.70)	(1.44)
After non-ESG profile	0.97	0.56	0.30	0.49	-0.45
	(0.70)	(0.99)	(0.68)	(0.61)	(0.63)
Observations	7,771	7,771	7,771	7,771	7,771

Notes: Each column corresponds to a separate regression of an evaluation outcome on treatment assignment dummies. "After non-ESG profile" is a dummy variable which is equal to 1 if the previous profile is profit-driven investors, and 0 otherwise. All regressions include participant fixed effects, with standard errors clustered at the participant level. $*$: $p < 0.10$, $**$: $p < 0.05$, $***$: $p < 0.01$.

Appendix Table 9. VC Investor Experiment Profile Evaluation Results: Sequential Dependence

	(1)	(2)	(3)	(4)	(5)
Dependent variable:	Contact Interest	Funding Amount	Profit-ability	Avail-ability	Informa-tiveness
1(ESG startup)	-2.47	-0.84***	-5.10***	-1.84	-6.49***
	(1.93)	(0.32)	(1.90)	(1.27)	(2.00)
1(ESG startup) × After non-ESG profile	-1.52	0.46	0.47	-3.11**	4.35*
	(2.50)	(0.38)	(2.21)	(1.29)	(2.24)
After non-ESG profile	2.39	-0.01	1.68	1.02	-1.18
	(1.62)	(0.28)	(1.35)	(0.76)	(1.34)
Observations	1,742	1,712	1,742	1,718	885

Notes: Each column corresponds to a separate regression of an evaluation outcome on treatment assignment dummy. "After non-ESG profile" is a dummy variable which is equal to 1 if the previous profile is profit-driven startups, and 0 otherwise. All regressions include participant fixed effects, with standard errors clustered at the participant level. ∗: $p < 0.10$, ∗∗: $p < 0.05$, ∗∗∗: $p < 0.01$.

Appendix Table 10. Correlation between Startup Founder's Real-world Fundraising Behavior and Experimentally Elicited ESG Attitude

	(1)	(2)	(3)
Dependent variable:	**1**(Raised $ from ESG investors)	**1**(Raised $ from E investors)	**1**(Raised $ from S investors)
Contact interest-ESG elasticity	0.0066***		
	(0.0023)		
Contact interest-E elasticity		0.0053**	
		(0.0024)	
Contact interest-S elasticity			0.0066**
			(0.0023)
Observations	43	43	43

Notes: This table presents the relationship between startup founders' attitudes toward VCs' ESG characteristics and their real-world fundraising behavior. The sample includes participants from the replication (Crunchbase) experiment where we can track real-world fundraising outcomes. For each founder, "Contact interest-ESG/E/S elasticity" is the $\beta^{ESG}/\beta^{E}/\beta^{S}$ coefficient from equation (5), estimated individually for that founder.

Appendix Table 11. Correlation between VC Investor's Real-world Investment Behavior and Experimentally Elicited ESG Attitude

	(1)	(2)
Dependent variable:	**1**(Invest in ESG startups)	**1**(Invest in ESG startups)
Contact interest-ESG elasticity	0.0076**	0.0062**
	(0.0026)	(0.0028)
Controls	No	Yes
Observations	129	129

Notes: This table presents the relationship between VC investor's attitudes toward startups' ESG characteristics and their real-world investment behavior. "1(Invest in ESG startups)" equals 1 if the participant's affiliated VC firm had made investments in ESG-focused startup based on Pitchbook data. For each investor, "Contact interest-ESG elasticity" is the β^{ESG} coefficient from equation (7), estimated individually for that investor.

Appendix Table 12. Profile Evaluation Results: Multiple Hypothesis Testing Adjustments

	(1)	(2)	(3)	(4)	(5)
Dependent variable:	Contact Interest	Funding Amount	Profit-ability	Avail-ability	Informa-tiveness
Reported statistics:	β/(se) [WY-*p*]	β/(se) [WY-*p*]	β/(se) [WY-*p*]	β/(se) [WY-*p*]	β/(se) [WY-*p*]
			A. Startup Experiment		
1(E investor)	-3.47	-2.80	-3.17	-3.40	-0.90
	(0.98)	(1.34)	(0.94)	(0.90)	(0.70)
	[<0.01]	[0.019]	[<0.01]	[<0.01]	[0.175]
Control group mean	60.4	90.3	63.3	59.5	66.9
Observations	8,180	8,180	8,180	8,180	8,180
			B. VC Investor Experiment		
1(ESG startup)	-3.12	-4.60	-4.34	-3.79	-2.93
	(1.45)	(0.19)	(1.07)	(0.86)	(0.88)
	[0.029]	[0.029]	[<0.01]	[<0.01]	[<0.01]
Control group mean	60.7	67.3	52.7	65.1	64.2
Observations	1,856	1,826	1,856	1,832	944

Notes: This table presents main estimation results for the startup experiment (Panel A) and the VC investor experiment (Panel B). Each column corresponds to a separate regression of an evaluation outcome on treatment assignment dummies. All regressions include participant fixed effects (startup founders in Panel A and VC investors in Panel B), with standard errors clustered at the participant level. Family-wise adjusted p-values based on the step-down resampling procedure of Westfall and Young (1993) are in brackets.

Appendix Table 13. Profile Evaluation Results: ESG Demand and Beliefs
Startup Experiment, Replication Sample

	(1)	(2)	(3)	(4)	(5)
Dependent variable:	Contact Interest	Funding Amount	Profit-ability	Avail-ability	Informa-tiveness
1(ESG investor)	-4.69	-9.45***	-5.49**	-5.62*	-2.15
	(3.11)	(3.43)	(2.64)	(2.92)	(2.34)
1(E investor)	-13.74***	-15.75***	-13.47***	-14.05***	-7.85**
	(3.60)	(4.20)	(3.21)	(3.47)	(2.96)
1(S investor)	-11.69***	-11.84***	-9.99***	-11.41***	-6.62**
	(3.17)	(3.59)	(2.80)	(2.89)	(2.79)
1(G investor)	-15.59***	-13.54***	-12.43***	-14.59***	-8.50**
	(3.61)	(3.91)	(3.55)	(3.43)	(3.22)
Observations	1,300	1,300	1,300	1,300	1,300

Notes: This table presents replication estimation results for the startup experiment. Each column corresponds to a separate regression of an evaluation outcome on treatment assignment dummies. All regressions include participant fixed effects, with standard errors clustered at the participant level. ∗: $p < 0.10$, ∗∗: $p < 0.05$, ∗∗∗: $p < 0.01$.

Appendix Table 14. Willingness-to-Pay Experiment Results: Taste for ESG Startup Experiment, Replication Sample

	(1)	(2)	(3)	(4)
Dependent variable:	**1**(Pay for recommendation list)			
1(Female-preferred list)	0.19	0.16	0.59	0.54
	(0.13)	(0.14)	(0.41)	(0.45)
1(ESG-preferred list)	0.26**	0.26**	0.93**	1.00**
	(0.13)	(0.13)	(0.47)	(0.49)
Specification	Linear	Linear	Probit	Probit
Other characteristics controls	No	Yes	No	Yes
Observations	65	65	65	65

Notes: This table tests whether startup founders are more willing to pay for contact information for additional matched ESG investors from the Crunchbase replication sample. The dependent variable is an indicator that equals one if the experimental participant chooses to pay for a comprehensive list, and zero if the participant chooses to receive all the monetary award from the lottery rather than purchasing a comprehensive list. "**1**(Female-preferred list)" is a dummy variable that indicates if the participant's offer is to receive more female investors' contact information. "**1**(ESG-preferred list)" indicates offers that receive more ESG investors' contact information. Robust standard errors are reported in parentheses. ∗: $p < 0.10$, ∗∗: $p < 0.05$, ∗∗∗: $p < 0.01$.