How Venture Capitalists and Startups Bet on Each Other: Evidence From an Experimental System*

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Abstract

We employ a dynamic search-and-matching model with bargaining between venture capitalists (VCs) and startups, utilizing two symmetric incentivized resume rating (IRR) experiments involving real US VCs and startups, to explain the matching outcome in the US entrepreneurial finance industry. Participants evaluate randomized profiles of potential collaborators, incentivized by the real opportunities for preferred cooperative partnerships. Using these experimental behaviors and real-world portfolio data as inputs to our structural estimation, we identify a significant impact of various human and non-human traits on equilibrium continuation values, matching likelihoods, and payoffs from matching for both startups and VCs. These traits include startups' human assets (i.e., educational background, entrepreneurial experiences) and non-human assets (i.e., traction, business model), as well as investors' human capital (i.e., entrepreneurial experiences) and organizational capital (i.e., previous financial performance, fund size). Results show that, while the total value of matching increases, the share of a startup/VC's payoff in the total value of matching diminishes substantially (in the range of .65 to .35) when the counterparty type becomes more attractive. Ultimately, we find that variations in the matching likelihood play a dominant role in explaining how the expected payoff from collaboration varies for startups and VCs when dealing with attractive and unattractive counterparty types.

Keywords: Entrepreneurial Finance, Search and Matching, Field Experiments, Venture Capital, Entrepreneurship, Human Capital

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1 Introduction

Fostering a thriving entrepreneurial ecosystem is paramount to driving innovation in an economy. The venture capital (VC) industry plays a pivotal role by providing vital funding, mentorship, and reputation to high-impact startups (Hsu, 2004; Bernstein et al., 2016). Unlike trading stocks in the public market, securing funding from the VC industry often entails a nuanced two-sided matching process (Sørensen, 2007; Ewens et al., 2022). In this environment, a central question revolves around identifying the traits of startups and VCs that influence the matching process, and understanding how these traits impact outcomes such as the value of a match, and the split of payoff between startups and VCs in the matching market equilibrium. Gaining insights into these relevant traits and corresponding equilibrium forces would shed light on the way startups tune their fundraising strategies and VCs optimize their deal flows. In this paper, we focus on traits related to human capital and organizational capital given their notable importance in the existing literature (Kaplan et al., 2009; Bernstein et al., 2017).

Financial economists encounter empirical challenges when identifying the influential traits of startups and VCs and the corresponding implications for payoffs in the matching process. One key challenge is that standard databases only record *realized* matching pairs. However, the payoff of a startup and VC is influenced by two channels: the likelihood of making a deal and the expected payoff *conditional* on the deal being made. To illustrate the point, an attractive VC or startup type may increase the chances of forming a match by adding more value to the collaboration. At the same time, an attractive type may set higher standards and hold more bargaining power in negotiations over the payoff of the match, which limits the counterparty's payoff from the realized match. Besides the variations in payoff over realized matches, ideally, researchers would need to observe the determinants of the selection into a match. Unfortunately, such information is not available in common data sources.

To address the empirical challenges above, this paper adopts a structural estimation framework based on a search and matching model with bargaining, leveraging both experimental data and real-world portfolio data. To gain insights into the selection process of startups and VCs, we conduct two symmetric incentivized resume rating (IRR) experiments in the field, involving real US-based startup founders and VCs. The IRR experimental paradigm, developed by Kessler et al. (2019), allows us to thoroughly examine evaluators' preferences across a rich set of candidate characteristics in a high-skilled labor market. Utilizing experimental data on the perceived value and expected collaboration likelihood between match pairs with heterogeneous traits, we can identify determinants of the matching formation, the payoff generated in a match, and the split of payoff in the matching equilibrium.

In the startup-side IRR experiment, we invite about 400 real US startup founders, who are seeking funding from the VC industry, to evaluate several dimensions (i.e., ability, availability, informativeness) of more than 8000 randomly generated VC investor profiles. Recruited founders also indicate their interest in contacting each investor and fund-raising. To incentivize founders to reveal their true preferences, we collect a unique, comprehensive global individual-level VC database and develop a matching algorithm that provides a customized investor recommendation service to startup founders. Revealing truthful preferences on different investor profiles enables the algorithm to generate a list with better-matched real investors.

The experimental findings demonstrate the significant impact of both VCs' human capital and organizational capital on startups' inclination to engage in collaborative endeavors. Relevant individual-level investor characteristics (i.e., human capital) mainly include previous entrepreneurial experience and investment experience. Relevant fund-level characteristics (i.e., organizational capital) mainly include fund size and historical financial performances. Startups significantly prefer investors with entrepreneurial experience and extensive investment experience. Moreover, startups also favor investors affiliated with larger VC funds and funds that exhibit better historical financial performances. Notably, the availability of investors, indicating their potential to invest in the startup, emerges as a critical factor influencing startups' decisions regarding contact and fundraising initiatives.

In the investor-side IRR experiment, we invite about 70 real US VCs to evaluate profitability and availability of more than 1200 randomly generated startup profiles. Investors also indicate their willingness to contact and invest in each startup. To incentivize investors to reveal their true preferences, we collaborate with several real incubators and develop another matching algorithm that helps investors to match startups in these collaborating incubators. Although investors know the startup profiles are hypothetical, revealing truthful preferences on different startup profiles enables the algorithm to identify better-matched real startups and offer investors potential real-world investment opportunities. Besides the "matching incentive", we also add a complementary "monetary incentive" to a randomly selected group of investors to increase the sample size.

The experimental findings demonstrate the significant impact of both startups' human and non-human assets on early-stage VCs' inclination to engage and invest in the startup. Relevant startup team characteristics (i.e., human assets) include entrepreneurs' previous entrepreneurial experience and educational backgrounds. Relevant startup project characteristics (i.e., non-human assets) include the firm's business model and previous traction. These characteristics influence investors' decisions by affecting their judgments of startups' profitability and availability (i.e., the potential to accept the investment offer). Perceived profitability is particularly influential, impacting both the likelihood of contacting the startup and the willingness to invest.

Combining these experimental findings and VCs' real-world portfolio data, we develop and estimate a search-and-matching model that incorporates bargaining between startups and VCs with heterogeneous human and non-human traits. Time is continuous in our setup. A discrete set of startup types match with a discrete set of VC types. Startups meet VCs randomly according to a Poisson process. The meeting probability for each individual depends on the search technology and the mass of the counterparty. The matching value includes a deterministic part, which depends on both startup type and VC type, and a random shock, which is realized upon meeting for both parties. The value of a match is perfectly divisible and transferable. If the matching value surpasses the continuation values of the startup and the VC, a matching takes place and parties divide the payoff from matching according to their bargaining power and outside options. Otherwise, agents keep searching for a better match. In equilibrium, the continuation value of a startup and a VC type is endogenously determined based on the expected payoff of a party from matching, and the likelihood of forming a match—both of which depend on the endogenous continuation values of all types of startups and VCs in a recursive format.

We estimate the model using data from the IRR experiments, by categorizing startups and VCs into a set of discrete types based on the key attributes identified in the experiments. We use the profitability evaluation question (Q_1) to infer the expected matching value between different startup and VC types, and we use the question on the perceived collaboration likelihood (Q_2) to set the matching probabilities between startup and VC types. The perceived collaboration likelihood identifies the continuation values in relative terms. For example, if a startup type i considers a particular VC profile of type j as more profitable (i.e., high Q_1), a larger matching value is identified; However, if at the same time, she doesn't consider a matching to be likely to happen (i.e., low Q_2), then a relatively high outside option and continuation values is assigned to the collaboration between startup type i and VC type j. Using the administrative data from the Pitchbook on realized matches, we also estimate the underlying distribution of startup types and VC types. Combining the estimated underlying distribution and the expected values of matching, we estimate the split of surplus and equilibrium payoffs for each startup and VC type.

Our estimation discovers a substantial variation in equilibrium continuation values across startups and VCs. When using the startup-side experimental data in estimation, we find that startups with a business-to-business (B2B) model get about 25% more value relative to the reference group. The average impact of being a serial founder, and having a prestigious education on equilibrium value is also substantial, equivalent to roughly 30-35% more value. The impact of "positive traction" is, however, insignificant. When incorporating VC-side experimental results for estimating startups' continuation values, we observe that the influence of educational background on the equilibrium values of startups is less, while the impact of traction is substantial. This disparity highlights the misperception of startup types on their value. Regardless of the experimental data sources, we find that having a B2B model and being a serial founder are both determinant factors for the equilibrium values of startups. On the VC side, we find that having investors with entrepreneurial experiences and better financial performance in the past have an average positive impact of about 20% and 15% relative to the reference group. However, the impact of size is about 5% and only marginally significant. Our findings, therefore, identify a sizable impact of both human and organizational traits on the equilibrium values of startups and VCs.

These variations in the equilibrium values of startups and VCs translate into variations in the *split* of the matching payoff between the startup and VC across different deals. This is because continuation values constitute the outside option for parties involved in a given deal. In our benchmark specification, the share of the VC from the total value generated by a match varies from .65 to .35, depending on whether the startup involved is the least or most attractive type. Our result, therefore, highlights a substantial variation in the split of payoff based on the human and organizational assets of the founder and startup involved in the deal. Likewise, the share of an average startup from the value of matching decreases by approximately 10 percentage points when dealing with an attractive VC type in our setup. This observation underscores the significance of VC human and organizational capital in determining the split of payoff. While the involvement of attractive startup or VC types increases the total value generated in a match, the share of the total payoff for a startup or VC decreases when dealing with an attractive counterparty. This reduction in the share of total payoff dampens the absolute conditional payoff from matching for both startups and VCs when dealing with a counterparty type with attractive traits. Indeed, we find that the variation in the expected payoff from collaborating with different counterparty types is primarily influenced by the change in the likelihood of matching (i.e., the extensive margin), rather than the payoff conditional on matching (i.e., the intensive margin).

Our results provide novel insights into the aggregate outcomes in the entrepreneurial finance industry as well. We find that in equilibrium, a representative VC gets more continuation value than a startup. This finding stems from the experimental result that, having controlled for profitability evaluation, collaboration likelihood is revealed to be more dependent on VC attributes rather than startup attributes. Based on the model estimation, an individual VC is much more likely to find a match because the matching market is populated with much more startups than VCs. Therefore, a VC has plenty of outside options when bargaining with a startup. In counterfactual analyses, we find that doubling the number of active VCs raises the equilibrium value of an average startup by 50% and reduces the value of an individual VC by 30%. We also demonstrate that reducing the time discount factor of startups would lead to a decrease in matching frequency and an increase (decrease) in the equilibrium value of startups (VCs). In this situation, startups are more willing to wait for a better realization of matching value, which hurts VC's bargaining power in equilibrium. It should be noted that while an average VC gets more equilibrium value than an average startup in our benchmark estimations, VCs altogether get 15-25% of the present value of the generated matching surplus (depending on the specification). Startups get the majority share in sum because the environment is populated with more startups.

Lastly, we justify the external validity of our results by discussing related testable simulation outcomes. Firstly, by assuming a Cobb-Douglass production technology, we show that the expected conditional matching value across startup-VC matches estimated by the model can predict variations in deal size in real-world data. Secondly, we show that attractive startup and VC types in our model expect to receive more offers and make more deals in a given period of time. Such types will also make matches with substantially higher expected values. This result confirms the findings of Hsu (2004), which documents better outcomes over startups with multiple offers. Thirdly, by extending Sørensen (2007) with search frictions and ex-ante unobservable shock to the matching value, we find a larger gap between the expected value *conditioned* on matching and the unconditional average of the matching value for *un*attractive startup and VC types (compared to the corresponding gap for attractive types). In our framework, unattractive types need to search more in the market to find a better draw of the shock to the matching value. This effect negatively impacts their continuation values and equilibrium payoffs, but it would lead to a larger payoff *conditional on matching* (relatively) for such types.

Related Literature. This paper contributes to the following strands of literature. Firstly, it provides novel experimental evidence on VCs' portfolio selection criteria and detailed mechanisms. Kaplan et al. (2009) first raise the question about whether VCs should bet on startup teams or projects. Bernstein et al. (2017) implement a field experiment with real US early-stage investors and highlight the role of startup teams' educational backgrounds. Block et al. (2019) implement a conjoint analysis with real private equity investors to study the role of revenue growth.[1] Unlike previous papers, we incorporate experimental results on

[1] Survey papers also help to study how investors make their decisions (see, e.g., Gompers et al., 2020).

VCs' selection criteria into a search and matching model to quantify the implications of VCs' preferences. This provides novel insights into how different startup traits affect the matching payoff and the split of payoff between VCs and startups in the market equilibrium. Regarding the underlying mechanisms, we observe that startup traits predominantly impact the VC's payoff at the extensive margin (i.e., the decision to engage in a deal or not), rather than at the intensive margin (i.e., the payoff given a deal is made). Moreover, besides reaffirming the significance of educational background and traction in VCs' portfolio decisions, this paper further sheds light on the importance of other less-explored startup characteristics, including founders' entrepreneurial experiences and business models. These findings offer pragmatic guidance on high-impact startups' fundraising endeavors.

Secondly, our paper contributes to the literature on startups' fundraising strategies. Hsu (2004) discover that startups are willing to be acquired by high-reputation VCs at a discount. Mayer and Scheck (2018) show that social entrepreneurs value several non-financial features of potential funders. Using structural estimation, we quantify the impact of startups' preferences for different VC characteristics on the payoff and split in the matching equilibrium. Our findings reveal that although startups receive a higher absolute payoff in equilibrium, their share of the matching value decreases when they secure funding from highly desirable VC types. This result aligns with evidence from Hsu (2004) regarding contract terms offered by reputable VCs. Our startup-side experiment further uncovers several investor characteristics that have a substantial impact on startups' fundraising behaviors. These characteristics encompass the human capital of investors (such as previous entrepreneurial and investment experiences) and the organizational capital of funds (including past financial performances and fund size). Consequently, our findings provide fresh insights into the significance of VCs' human and organizational capital in the matching process.

Thirdly, this paper contributes to the literature explaining the performances of PE/VC funds and portfolio companies. The outcome of a deal is influenced by two key factors: the value added by VCs (direct influence channel) and the ability to attract high-quality deal flows (sorting channel). While most papers in this area focus on the value-added role of investors (Hellmann and Puri, 2002; Bottazzi et al., 2008; Bernstein et al., 2016), Sørensen (2007) is the first paper that quantifies the importance of the sorting channel, finding that sorting is almost twice as important as a direct influence when it comes to the portfolio companies' outcome. Following Sørensen (2007), our paper examines the impact of equilibrium forces in the matching environment on the payoff of startups and VCs. On the VC side, we demonstrate that startups prefer VC funds with stronger historical financial performances. This preference first leads to a higher matching likelihood and further deals for well-performing VCs, which aligns with Nanda et al. (2020) that show initial success leads to better deal flow in the future. This preference further results in significantly higher expected payoffs for well-performing VCs due to increased bargaining power and favorable split of surplus in subsequent deals. Hence, besides the "deal flow" channel and "value-added" channel, our paper shows that higher bargaining power by equilibrium forces also contributes to VCs' persistent performance.[2] Similarly, regarding startups' payoff, we find that startups with attractive traits have a higher likelihood of receiving offers, leading to a more favorable split of the total matching value and increased payoff upon matching.

Methodologically, we adopt a different approach to estimating the two-sided matching model between entrepreneurs and VCs. Specifically, experimental data allows us to directly identify selection and payoff in a generalized matching framework without imposing further structural assumptions. Sørensen (2007) estimates the effect of influential VC traits on company outcomes while controlling for endogenous sorting in the matching equilibrium. We extend his model by further incorporating search friction and allowing for sorting based on ex-ante unobservable shocks in the value of a match between a startup and VC. Moreover, the utilization of experimental data enables us to estimate the bargaining power and the split of payoff between startups and VCs. Ewens et al. (2022) estimate a dynamic search-and-matching model to study the relationship between contract terms and the split of payoff between startups and VCs. We complement their research by explaining the split of payoffs based on observable influential traits of the involved parties. Specifically, we quantify the impact of human and organizational assets of startups, as well as the human and organizational capital of VCs, on the payoff of startups and VCs in the matching market equilibrium. We further explore the sources of variations in expected payoff from matching for startups and VCs when dealing with counterparties with identified attractive traits.

Lastly, this paper adds to the recent trend of applying lab-in-the-field experiments in financial markets. Since the creation of the IRR experimental method by Kessler et al. (2019), several papers have applied this method to address important questions in the entrepreneurial finance literature (Zhang, 2020, 2021; Colonnelli et al., 2022). The idea of running an experimental system is often used in natural scientific research. In a two-sided matching market, the US entrepreneurial financial system is one of the simplest economic systems with two major players: investors and startups. By implementing symmetric IRR experiments on both the investor side and the startup side, we can directly infer both parties' preferences. Using such micro-level empirical foundations, researchers can estimate a theoretical model with search friction and study the bargaining power and split of payoff across parties with heterogeneous attributes in a matching environment.

[2] An extensive literature has documented the persistent performance of VC funds, see Kaplan and Schoar (2005), Chung (2012), Robinson and Sensoy (2016).

Layout. This paper is organized as follows. Section 2 presents the set-up of our two-sided search-and-matching model and discusses the empirical challenges of its estimation. Section 3 presents the design, implementation details, and results of the symmetric IRR experiments. Section 4 introduces the estimation procedures of the structural model and discusses the identification of the model. Section 5 shows our main results, including the estimated continuation values of startups and VCs, the split of payoff, and matching outcomes in counterfactual analysis. Section 6 discusses and validates our simulation results with real-world data and extant literature. Section 7 concludes.

2 A Search-and-Matching Model with Bargaining

In this section, we present a dynamic model of search and matching with bargaining between startups and VCs. Our goal is to analyze the impact of joint matching values between startups and VCs with different characteristics on the payoffs obtained by startups and VCs conditional on matching likelihood, matching likelihood, and the continuation value of startups and VCs in equilibrium. As we discuss below, with experimental data, our approach solves several empirical challenges of estimating the model of matching between startups and VCs based on solely observable outcomes recorded in standard databases.

2.1 Model Set-up

Our model builds on a conventional search and matching model presented by Shimer and Smith (2000). There are two important extensions. First, we introduce uncertainty in matching values, which is realized after startups and VCs meet each other, to account for any idiosyncratic factors influencing the value generated in the match. Second, we consider non-trivial shares over the matching surplus between the two parties, as in Manea (2011).

The set of types is discrete in our model. There are I types of startups and J types of investors/VCs. Time is continuous. The time discount rate of a startup is r^S and that of a VC is r^{VC}. The discrete distribution of types in the population is $\{m_i\}_{i=1}^{I}$ and $\{n_j\}_{j=1}^{J}$, for startups and VCs, respectively, where $\sum_{i=1}^{I} m_i = 1$ and $\sum_{j=1}^{J} n_j = 1$ by definition. The mass of each party in the population is M^S and M^{VC}. Startups and VCs meet randomly according to a Poisson process at rate $\rho\sqrt{M^S \cdot M^{VC}}$, where ρ represents the search technology. The likelihood that a given startup meets a VC is the unconditional likelihood of a meeting divided by the mass of all startups $\rho^S := \rho/M^S = \rho\sqrt{M^{VC}/M^S}$, and likewise for a given VC fund this likelihood is $\rho^{VC} := \rho/M^{VC} = \rho\sqrt{M^S/M^{VC}}$. If a meeting happens, it is between a startup of type i and a VC of type j with probability $m_i n_j$.

The joint value of matching of a startup of type i and a VC of type j is $z_{ij}+\epsilon$. We assume ϵ is *i.i.d.* across matches, startups, and VCs. ϵ is realized upon a meeting between two parties. We assume ϵ is normally distributed, with the standard deviation being normalized to one. The joint value of the matching is perfectly divisible and transferable between parties (by means of cash transfers and other terms of the financial contract in practice). Matching takes place if the joint value $z_{ij}+\epsilon$ is greater than the sum of the outside option value of the two parties. In that case, the startup and the VC divide the matching *surplus* (matching value net of the sum of outside option values) according to a nonsymmetric Nash bargaining: the startup gets the fraction π and the VC gets the fraction $1-\pi$ of the surplus. If a matching takes place, both parties exit the searching process and are replaced by agents of the same type. Hence, the distribution of startups and VCs remains the same over time. If the matching value is less than the sum of the outside option values, the matching does not take place and both parties keep searching for another match. Finally, we normalize the flow of payoff obtained by unmatched agents to zero.

2.2 Equilibrium

We consider a Markov Perfect Equilibrium in which the matching likelihoods and the continuation values of startup and VC types remain the same over time.

Denote the equilibrium continuation value for an unmatched startup by u_i, and that of an unmatched VC by v_j. We define p_{ij} as the equilibrium probability of matching between a startup of type i with a VC of type j, conditioned on that a meeting happens between such types. Given the matching value is perfectly divisible and transfers are allowed, a meeting between a startup of type i and a VC of type j turns into a successful match if and only if the matching value is larger than the option to wait for both parties: $z_{ij}+\epsilon \geq u_i+v_j$. Therefore, the expected conditional likelihood of matching can be written as

$$p_{ij} = \text{Prob}[\ z_{ij}+\epsilon \geq u_i+v_j\ ] = 1 - CDF_{\epsilon}(u_i+v_j-z_{ij}) \tag{1}$$

If $z_{ij}+\epsilon \geq u_i+v_j$ the startup and the VC divide the matching surplus $z_{ij}+\epsilon-u_i-v_j$ based on a nonsymmetric Nash bargaining: the startup gets $u_i+\pi(z_{ij}+\epsilon-u_i-v_j)$ and the VC gets $v_j+(1-\pi)(z_{ij}+\epsilon-u_i-v_j)$. The expected payoff of a startup and that of a VC conditioned on matching is

$$\begin{aligned} \text{expected cond. payoff of the startup:}\quad & \Pi_{ij}^{S} = u_i + \pi * \mathbf{E}_{\epsilon}[z_{ij}+\epsilon-u_i-v_j \mid \textit{positive}] \\ \text{expected cond. payoff of the VC:}\quad & \Pi_{ij}^{VC} = v_j + (1-\pi) * \mathbf{E}_{\epsilon}[z_{ij}+\epsilon-u_i-v_j \mid \textit{positive}] \end{aligned}$$

Note that the sum of expected conditional payoffs of the startup and the VC equals the joint expected conditional matching value: $\Pi_{ij}^S + \Pi_{ij}^{VC} = \mathbf{E}_\epsilon[z_{ij} + \epsilon \mid z_{ij} + \epsilon \geq u_i + v_j]$.

The recursive formulation of optimization problems in continuous time (HJB equations) is derived by setting $u_i = (1-\rho^S dt)u_i + \rho^S dt *$matching prob.$*$cond payoff of type i startup for startups, and likewise $v_j = (1-\rho^{VC} dt)v_j + \rho^{VC} dt *$matching prob.$*$cond payoff of type j VC, which can be summarized as:

$$\forall i: \quad r^S u_i = \rho^S \pi \sum_{j=1}^{J} n_j \; p_{ij} \; \mathbf{E}_\epsilon[z_{ij} + \epsilon - u_i - v_j \mid z_{ij} + \epsilon \geq u_i + v_j] \tag{2}$$

$$\forall j: \quad r^{VC} v_j = \rho^{VC}(1-\pi) \sum_{i=1}^{I} m_i \; p_{ij} \; \mathbf{E}_\epsilon[z_{ij} + \epsilon - u_i - v_j \mid z_{ij} + \epsilon \geq u_i + v_j] \tag{3}$$

The right-hand side of the above equations shows the product of the following components: 1) the expected surplus of a match conditioned on the matching taking place; 2) the probability of a matching upon a meeting; 3) the share in the matching surplus of a party; and 4) the frequency of a meeting with various counterparty types over time. In short, the right-hand side represents the expected *flow* of surplus. The left-hand side shows the continuation value times the discount rate of each party. The HJB equations above simply state that the value of a funding/investment opportunity is equal to the expected flow of payoff, divided by the discount rate (i.e., the Gordon formula).

We define equilibrium as a set of $\{u_i\}_{i=1}^I$, $\{v_j\}_{j=1}^J$, and $\{p_{ij}\}_{i=1,j=1}^{I,J}$, such that equations (1) to (3) hold. In our stationary equilibrium, a flow of surplus is realized in a time interval dt through the matching of startups with VCs as

$$dt\rho \sum_{i,j} m_i n_j p_{ij} \; \mathbf{E}_\epsilon[z_{ij} + \epsilon - u_i - v_j \mid z_{ij} + \epsilon \geq u_i + v_j]$$

To get the present value of this flow of surplus in all future realizations, we discount the portion π of this value—that is claimed by startups—by the discount rate of startups r^S and the portion $1-\pi$ of this value—that is claimed by VCs—by r^{VC}:

$$\begin{aligned} PV =& \left(\frac{\pi}{r_S} + \frac{1-\pi}{r^{VC}}\right) \rho\sqrt{M^S M^{VC}} \sum_{i,j} m_i n_j p_{ij} \; \mathbf{E}_\epsilon[z_{ij} + \epsilon - u_i - v_j \mid z_{ij} + \epsilon \geq u_i + v_j] \\ =& M^S \bar{u} + M^{VC} \bar{v} \end{aligned}$$

where $\bar{u} = \sum_i m_i u_i$ and $\bar{v} = \sum_j n_j v_j$ are the average across-type continuation values of startups and VCs, respectively. The second equality is obtained by substituting for u_i and

v_j from equations (2) and (3) and definitions $\rho^S = \rho/M^S$ and $\rho^{VC} = \rho/M^{VC}$. The total present value of matching surpluses is simply the sum of the average continuation values of startups and VCs multiplied by their masses.

2.3 Empirical Challenges

Economists face several empirical challenges when estimating the elements of the model above if using solely observable matching equilibrium outcomes recorded by standard databases.

Firstly, econometricians only observe the representation of startup and VC types in the *realized* matches. However, the frequency of observed matches between startup type i and VC type j (i.e., μ_{ij}) is proportionate to the underlying mass of types *times* the conditional probability of a match between the two types (i.e.,p_{ij}). Mathematically speaking, $\mu_{ij} \propto m_i n_j p_{ij}$. We may not identify $\{m_i\}$, $\{n_j\}$, and $\{p_{ij}\}$ through the observed matching frequencies μ_{ij}. For example, assume that we observe frequent matches in the data that involve a given VC type j. This observation can be justified either by a large mass of all *potential* VCs of type j searching for a match or by the higher likelihood that matches involving type j VCs can happen.

Secondly, the conditional matching probabilities $\{p_{ij}\}$ are endogenous model outcomes that depend on the underlying matching values $\{z_{ij}\}$ and the continuation values of startups and VCs, $\{u_i\}$ and $\{v_j\}$ (see equation 1). A match is more likely to happen if the average matching value between the two parties, z_{ij}, is high, or if the outside options— the continuation values of the startup and VC, $u_i + v_j$, is low. We may proxy for the matching value z_{ij} by observable outcomes, such as IPO/Acquisition likelihood, ignoring other possibly (non-pecuniary) benefits of the collaboration. However, if the observable outcomes are partial/noisy predictors of the matching value, one would underestimate the variation in z_{ij} across types by only focusing on the observable outcomes.

Thirdly, the continuation values $\{u_i\}$ and $\{v_j\}$ are the endogenous outcomes of the model. One could infer $\{u_i\}$ and $\{v_j\}$ from the equilibrium relationships implied by HJB equations (2) and (3), via imposing structural assumptions on z_{ij} and using proxies based on observable outcomes. However, to estimate $\{u_i\}$ and $\{v_j\}$, one needs to further know the share of the matching surplus assigned to startups and VCs in the negotiation, determined by π. This share is essentially an unknown underlying parameter of the environment.

Facing these empirical challenges above, Sørensen (2007) links matching outcomes to underlying payoffs via observed matches in the data. Without incorporating search frictions, all types by construction are matched in equilibrium in his model. This helps to set the underlying mass of types $\{m_i\}$ and $\{n_j\}$. The conditional matching probabilities $\{p_{ij}\}$ are indeed zero-one values, set from the observed matches in the data. Given the equilibrium concept of "stable matching", potential matching values between any arbitrary startup and VC $\{z_{ij}\}$ are then backed out from the observed set of $\{p_{ij}\}$, irrespective of the share in surplus for each party (represented by π). As the object of interest in Sørensen (2007) is the relationship between IPO outcomes and the estimated matching values associated with VCs of different characteristics, there is no need to estimate the bargaining power parameter π, and continuation values $\{u_i\}$ and $\{v_j\}$ separately.

Ewens et al. (2022) considers search friction and set parametric distributions for the mass of underlying types, $\{m_i\}$ and $\{n_j\}$, which in part is identified by the frequency of deals per unique VC id observed in a given period of time in the data. In their setup, investors get the entire matching surplus (i.e., $\pi = 0$). Contract terms (observed in the data) offered by VCs, however, affect the joint matching value (i.e., $\{z_{ij}\}$) by considering moral hazard friction and the fact that startups need to have skin in the game. Continuation values $\{u_i\}$ and $\{v_j\}$ are endogenously obtained from the specification of matching values $\{z_{ij}\}$. Finally, a deterministic set of matching values $\{z_{ij}\}$ are inferred from observable matching outcomes (likelihood of IPO and high-value acquisitions). There is no ex-post shock to the matching value, conditional on startup and VC type, and there is no identified link between underlying types and observable characteristics of startups and VCs.

We take an alternative approach to infer the underlying matching values $\{z_{ij}\}$ and the matching likelihoods $\{p_{ij}\}$ in isolation using field experiments. By running two-sided IRR experiments with real US startups and VCs, we are able to directly solicit the matching values (abstracting from the matching likelihood) and the matching likelihoods across startups and VCs with heterogeneous traits. We then accommodate search frictions and infer $\{m_i\}$ and $\{n_j\}$ via the observed matching frequencies $\{\mu_{ij}\}$ in the real-world portfolio data and perceived collaboration likelihoods $\{p_{ij}\}$ revealed in these experiments. This enables us to estimate the bargaining power of each side—determined by the parameter π in our model, as well as continuation values $\{u_i\}$ and $\{v_j\}$ via revealed matching values $\{z_{ij}\}$, without further structural assumptions. We are therefore able to estimate the division of surplus between startups and VCs in equilibrium, as well as the role of human versus non-human capital on conditional payoffs and continuation values across startup and VC types.

Before discussing the estimation process and results of our structural model, we first present the design and implementation details of the two-sided IRR experiments. This experimental system not only provides novel findings on what human and non-human characteristics of startups and VCs influence the collaboration intention of the other side but also collects crucial statistics serving to estimate our model.

3 Two-Sided IRR Experiments

3.1 Startup-side IRR Experiment

The startup-side IRR experiment is designed to identify which VC characteristics influence startups' fund-seeking preferences. Experimental subjects need to evaluate randomly generated synthetic VC profiles to obtain a recommendation list of real-world matched VC investors' contact information. Multiple companies have provided similar commercial matching services by collecting basic background information of both startup founders and investors.[3] Following this trend, our startup-side IRR experimental setting closely mimics the real world by providing a data-driven investor recommendation service to startup founders.

3.1.1 Recruitment Process and Sample Selection

To recruit a large number of real US startup founders who fit the research purpose, we collaborated with a third party that provides recruitment services targeting real US small business owners and startup founders between 03/2021-04/2022. The experiment further adds two filter questions and several screeners to recruit founders satisfying the following three criteria: 1) being a startup founder or business owner who plans to raise funding for his/her company from the venture capital industry, 2) understanding the designed incentive and agreeing that the more truthfully they reveal their preferences, the more benefits they can obtain from the study, 3) passing several carefully designed attention checks based on participants' evaluation time, inserted attention check questions, and Bot Detection algorithms designed by Qualtrics system. If participants fail any of these criteria, the Qualtrics system will automatically terminate the experimental process and inform experimental participants that they are no longer qualified for this study. Unqualified participants do not have a second chance to join the study. Similar to the classical IRR experimental design, all experimental participants are informed of the research purpose, as required by Columbia IRB and SSE IRB. However, the consent form emphasizes the matching purpose of this created "investor-startup" matching tool.

The response rate of this study is roughly 6%. Online Appendix Table A1 summarizes the background information of the recruited startup founders. Female startup founders account for 41.61% of all recruited startup founders. 89.44% founders' startups are still in the seed stage, consistent with the fact that mainly early-stage startups value the provided "matching incentives" more than later-stage startups. Roughly 50% recruited startup founders are

[3] These companies include dealroom.co, VC Match, the Community Fund, VCWiz, etc.

Democratic, and 24% subjects are Republicans. Also, 63.98% of startups are B2C startups, and only 26.09% of the startups are in the Information Technology industry. According to the geographical distribution of recruited US startups, most of our sample startups are located in US startup hubs and tech centers. To the best of our knowledge, there is no data that records all US startups that consider funding from the VC industry. Hence, there is no benchmark to compare the demographic information of recruited startups. Fortunately, our structural model accounts for various heterogeneity based on observable startups and investors' characteristics when discussing the welfare implications.

3.1.2 Structure of the Startup-side Matching Tool

We design the startup-side matching tool using Qualtrics (i.e., the startup-version "Nano-Search Financing Tool"), which enables dynamic and simultaneous randomization of both VCs' individual-level characteristics (i.e., investors' human capital) and fund-level characteristics (i.e., VC funds' organizational capital). After potential experimental subjects receive the recruitment email from the third-party company, they need to open the inserted survey link, acknowledge the consent form, and answer a few standard background questions about their startups' industries and stages before entering the VC profile evaluation section.

To generate VC investors' hypothetical profiles, each VC characteristic is dynamically populated from a pool of options and assembled together. Profile templates are built in HTML for display in a web browser and populated dynamically in Qualtrics using Javascript. The detailed randomization process is described in Online Appendix Table A2.

The following efforts have been made to improve the realism of generated VC profiles. Firstly, the wording used to describe investors' experiences and funds' characteristics is extracted from real-world investors' biographies and funds' descriptions posted on their websites. Secondly, most selected investors' characteristics try to mimic real-world distribution as much as possible. The number of deals is adjusted based on the investor's seniority, avoiding generating any unrealistic investor profiles. Thirdly, generated profiles are essentially a combination of investors' publicly available information rather than their resumes.[4] To further enhance participants' experiences of participating in this study, the tool also provides a progress bar.

All investor profiles contain three sections in the following order: i) individual-level characteristics, including first name, last name, investment experience, educational background,

[4]Unlike the job-seeking process, investors rarely post their resumes online. Instead, startup founders do due diligence on investors by collecting information from multiple online platforms, such as LinkedIn, personal websites, Crunchbase, AngelList, Pitchbook, etc. Therefore, the format of investor profiles mimics information posted on these platforms, displaying key points of investors' characteristics.

and previous entrepreneurial experience or other working experience; ii) fund-level sensitive characteristics, including the fund's investment philosophy and type; iii) fund-level nonsensitive characteristics, including the fund's previous performance measured by the internal rate of return, investment style, fund size measured by AUM (i.e., asset under management) & dry powder, and location.[5] Since this paper focuses on the implications of startups' and VCs' human assets and non-human assets on the matching outcomes, we only present the construction details of these characteristics in this paper.[6]

i) Relevant Individual-level Human Capital Characteristics

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

Educational Background. Educational background is another human capital characteristic that correlates with investors' investment strategies. We independently randomize both investors' degrees (bachelor's degree versus graduate degree) and graduated schools (top university versus common university).[7] All selected schools have been verified to have alumni who are working in the US VC industry based on a Google search. Detailed randomization process and school lists are provided in the Online Appendix.

Years of Experience and Total Number of Deals. VCs with more experience are more likely to be put in charge of investment activities (Bottazzi et al., 2008; Gompers et al., 2009). Therefore, we use both investors' years of investment and the total number of involved deals to indicate their working experience. The total number of involved deals is positively

[5] This experiment only includes investor characteristics that are publicly available online because the recommendation algorithm is based on the public information of a large number of VCs.

[6] For the effects of VCs' gender, race, and investment philosophies (i.e., ESG investing strategy versus profit-driven investing strategy), see Feng et al. (2022) and Zhang (2022).

[7] Graduate degrees include MBA, JD, master, and PhD. Bachelor's degrees include BA and BS. Top universities include Ivy League colleges, California Institute of Technology, Duke University, MIT, Northwestern University, Stanford University, the University of California Berkeley, and the University of Chicago. Common universities are defined as other universities which also foster real startup founders and VCs.

correlated with investors' years of investment in our design. This design helps to avoid any unrealistic cases where junior investors have completed an extremely large number of deals.

ii) Relevant Fund-level Non-human Characteristics

Fund Size. We use AUM (i.e., "asset under management") and dry powder to indicate the size of the VC firm that each investor works for.[8] This information exists on the Pitchbook platform and is summarized by the annual National Venture Capital Association (NVCA) Yearbook. The information about fund size exists on the Pitchbook Platform and other standard databases. The distribution used in the randomization process mimics the fund size distribution of early-stage VC firms recorded by the Pitchbook database.

Investment Style. Ewens et al. (2018) document that there are two types of investment styles: the burgeoning "spray and pray" style and the traditional "value added" style. "Spray and pray" investment strategy refers to an investment approach where investors spend a relatively smaller amount of funding and effort to a large number of startups. Most VC firms would choose the wording "diversified investment strategy" instead of "spray and pray" to describe their investment strategies. In this experiment, we describe this strategy as "(Diversified investment strategies) prefer a high volume and diversified investments". On the other hand, the traditional "value-added" investment strategy is still popular among many VC firms. We describe this traditional strategy as "(Value added strategy) concentrate towards startups with good prospects and add value to them".

Fund Previous Performance. We use the internal rate of return (IRR) to indicate a VC fund's previous investment performance. For 80% of profiles, their fund returns are randomly drawn from a normal distribution, which mimics the distribution of return for early-stage VC funds recorded in Pitchbook. For the remaining 20% randomly selected profiles, they are assigned to be first-time funds without previous performance records.

Location. It is well documented that the distance between startups and investors plays an important role in venture capitalists' investment decisions and the startup monitoring process. Therefore, although 90% profiles are affiliated with US VC funds, we randomly assign the remaining 10% profiles to be affiliated with foreign funds.

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

3.1.3 Evaluation Questions

A key design feature, which enables IRR experiments to directly identify the detailed nature of preferences, is its carefully designed, theory-based evaluation questions. For each investor profile, we ask startup founders to answer i) three mechanism questions and ii) two decision questions (see Appendix Figure A1 for an example of designed evaluation questions). Given that startup founders are generally well-educated and sophisticated, we use probability or percentile ranking questions instead of Likert scale questions. This provides two advantages. First, probability or percentile ranking questions are relatively more objective. Second, the wide range from 1 to 100 enables more detailed evaluation results and additional statistical power.

Mechanism Questions. Three mechanism questions are designed to test the following three standard belief-driven sub-mechanisms that explain why investors' individual-level and fund-level characteristics might affect startup founders' willingness to collaborate. The first sub-mechanism is that subjects might use certain investors' characteristics as signals of investors' quality (i.e., the ability to help startups to achieve higher financial returns). To test this mechanism, startup founders need to evaluate the quality of each hypothetical investor (i.e., "Q_1"). The second sub-mechanism (i.e., "strategic channel") is that investors' characteristics might be suggestive of their intention of investing in certain types of startups. The likelihood of successfully raising funding from an investor theoretically also affects startup founders' fundraising behaviors, given the high search cost. To test this channel, subjects need to evaluate the likelihood that each investor would show interest in their own startups (i.e., "Q_2"). The third sub-mechanism is that founders' beliefs of the informativeness of investors' profiles (i.e., higher moment beliefs "Q_5") theoretically also affect their decisions (Neumark, 2012; Heckman, 1998) in a situation with information asymmetry. For example, if small VC funds suffer from more severe information asymmetry problems, founders might rationally choose large VC funds to avoid any potential uncertainties.

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

Background Questions. To check the representativeness of our recruited startup founders and test potential alternative stories, we ask several background questions about subjects' gender, entrepreneurial experience, educational level, likelihood to talk with friends about the study, startup team composition, and the goal of their startups.

Payment Game. At the end of the matching tool, all experimental participants are informed that they could receive a lottery opportunity. Basically, two participants will be randomly selected as the lottery winners. The winners are offered the following two options. Option 1 is to receive \$500. For Option 2, participants can purchase a comprehensive investor recommendation list of the top 200 most matched venture capitalists at a randomly generated price. If they choose Option 2, they will receive (\$500 − "price of the recommendation list"). As participants' decisions in this payment game are incentivized by real-money lottery opportunities, choosing Option 2 is a clear signal that some participants value the incentive (i.e., the recommendation service).

3.1.4 Incentives

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

We merge multiple commercial databases to create a comprehensive global venture capitalists' database, comprising the demographic and contact information of over 17,000 venture capitalists worldwide. After evaluating 20 hypothetical investor profiles, each startup founder will receive 10 real VCs' contact information recommended by the matching algorithm. This recommendation service relies on our extensive global VC investor database, which is typically unavailable to startup founders and often requires payment for similar services in the market. Hence, we provide valuable benefits to experimental participants. To justify the validity of the provided incentive, we demonstrate that the reduced-form results remain stable when analyzing the subgroup of participants who choose to pay real money for this recommendation service.

Lastly, we employ several standard pre-registered noise reduction techniques to ensure careful participant recruitment and minimize the noise in our experimental study. These techniques include attention check questions, evaluation time and variation thresholds, validity checks for text-input answers, and other subsidiary methods. Additional details can be found in Online Appendix A.1.

3.1.5 Relevant Human Capital and Organizational Capital Characteristics

Ewens and Rhodes-Kropf (2015) discuss the relative importance of the individual-level venture capitalists' characteristics and firm-level organizational capital-related characteristics for VC portfolio company performance. Building upon their research, we investigate particular individual and fund-level traits that matter for startup founders. Table 1 reports the regression results about how various investor characteristics causally influence multiple dimensions of startups' fund-seeking decisions. For Column (1), the dependent variable is the startup's evaluation results of Q_1 (i.e., quality evaluation), indicating the investor's probability of helping the startup to succeed. In Column (2), the dependent variable is the evaluation results of Q_2 (i.e., investment intentions), indicating the investor's probability of showing interest in the startup. In Column (3), the dependent variable is the evaluation results of Q_5 (i.e., informativeness of investors' profiles), indicating whether the investor's profile is informative. The dependent variable of Columns (4)-(5) is the startup's fundraising plan (i.e., Q_3), indicating the relative amount of money that startups are comfortable asking for from the investor. The dependent variable of Columns (6)-(7) stands for the startup's likelihood of contacting the investor (i.e., Q_4), which directly measures the investor's attractiveness. All regressions include subject fixed effects and cluster the standard errors within each startup founder. Standard errors are reported in parentheses.

Insert Table 1 here

Column (1) finds that startups give higher profitability evaluations to investors with the following characteristics. In terms of human capital-related characteristics, having entrepreneurial experiences and one-extra year longer investment experience all casually improve startups' judgments on the investor's quality. On average, investors with previous entrepreneurial experiences are considered to be 3.87 percentage points more likely to facilitate the success of startups. This result is statistically significant at the 1% level. Similarly, one more year of investment experience improves the perceived likelihood of being a helpful investor by 0.41 percentage points, which is statistically significant at the 5% level. In terms of organizational capital-related characteristics, larger size and better historical financial performances of the VC fund also contribute to higher profitability evaluations of the investor. On average, investors working in a large VC fund are perceived to be 1.96% more likely to foster successful startups compared to investors working in a small VC fund. Also, investors in outperforming VC funds are considered to be 4.99 percentage points more likely to nurture successful startups due to their higher historical financial performances as measured by internal rate of return. These results are statistically significant at the 1% level. In Online Appendix A.2 we find that the effects of these VC characteristics exist in most market conditions by analyzing their distributional effects. Additionally, quantile regressions discussed in Online Appendix A.3 show that these effects exist among VCs with different levels of quality.

Columns (2) and (3) of Table 1 show that these attractive investor characteristics also improve startups' evaluations of the investor's availability (i.e., the likelihood of showing interest in the startup) and the perceived informativeness of the investor's profile. Based on Column (2), previous entrepreneurial experience and the larger size of the VC fund help to improve the perceived investor's "availability" by 4.03 and 1.21 percentage points separately. In Column (3), previous entrepreneurial experience and the larger size of the VC fund improves startups' judgments on the informativeness of the investor profile by 2.75 and 0.89 percentage points. Columns (2) and (3) also show that compared to VC funds with below-average historical financial performances, first-time VC funds and outperforming VC funds improve startups' judgments on the investor's availability by 1.25 and 3.06 percentage points separately, and further improve the perceived informativeness of investor profile by 1.41 and 3.11 percentage points. All the regression results are statistically significant.

Columns (4) and (6) of Table 1 find that attractive investor characteristics directly influence startups' fund-seeking behaviors. Attractive investor characteristics increase both the startup's willingness to contact the investor and to ask for more funding from investors. Since most startups generally ask for less amount of funding (i.e., roughly 90% on average) from investors compared to their ideal amount of funding needed, this adjustment of fundraising plan potentially helps startups to get a more appropriate level of capital to support their business. Columns (5) and (7) show that controlling belief mechanisms absorb most of the significant effects of VCs' traits. Specifically, compared to Q_1 (i.e., evaluations of VCs' quality) and Q_5 (i.e., evaluations of VCs' informativeness), Q_2 (i.e., evaluations of VCs' availability) correlate the most with startup founders' indicated fundraising decisions.

In Section 5, we show that the startups' preferences that we documented above can explain variations in the payoff of venture capitalists through equilibrium forces in the matching environment. In particular, our experimental result on the effect of the historical financial performance of VC funds on startups' evaluation relates to several papers that have documented the persistent performances of VC funds compared to mutual funds or hedge funds (Robinson and Sensoy, 2016; Harris et al., 2020; Chung, 2012; Kaplan and Schoar, 2005). We argue that outperforming VC funds have more advantages of attracting startups, which further increases the future financial performance of such VCs through access to more deals (as shown in Nanda et al., 2020) and also more payoff per deal through endogenous changes in bargaining power. Unlike mutual funds and hedge funds, this special two-sided matching nature of the entrepreneurial financing process can contribute significantly to VC funds' persistent performances through matching equilibrium forces.

3.2 Investor-side IRR Experiment

The investor-side IRR experiment is designed to identify which startup characteristics influence VCs' investment preferences. We invite real US VCs from our comprehensive list of venture capitalists to try a "Nano-Search Financing Tool", which is an algorithm-based matching tool that seeks potential investment opportunities. Investors need to evaluate multiple randomly generated startup profiles. Despite knowing these profiles are hypothetical, investors are willing to provide truthful evaluations in order to be matched with high-quality real startups from our collaborating incubators.

This experimental setting closely mimics the real world. It is not unique to the VC industry to develop data-driven methods to identify the best deals from thousands of potential investment opportunities in the screening stage. For example, Techstars, Social+ Capital, and Citylight Capital have all done extensive work on developing machine learning algorithms to facilitate their deal sourcing.[9] Investors chose to participate in this experiment mainly to build closer connections with startups from prestigious universities and get more potential high-quality deal sources. The incubators, who collaborated with this project, usually work with startup teams from prestigious universities in North America, such as Stanford University, Columbia University, and the University of British Columbia. Many of their startups have international backgrounds and have run successful fundraising campaigns. Considering that some startup characteristics, such as founders' personalities, are difficult to quantify, these data-driven methods are often used before investors invite founders to the face-to-face due diligence process. Therefore, this experiment mainly captures investors' preferences in the *pre-selection* stage.

[9] See "Using Machine Learning In Venture Capital" and "Venture Capital Due Diligence: The Screening Process.", accessed June 1, 2023.

3.2.1 Recruitment Process and Sample Selection

This IRR experiment was mainly implemented between 03/2020 and 07/2020. In total, 69 investors from different VC funds chose to participate in this experiment through online recruitment, providing 1,216 total startup profile evaluation results. The number of recruited experimental participants is comparable to Kessler et al. (2019). Both the recruitment emails and posters emphasized the matching purpose of this tool (see Online Appendix Figures B1 and B2 for the recruitment emails, Figures B3 and B4 for the instruction posters). Nonetheless, we also notify them that their anonymized data will be used for some research purposes as required by IRB.

Online Appendix Table B1 summarizes the observed background information of all recruited VCs and compares it with the background information of US-based VCs recorded in the Pitchbook database. Panel A shows that recruited investors' sectors of interest are diverse and representative, covering all the major industries that VCs typically focus on (Bernstein et al., 2017). Panel B shows that 67.1% of recruited investors focus on the Seed Stage. Panel C shows that the sample investors are representative in terms of gender, with 20.0% female investors. This is consistent with the NVCA 2018 VC report, showing that women hold 21% of investment positions in the VC industry. Furthermore, 86% of recruited investors are in senior positions, as their contact information is more readily available in existing databases. Roughly 11% of investors explicitly claim that their investment strategies involve ESG criteria or that their sectors of interest are typical ESG sectors, such as Clean Energy. Regarding the size of recruited VC firms, Panel E shows that the medium value of recruited VCs' total active portfolio companies, total exits, AUM, and dry powder is all larger than the market-level medium values. During the pandemic recession, only larger and more active VCs pursued new investments, while smaller VCs shifted to survival mode.

3.2.2 Survey Tool Structure and Consent Form

If investors are interested in participating in this experiment, they need to open the link inserted in the recruitment email and start the Qualtrics survey online using their browsers. After acknowledging the consent form, investors will enter the profile evaluation section (i.e., the IRR experiment) where they need to evaluate multiple randomly generated startup profiles and answer standard background questions.

To make sure that investors understand the incentive structure, we provide an extra instruction page emphasizing that "the more accurately they reveal the preferences, the better outcomes the matching algorithm will generate (and the more financial returns that the lottery winner will obtain)." Given that most VCs only invest in startups in their interested industries and stages (i.e., "the qualify/disqualify test"), we require all subjects to assume that the generated startups are in their interested industries and stages.

Following the factorial experimental design, multiple startup team and project characteristics are randomized dynamically, orthogonal, and simultaneously. This enables us to systematically examine investors' preferences on a rich set of startup characteristics. As suggested by corporate finance theories, we first include multiple team characteristics to test the importance of human assets, mainly including entrepreneurs' educational backgrounds and previous entrepreneurial experiences. We also include multiple project characteristics to test the importance of non-human assets, including business models, traction, comparative advantages, locations, and company ages. The back-end Javascript code randomly draws different characteristics and combines them together to create a hypothetical startup profile.[10]

To generate reasonable startup profiles, we make the following efforts. First, the used wording describing these startup characteristics are extracted from real startups' backgrounds documented by Pitchbook Database. Second, the information provided follows the Crunchbase format.[11] We only provide startup information that is publicly available in the pre-selection stage. That is to say, if information about certain startup characteristics is determined during the negotiation between investors and startups, such as equity sharing plans, we exclude them from our experiments. Randomization of different startup components is provided in Online Appendix Table B2.

3.2.3 Evaluation Section

To identify the nature of investors' preferences, we include i) three mechanism questions designed to test belief-based preferences, and ii) two decision questions designed to compare investors' interests in the contact decisions and investment decisions. Screenshots of evaluation questions are provided in Online Appendix Figures B5 and B6. Similar to the startup-side experiment, here we also choose probability or percentile ranking questions instead of Likert scale questions. This allows us to do infra-marginal analysis and distributional analysis, as well as more precise estimation in Section 5.

Mechanism Questions. Three mechanism questions are designed to test the following three standard belief-based mechanisms influencing investors' preferences. First, some

[10] Random combination of different characteristics might create some special cases, such as a startup with 50+ employees and no profits. This case might apply to some high-tech startups that burn money quickly in their early stages. However, these situations account for only a small percentage of total cases.

[11] Crunchbase is a commercial platform that provides public information of startups mainly in the US.

startup characteristics may serve as indicators of the startup's quality. To test this channel, investors need to evaluate a profitability evaluation question (Q_1) and give the percentile rank of each startup profile compared with their previously invested startups. Second, some startup characteristics may be suggestive of the startups' willingness to collaborate with certain investors. Hence, investors need to evaluate an availability question (Q_2), judging the probability that the startup will accept their investment offer rather than choose other fundraising methods.[12]

Decision Questions. Two decision questions are designed to examine how the investors' preferences evolve from the initial contact interest to the investment interest. Traditional experimental methods, such as correspondence tests, generally observe evaluators' preferences in the initial contact stage. However, it is still unknown whether preferences in the contact stage can be fully transformed into preferences in investment decisions. Therefore, we ask each experimental participant to indicate both their likelihood of contacting the startup (i.e., Q_3) and their interest in investing in the startup (i.e., Q_4). Q_4 elicits the relative intended investment amount rather than the absolute magnitude of the intended investment. This is mainly because different investors have different ranges of targeted investment amounts. To accommodate more investors, we try to make the question as standardized and generally applicable as possible.

Background Questions. At the end of the matching tool, we also collect participants' standard background information to check the representativeness of our sample investors and implement heterogeneous effect analysis. Such background information includes investors' preferred industries, stages, special investment philosophies, gender, race, educational background, and others. It is important to ask these background questions after the evaluation section to avoid priming subjects.

3.2.4 Incentives

As an incentivized preference elicitation technique, the key point of the IRR experimental design is its incentive structure. Therefore, for all investors, we provide a "matching incentive" originally used by Kessler et al. (2019). To increase the sample size, for a randomly selected subset of investors, we provide both the "matching incentive" and a "monetary incentive" used by Armona et al. (2019). Details and justifications of both incentives are

[12] In the experimental design, a risk question was also added to a subset of investors. However, we do not report the related results because only a small number of investors answered this question.

provided below.[13]

Matching Incentive. For a randomly selected subgroup receiving the recruitment email (Version 1), we only provide a "matching incentive". After each investor evaluates 16 hypothetical startup profiles, a machine learning algorithm is used to identify matched startups from a comprehensive list of candidate startups in our collaborating incubators based on both the investor-side experimental data and the incubators' confidential data of their own startups. Matched startups will contact investors for a potential collaboration opportunity if they are also interested in the investor's investment philosophy. The matching algorithm uses investors' all evaluation answers to identify their preferences for different startup characteristics. Therefore, all evaluation questions are incentivized and the description of the algorithm is provided in the consent form.

Monetary Incentive. To increase the sample size, besides "matching incentive", we provide a "monetary incentive" to a randomly selected subset of investors who receive the recruitment email (Version 2). Following Armona et al. (2019), the "monetary incentive" is essentially a lottery in that two experimental participants are randomly selected to receive \$500 each plus an extra monetary return closely related to their evaluation of each startup's quality. Based on this monetary incentive, the more accurate their evaluations of each startup's quality are, the more financial return they will obtain as a lottery winner.[14] The evaluation results will be determined based on the Pitchbook data published in the next 12 months after the recruitment process is finished. We informed the two randomly selected lottery winners separately by email at the end of July 2020.

[13]Some may concern about alternative motivations for investors to participate in this experiment. For example, some investors may just want to understand the algorithm and research methods used for this matching tool. For these investors, the optimal decision is to read the consent form, evaluate a few startups and stop because the evaluation process is repetitive and time-consuming. Other investors may just want to get potential monetary rewards. This will bring additional noise to this experiment and make it harder to detect significant effects. We find that these noises do not distort the preferences systematically by comparing evaluations of VCs who receive only the "matching incentives" and those who receive both incentives.

[14]For example, Peter Smith participates in this experimental study and is chosen as one of the two lucky draw winners. In his survey, he indicates that on average, he believes that male teams are of higher quality and more likely to generate higher financial returns. Then we would construct a portfolio containing more real startups with male teams. After one year, based on the financial performance of the portfolio on the Pitchbook Platform, this portfolio containing more startups with male teams generates a 10% return. Then Peter Smith will receive \$500 + \$500*10% = \$550 as his finalized monetary compensation one year after he participates in the survey. \$500*10%=\$50 is the "extra monetary return". The historical return of the VC industry is between -15% and +15%, which means that the range of expected monetary compensation is roughly between \$425 and \$575.

Justification. One concern with adding the "monetary incentive" is the possibility of attracting participants who do not value the matching incentive, which results in extra noise. The additional noises imply that some insignificant startup characteristics can also be important in the real investment process when the sample size is large enough. However, it does not affect the relative "signal-to-noise" ratio of each startup characteristic.

3.2.5 Relevant Human Capital and Non-human Asset Characteristics

Table 2 reports regression results of how investors' evaluations respond to multiple startup team characteristics and startup project characteristics. For column (1)-(6), the dependent variable is the evaluation results of Q_1 (profitability evaluation), Q_2 (availability evaluation), Q_3 (contact decision), and Q_4 (investment decision), separately. "Serial Founder", "Ivy", and "US Founder" are indicators that are equal to one if the founder is a serial entrepreneur, an alumnus from Ivy League Colleges, and lives in the US. "Has Positive Traction", "Is B2B", and "Domestic Market" are indicators that equal one if the startup project has positive traction, is a business-to-business startup, and focuses on the domestic market. These variables are equal to 0 if the startup does not have such characteristics. The total number of founders is either 1 or 2; The number of comparative advantages and company age can be $\{1,2,3,4\}$; Company Age^2 is the square of the company age. All regressions include investor fixed effect and report robust standard errors (in parentheses). Clustering standard errors on the individual level does not change our results. We use Bonferroni Method in Table 2 to implement the multiple hypothesis testing. Online Appendix Table B3 provides results with the q-value method.

Insert Table 2 here

In Columns (1), (3), and (5) of Table 2, we find multiple startup characteristics and project characteristics that are causally important for investors' profitability evaluations, contact interest ratings, and investment interest ratings. Such important team characteristics include the founder's educational background and previous entrepreneurial experiences. Important project characteristics include the startup's traction, location, comparative advantages, and business model. Specifically, Column (1) shows that founders' previous entrepreneurial experiences and impressive educational backgrounds both increase investors' quality judgment by 5 percentile ranks. This result is in line with Bernstein et al. (2017) that emphasize the role of the founding team's educational background in attracting early-stage investors. However, unlike their study, we find that the positive traction of startup projects is almost twice as important as educational backgrounds—it affects investors' quality judgments by 12.7 percentile ranks. This finding confirms the hypothesis of Kaplan et al. (2009), which suggests that investors should place greater emphasis on projects rather than teams. In Online Appendix B.1 we show that the effects of the aforementioned startup characteristics exist in most market conditions. Additionally, quantile regressions discussed in Online Appendix B.2 show that these effects exist among startups with different levels of quality. Finally, Online Appendix Table B4 shows that after standardizing all coefficients, project traction remains the most influential characteristic among all other influential factors in all regressions.[15]

Column (2) of Table 2 shows that VCs' evaluations of startups' collaboration likelihood are higher for startups with positive traction, smaller startups, relatively younger startups, and B2B startups. However, the impact of positive traction is relatively weaker compared to the profitability evaluation in Column (1). Moreover, the effect of educational background and entrepreneurial experience is not significant. This result indicates that investors perceive better outside options for startups with such characteristics, which makes collaboration less likely.

Startup characteristics can influence investors' decisions through profitability judgments and availability judgments. Columns (4) and (6) of Table 2 demonstrate that, after controlling for the evaluations of Q_1 and Q_2, the impact of most startup characteristics decreases, particularly the influence of previous entrepreneurial experiences and traction. Additionally, the coefficient of Q_1 is approximately five times larger than the coefficient of Q_2 in explaining investors' contact interest ratings. This provides suggestive evidence that investors' beliefs about startups' profitability are the primary factors that strongly correlate with their contact and investment interest ratings. The availability evaluation (i.e., Q_2) plays a marginal role in the contact stage and does not affect investors' investment decisions.

In the following section, we utilize different sources of variation (profitability evaluations, availability evaluations, and contact interest ratings) in the experimental results to estimate a search and matching model with bargaining between startups and VCs. Using this model, we analyze the equilibrium payoff of startups and VCs in the matching outcome, by focusing on the role of relevant human and non-human traits identified earlier in the experiments.

[15] The study conducted by Bernstein et al. (2017) recruits investors listed on AngelList, a platform that may attract more angel investors who prioritize the team over the project. In contrast, our sample primarily consists of institutional VCs. Additionally, the signal-to-noise ratio of startup team characteristics and project characteristics is likely to be asymmetric in their correspondence test experimental setting. This can explain why we get a stronger result for the role of traction in our IRR experimental setting. In a conjoint analysis experimental setting involving private equity (PE) investors, Block et al. (2019) reveals similar findings to our IRR experiment, demonstrating the importance of firms' revenue growth to PE investors.

4 Estimation

In this section, we estimate the search and matching model with bargaining between startups and VCs presented in section 2 via IRR experiment results presented in section 3. We first discuss the attributes that we use to set startup and VC types. We then explain the source of variations in the experimental results that we rely on in the identification. We further sketch out the estimation procedure and explicitly explain how we combine the results of IRR experiments together with the administrative data on the real-world matching frequencies from the Pitchbook to estimate the underlying matching values between pairs of startups and VCs as well as search and bargaining parameters of the model. We provide parameter estimates and discuss the model fit in explaining variations in the experimental results and matching frequencies recorded in the Pitchbook. In section 5, we provide estimation results.

4.1 Startup and VC Types

We consider 16 types of startups and 8 types of VCs. To define types, we use attributes on either side that appear determinant in our empirical results in the previous section. As representatives of human and organizational assets on the startups' side, we consider whether a startup has a business-to-business model, whether it has positive traction: has generated revenue so far, whether the founder has further entrepreneurial experience (is a serial founder), and whether the founder has a prestigious education background (graduate degree or Ivy-league graduate). 4 attributes as dummy variables determine the type of a given startup, which rises to $I = 2^4 = 16$ startup types in total. To assign VC types, we consider the historical performance and size, and entrepreneurial experience of investors in a VC fund as categorized variables, which together represent human and organizational capital. 3 attributes as dummy variables determine the type of a given VC, which rises to $J = 2^3 = 8$ VC types in our setup.

We follow the same criteria that we apply in the experimental data to assign startup types and VC types in the administrative data. We use data from Pitchbook to count the number of actual matches between startup- and VC-type pairs. We split our Pitchbook data recorded from 2017 to 2021 in half; We use the first half to set attributes of VCs based on historical performance, while we use the second half to count realized matches across startup and VC types. In sum, we observe nearly 17,000 matches per year in our sample period. We collapse the data at the i/j type level and count realized matches for $16 * 8 = 128$ pairs of startup and VC types.

4.2 Identification

We use the profitability evaluation question Q_1, which asks a participant to evaluate the potential benefits of collaborating with various counterparties (ignoring strategic considerations) to infer the expected matching value z. And we use the strategic question Q_2, which asks toward the perceived collaboration likelihood, to set the matching probabilities p_{ij}. We then infer outside options reflected in continuation values u_i and v_j. The aforementioned sources of variations would identify primitives of the matching setup in the following sense. If, for example, a startup considers a particular VC profile as valuable (high Q_1), a larger z is identified; having fixed Q_1, however, if a startup does not consider a matching to be likely to take place (low Q_2), then a higher outside option u_i or v_j (in a relative sense) is assigned to the collaboration between startup type i and VC type j. By observing variations in both Q_1 and Q_2 in IRR experiments the estimation toolbox identifies matching surplus and continuation values, in *relative* terms. We then impose equilibrium relationships imposed by HJB equations (2) and (3) to obtain continuation values in absolute terms and estimate the bargaining power of startups and VCs.

In what follows we describe the estimation procedure in detail. We further list calibrated parameters of the model. And we discuss our approach to correct for potential bias implied by measurement errors. We first describe a version of the estimation in which we use startup-side experimental results regarding matching values and collaboration likelihood with VCs. Then we extend the methodology to use experimental results from both sides—startups evaluating VC profiles and VCs evaluating startup profiles—in estimating model primitives. Using experimental results from both parties to assess the variations in perceived values and matching likelihoods across counterparty types would mitigate concerns of absolute versus relative rankings of profiles in IRR experiments and would also address possible errors in self-assessment and misperceptions of joint matching values and outside options. Lastly, we discuss the possibility to use an alternative source of information in experimental results in setting the collaboration likelihood.

4.2.1 Estimation Procedure

We denote all the estimated values and parameters with a "hat" notation. We estimate model parameters in the following steps.

Step 1. In the first step, we estimate the underlying distribution of startups and VCs, $\{m_i\}_{i=1}^{I}$ and $\{n_j\}_{j=1}^{J}$, respectively. To do so, we first introduce the following notation; denote the equilibrium *observed* frequency of matches between startup of type i and the VC of type

j by μ_{ij}, which follows

$$\mu_{ij} = \rho\sqrt{M^S \cdot M^{VC}} m_i n_j p_{ij} \tag{4}$$

Now, we rearrange terms in equation (4) to write the left-hand side based on μ_{ij}/p_{ij}. Then take the sum over i and j and use $\sum_i m_i = \sum_j n_j = 1$ to get

$$\rho\sqrt{M^S \cdot M^{VC}} = \sum_{i,j} \frac{\mu_{ij}}{p_{ij}} \tag{5}$$

And take the sum over either i or j and substitute for $\rho\sqrt{M^S \cdot M^{VC}}$ from equation (5) to get

$$\hat{m}_i = \frac{\sum_j \frac{\hat{\mu}_{ij}}{\hat{p}_{ij}}}{\sum_{i,j} \frac{\hat{\mu}_{ij}}{\hat{p}_{ij}}} \quad , \quad \hat{n}_j = \frac{\sum_i \frac{\hat{\mu}_{ij}}{\hat{p}_{ij}}}{\sum_{i,j} \frac{\hat{\mu}_{ij}}{\hat{p}_{ij}}} \tag{6}$$

To estimate right-hand side variables, we set the observed frequency of matches of startups of type i with VCs of type j, called $\hat{\mu}_{ij}$, from Pitchbook as described above. Furthermore, we set $\hat{p}_{ij}$ from the revealed matching likelihood, taken directly from the answers to the experiment survey Question 2. We collapse all data and responses at the i/j type level by taking averages across participants/profiles: $p_{ij} \to \hat{p}_{ij} = \overline{ans(Q_2)_{ij}}$. We achieve an estimate for the underlying distribution of masses by substituting $\hat{\mu}_{ij}$ and $\hat{p}_{ij}$ in equation (6). We also estimate the search and matching frequency $\rho\sqrt{M^S \cdot M^{VC}}$ by plugging $\hat{\mu}_{ij}$ and $\hat{p}_{ij}$ into equation (5).

Step 2. In this step, we estimate the variations in continuation values, $\{u_i\}$ and $\{v_j\}$, across startup and VC types. First, We infer the mean matching value z_{ij} directly from the answers to the experiment survey Question 1. We assume that the experiment survey Question 1 is informative on the matching value. I.e., at the type level:

$$\hat{z}_{ij} = \tau_0 + \tau_1 * \text{log-odds}(ans(Q_1)_{ij}) \tag{7}$$

where τ_1 transfers the questionnaire output to z with the appropriate unit. At this stage, take the value of τ_1 as given and known. We perform the log-odds transfer, log-odds$(x) := \log(\frac{x}{1-x})$, to get the responses to the survey question 1 from a zero-to-one scale into the real line. Results are robust when using other transfers, such as the inverse cumulative distribution function of standard normal distribution. For the purpose of estimating parameter values, we normalize the standard deviation of the shock to matching values ϵ to 1. Given that values and payoffs are scale-free and the unit is not identified in the model and estimation, this normalization sets the unit of the mean matching values z_{ij}.

Next, we estimate $\{u_i\}$ and $\{v_j\}$ as fixed effect terms in the equation (1). To do so, first note that by inverting equation (1) we get:

$$-CDF_{\epsilon}^{-1}(1-p_{ij}) = -u_i - v_j + z_{ij} \tag{8}$$

where CDF is the cumulative distribution function of the standard normal distribution (the distribution of ϵ). We perform a fit to equation (8), by assuming that the conditional matching odds p_{ij} is revealed from the answers to the survey Question 2 directly: $p_{ij} \to \hat{p}_{ij} = ans(Q_2)_{ij}$ and by substituting for z_{ij} from equation (7). We run the following OLS regression in the experimental data reported at the individual level

$$-CDF_{\epsilon}^{-1}(1-ans(Q_2)_{ij}) - \hat{\tau}_1 * \text{log-odds}(ans(Q_1)_{ij}) \ \sim \ \hat{\tau}_0 - \hat{u}_i - \hat{v}_j \tag{9}$$

We estimate $\hat{u}_i$ and $\hat{v}_j$ as fixed effect terms in this specification. Note that the mean of $\{u_i\}$ and $\{v_j\}$ are not identified from τ_0 in this fit. To demonstrate such indeterminacy we introduce two new unknown objects, average continuation values $\bar{u}$ and $\bar{v}$, to be estimated later:

$$\hat{u}_i \to \hat{u}_i^r + \bar{u}$$
$$\hat{v}_j \to \hat{v}_j^r + \bar{v}$$

The fit to equation (9) identifies the deviation from means, $\{\hat{u}_i^r\}$ and $\{\hat{v}_j^r\}$, but not $\bar{u}$ and $\bar{v}$. We define $\bar{u}$ and $\bar{v}$ as *weighted* average of continuation values across startups and VCs. Therefore, by definition, the identified deviations in continuation values, $\{\hat{u}_i^r\}$ and $\{\hat{v}_j^r\}$, meet $\sum_i \hat{m}_i \hat{u}_i^r = \sum_j \hat{n}_j \hat{v}_j^r = 0$.

Step 3. In the next step, we estimate the expected flow of the matching surplus—the right-hand side of equations (2) and (3). To ease illustration, we first define

$$d_i := \sum_{j=1}^{J} n_j \ p_{ij} \ \mathbf{E}_{\epsilon}[z_{ij} + \epsilon - u_i - v_j \mid z_{ij} + \epsilon \geq u_i + v_j] \tag{10}$$

$$e_j := \sum_{i=1}^{I} m_i \ p_{ij} \ \mathbf{E}_{\epsilon}[z_{ij} + \epsilon - u_i - v_j \mid z_{ij} + \epsilon \geq u_i + v_j] \tag{11}$$

Now, we replace for $z_{ij} - u_i - v_j = -CDF_{\epsilon}^{-1}(1-p_{ij})$ from equation (8), where we substitute for $p_{ij} \to \hat{p}_{ij} = \overline{ans(Q_2)_{ij}}$ directly from the survey Question 2 (collapsed at the i/j type levels). Moreover, we use m_i and n_j as estimated in step 1. We then estimate $\hat{d}_i$ and $\hat{e}_j$ as:

$$\hat{d}_i = \sum_{j=1}^{J} \hat{n}_j \; \hat{p}_{ij} \; \mathbf{E}_\epsilon[\epsilon - CDF_\epsilon^{-1}(1-\hat{p}_{ij}) \mid \epsilon \geq CDF_\epsilon^{-1}(1-\hat{p}_{ij})] \tag{12}$$

$$\hat{e}_j = \sum_{i=1}^{I} \hat{m}_i \; \hat{p}_{ij} \; \mathbf{E}_\epsilon[\epsilon - CDF_\epsilon^{-1}(1-\hat{p}_{ij}) \mid \epsilon \geq CDF_\epsilon^{-1}(1-\hat{p}_{ij})] \tag{13}$$

Step 4. Having estimated the expected flow of surplus from equations (12) and (13), we then estimate the mean continuation values $\bar{u}$ and $\bar{v}$, and the parameters that relate the expected flow of matching surplus to continuation values, being meeting intensity times the share in surplus divided by the discount rate, $\beta^S := \frac{\rho^S \pi}{r^S}$ and $\beta^{VC} = \frac{\rho^{VC}(1-\pi)}{r^{VC}}$, for startups and VCs, respectively. We do so by imposing the HJB equations, which imply linear fits with a zero intercept between continuation values in *absolute* terms and the expected flow of matching surplus. To show the details, we rewrite equations (2) and (3) using the notation for the expected flow of payoffs and continuation values (all estimated in previous steps)

$$\hat{u}_i^r + \bar{u} = \beta^S \; \hat{d}_i \tag{14}$$

$$\hat{v}_j^r + \bar{v} = \beta^{VC} \; \hat{e}_j \tag{15}$$

We estimate the unknown parameters/average values, by matching the slope and intercept in the linear equilibrium equations (14) and (15). We estimate $(\bar{u}, \beta^S)$ and $(\bar{v}, \beta^{VC})$ by a weighted OLS fit of $\{\hat{u}_i^r\}$ on $\{\hat{d}_i\}$, and of $\{\hat{v}_j^r\}$ on $\{\hat{e}_j\}$, where we use mass of types, $\hat{m}_i$ and $\hat{n}_j$ as the weights

$$\hat{\beta}^S = \frac{\sum_i \hat{m}_i \hat{d}_i \hat{u}_i^r}{\sum_i \hat{m}_i \hat{d}_i (\hat{d}_i - \sum_i \hat{m}_i \hat{d}_i)} \quad , \quad \bar{u} = \hat{\beta}^S \sum_i \hat{m}_i \hat{d}_i \tag{16}$$

$$\hat{\beta}^{VC} = \frac{\sum_i \hat{n}_j \hat{e}_i \hat{v}_j^r}{\sum_j \hat{n}_j \hat{e}_j (\hat{e}_j - \sum_j \hat{n}_j \hat{e}_j)} \quad , \quad \bar{v} = \hat{\beta}^{VC} \sum_j \hat{n}_j \hat{e}_j \tag{17}$$

Note that all we can estimate in this last step is meeting frequency times the share in surplus divided by the discount rate, being $\beta^S := \frac{\rho^S \pi}{r^S}$ for startups and $\beta^{VC} = \frac{\rho^{VC}(1-\pi)}{r^{VC}}$ for VCs. Each component here, meeting frequency, the share in surplus, and discount rate, is not separately identified. We plug in our estimates of the continuation values $\{\hat{u}_i\}$ and $\{\hat{v}_j\}$ in equation (8), with the answers to the survey Question 2 being used for $p_{ij} \to \hat{p}_{ij} = \overline{ans(Q_2)_{ij}}$, to get an estimate of the mean matching values for a startup of type i with a VC of type j, z_{ij}. We use z_{ij}, together with β^S and β^{VC} as the basis for our analyses in the next section.

Step 5. Lastly, we iterate over the choice of τ_1 in equation (7) such that the following structural relationship holds

$$\overbrace{\beta^S r^S/\rho^S}^{=\pi} + \overbrace{\beta^{VC} r^{VC}/\rho^{VC}}^{=1-\pi} = 1 \Rightarrow \left(\frac{r^S M^S}{\rho\sqrt{M^S M^{VC}}}\right)\beta^S + \left(\frac{r^{VC} M^{VC}}{\rho\sqrt{M^S M^{VC}}}\right)\beta^{VC} = 1 \quad (18)$$

Note that both β^S and β^{VC} are linear transforms of τ_1, hence τ_1 can be obtained analytically.

4.2.2 Calibrated Parameters

We externally calibrate M^S, M^{VC}, and ρ, as well as r^S and r^{VC}, as determinants of the coefficients behind β^S and β^{VC} in equation (18). From Pitchbook we get a total number of realized matches between types $\sum_{i,j} \mu_{ij}$, so given our estimates of $\hat{p}_{ij}$, we pin down $\rho\sqrt{M^S M^{VC}} \simeq$ 27000 (on a per annum basis) from equation (5). The number of unique VC company IDs in our sample period in Pitchbook is 4576, while based on the CrunchBase platform, it is 5,679. We calibrate M^{VC} =5,000. It is challenging to set the number of (potential) startups who search for funds, who may or may not eventually get funded in a given period (or at any time). Given our sample criteria, the number of unique Startup IDs in Pitchbook in 2019 is 20,564, during 2019-2020 it is 36,579, and during 2018-2020 it is 49,071. DemandSage reports a total number of 72,560 US startups. We set M^S =50,000. Given our calibrated masses M^S and M^{VC} we find $\rho \simeq 1.7$, on a per annum basis: if there were only 1 startup and 1 VC, they expect to meet each other in about 7 months.

The cost of capital for VCs (risk-adjusted) would inform us about the time discount rate for VCs, i.e., r^{VC} in our model. The literature documents a wide range of estimates, depending on VC type, sample period, and method of calculation (see, e.g., Ewens et al., 2013; Harris et al., 2014; Korteweg and Nagel, 2022).[16] We calibrate $r^{VC} = 10\%$ (on a per annum basis) in our benchmark calibration. The (opportunity) cost of capital for startups depends on various elements, such as the extent to which a given startup is cash constrained. Theoretically, one might consider a wedge between the cost of capital for startups and VCs, to justify the flow of capital from VCs to startups as an efficient (re)allocation of resources in the real world. This wedge is endogenous and possibly varies across startup types in our model. We consider a fixed wedge of 5% between the (opportunity) cost of capital for startups and VCs, implying $r^S = 15\%$ (on a per annum basis). As we will discuss below, our estimation delivers a high fit R^2, even with the same r^S for all types in the proposed stylized setup. Overall, our robustness checks show that changing discount rates affect estimated

[16] See recent reports on raw returns from Burgiss at https://www.burgiss.com/burgiss-global-private-capital-performance-summary, accessed November 15, 2022.

values in absolute terms, but not much in the *relative* sense (e.g., the equilibrium payoff of a given startup type *relative* to the average startup and to an average VC is stable).

4.2.3 Correcting for "Attenuation" Bias

Our estimation of β^S and β^{VC} from equations (16) and (17), as well as the estimate of τ_1, may be biased because it requires the estimated deviation values $\hat{u}^r$ and $\hat{v}^r$ as inputs—which include measurement errors. The direction of bias is not clear though (and whether there is a bias, to begin with) as the potential error in $\hat{u}^r$ and $\hat{v}^r$ is not necessarily in the form of classical measurement error. We run Monte Carlo simulations to assess and correct for bias in our objects of estimates. To do so, we consider the deviation from average reports collapsed at the i/j type level of individual answers to experimental questions as statistical errors. We then draw random numbers from a normal distribution with the same variance-covariance matrix as the underlying error in reports and assign them to survey data inputs in 100 rounds of estimation. We take into account the correlation in error terms in answers to different survey questions in our re-draws of error terms. We replicate all estimation steps described above for each set of new draws. We use Monte Carlo results from 100 replicates to correct for the bias in our estimation reports. We find that the size of the bias in our estimates is indeed not significant.[17]

4.2.4 Mapping Model to Data and Alternative Sources of Experimental Data

Question 1 in the experimental data asks about perceptions of generating financial returns on a zero-to-one scale. The mapping to the matching value in the model, z_{ij}, is, however, subject to interpretations. In the estimation procedure described above, we use a log-odd transfer to map responses to the real line, and we use a factor of transfer τ_1 (to be estimated) to map expected returns in normalized scale to the matching value in the model. We highlight that the matching value in the model can include both pecuniary and non-pecuniary benefits, provided that the *total* benefits scale with financial returns (picked up by the factor τ_1). Moreover, question 1 may be linked to $z_{ij} + \epsilon_{ij}$ instead of z_{ij}, or any arbitrary transfer, such as $\text{Prob}[z_{ij} + \epsilon > 0]$. The aggregation up to the i/j type level in specification (9) will presumably wash out the noise terms in the questionnaires, including ϵ_{ij}s. Also, other interpretations such as $Q_1 = \text{Prob}[z_{ij} + \epsilon > const]$ are eventually associated with a particular

[17] Specifically, for any object of interest, called X, we report $2X_0 - \sum_{s=1}^{S} X_s/S$ as our final estimate of X, where X_0 is the estimation with benchmark experimental data and X_s is the estimation in the simulation draw s, and $S = 100$ is the total number of draws.

We also use these Monte Carlo results to obtain and report standard errors of our objects of estimates. With the notation above, the standard error would be $\sum_{s=1}^{S} X_s^2/S - (\sum_{s=1}^{S} X_s/S)^2$.

transfer of Q_1 ($z_{ij} = const + \tau_1 * CDF^{-1}(Q_1)$ in the example above) for which we show that the results are indeed robust in the end.

We highlight that the estimation procedure above requires that Q_1 be an *absolute* measure of profitability in a respondent's view (not depending on u_i or v_j, for example). This condition is supported by the startup-side experiment design, in which we require respondents to ignore strategic considerations in the framing of Q_1. Startup-side experimental data may then identify model parameters in the following sense: The variation in Q_1 across VC profiles revealed by startups can identify variations in the index j of z_{ij}, and therefore the VCs' continuation values v_js in the specification (9); And the variation across startups of their revealed Q_1 can identify variations in the index i of z_{ij}, and so terms of Startups' continuation values u_is in the same specification (9).

One critique, however, is that in the startup-side experiment startups reveal variations in perceived values (Q_1) only in a *relative* sense. Although the question is framed to solicit the absolute values, revealed values might be informative only about the variation in the index j of z_{ij}, but not in the index i. For example, *each* startup may rank VCs based on her priors and/or her outside options reflected in u_i. For example, Q_1 may link to prob$[z_{ij} + \epsilon > u_i]$. In that case, specification (9) is unidentified up to an i-level fixed effect term, which makes it impossible to identify continuation values of startups $\{u_i\}$. The same critique applies if we use only VC-side experimental reports, especially because we ask VCs to rank startup profiles relative to the set of startups that they have experienced before and historical matches are correlated with v_j.

To address this concern, we use information from both startup-side and VC-side experiments in an alternative estimation. To elaborate, we run specification (9) using the startup-side experimental data on quality evaluations and perceived matching likelihoods to estimate the variations in VCs' continuation values $\{v_j\}$. And we run the same specification (9) using the VC-side experimental data on revealed values and matching likelihoods to estimate the variations in startups' continuation values $\{u_i\}$. We also use an average of perceived matching likelihoods from both startup-side and VC-side experiments (weighted by the number of reports on each side) to set $\hat{p}_{ij}$. Thereby we obtain the underlying mass of types, $\{m_i\}$ and $\{n_j\}$, from equation (6), and expected flow of matching payoffs for both startups and VCs, $\{\hat{d}_i\}$ and $\{\hat{e}_j\}$, from equations (12) and (13) as in the benchmark estimation procedure. Similarly, we use specifications (14) and (15) to estimate average continuation values, $\bar{u}$ and $\bar{v}$, and parameters of search and share in surplus for both parties, β^S and β^{VC}.

The next critique applies to the mapping between the revealed collaboration likelihoods (Q_2) in experiments and the matching likelihood p_{ij} in the model. Q_2 may only reflect interests in (early) examinations on one side, instead of the likelihood to form a match.

To address this issue, we may alternatively use the revealed contact interest on either side (Q_4 in the startup-side experiment and Q_3 in the VC-side experiment) to back out the perceived matching likelihoods. The revealed contact interest maps to the expected gain from matching in the model: $p_{ij} \cdot \mathbf{E}_\epsilon[z_{ij} + \epsilon - u_i - v_j \mid z_{ij} + \epsilon \geq u_i + v_j]$, where $p_{ij} = \text{Prob}[z_{ij} + \epsilon \geq u_i + v_j]$. We may link the revealed contact interest to the perceived matching probability p_{ij} via rewriting the matching surplus as: $p_{ij} \cdot \mathbf{E}_\epsilon[\epsilon - CDF^{-1}(1 - p_{ij}) \mid positive]$, which is a strictly increasing function of p_{ij}. Intuitively, if matching is more expected to happen, a higher expected value is attached to the matching, hence contact interest is more. We may then back out p_{ij} from the revealed contact interest in the experiment data (Q_4 in the startup-side experiment and Q_3 in the VC-side experiment) by inverting the function $p_{ij} \cdot \mathbf{E}_\epsilon[\epsilon - CDF^{-1}(1 - p_{ij}) \mid positive]$.

We check the consistency in the experimental data between collaboration likelihoods and contact interests. Online Appendix figure C1 shows the relationship between the revealed contact interests in the experimental data, and the model-implied measure $p_{ij} \cdot \mathbf{E}_\epsilon[\epsilon - CDF^{-1}(1 - p_{ij}) \mid positive]$ in which we set p_{ij} from the revealed collaboration likelihoods. A positive covariation is verified. The mapping is not precise though, especially on the VC-side experimental data, likely due to noises in the two proxies (e.g., residual motives to make a contact). We also note that the VC-side experiment has fewer subjects—roughly one-tenth of the startup-side experiment, which amplifies standard errors in reported variables. In any case, we provide alternative estimation results in which we set the matching likelihood p_{ij} both directly from the revealed collaboration likelihoods, Q_2, and indirectly by inferring from the revealed contact interest, Q_4 in the startup-side experiment and Q_3 in the VC-side experiment (after appropriate scaling via the implied slopes in Online Appendix figure C1).

In what follows, we demonstrate parameter estimates and model fit using only startup-side experimental data in the estimation and using the revealed collaboration likelihoods to set the matching likelihoods. However, in the next section, we report results on continuation values and payoffs from matching via alternative specifications, in which we use various sources of experimental data on the startup-side, and on the startup and the VC side combined, as described above.

4.3 Parameter Estimates and Model Fit

Figure 1 shows the estimates of $\hat{u}_i^r + \bar{u}$ versus $\hat{d}_i$, and $\hat{v}_j^r + \bar{v}$ versus $\hat{e}_j$. According to the model, given the appropriate estimate of $\bar{u}$ and $\bar{v}$, the plot should be linear with a zero intercept and with the corresponding slopes $\beta^S = \frac{\rho^S \pi}{r^S}$ and $\beta^{VC} = \frac{\rho^{VC}(1-\pi)}{r^{VC}}$, implying that the continuation value of a type equals the expected matching surplus, conditioned on that matching takes place, times the share in the matching surplus, divided by the time discount rate. Ideally, all points would lie on the linear fit, given that we consider the same rule in dividing surplus, search technology, and discount rate for all startup types and for all VC types. The fit is overall satisfactory. Slope estimates are β^S =3.19 (0.11) and β^{VC} = 5.73 (1.18). Given the calibration for ρ^S and ρ^{VC}, and r^S and r^{VC}, we back out a share in the matching surplus of π= 0.893 (0.022), which is in favor of startups. Note, however, that the expected payoff for each party is the share in matching surplus plus her outside option, which is determined by her continuation value. Continuation values in turn depend on βs, which depend on the share in surplus, as well as the meeting probability and patience, and is indeed more on average for VCs. We further discuss equilibrium payoffs in section 5.

Insert Figure 1 here

The gap between point estimates for continuation values from experimental data using equation (9) and the linear fit (dashed lines) in figure 1 shows the error in the model prediction for $\hat{u}_i$ and $\hat{v}_j$. Given the estimates of β^S and β^{VC} and the estimated $\{\hat{z}_{ij}\}$ we can simulate the recursive optimality conditions (1)-(3) to obtain the model-implied continuation values u_i and v_j, and the conditional matching likelihoods p_{ij}. We may also use equation (4) to obtain the model-implied observed matching frequencies μ_{ij}. Figure 2 shows simulated versus estimates of continuation values, matching probabilities, and matching frequencies from the experimental data and Pitchbook. Simulation results align with the estimations and data quite well. We use simulation outcomes in showing results in the coming section 5.

Insert Figure 2 here

5 Results

In this section, we provide estimation results for continuation values and the expected matching payoffs for an average startup and an average VC, as well as the role of human and non-human traits for variations in values and payoffs across startups and VCs. Specifically, we discuss the role of such traits in the split of payoff across different deals. We further report estimates of the present value of the total surplus, as well as the share of all startups and all VCs of the total surplus, and run counterfactual analyses regarding primitives of the search-and-matching environment. Recall that we normalize the standard deviation of shocks to matching values ϵ to 1 in our estimation, as the normalization for welfare variables.

We may indeed correspond one unit of utility to roughly *$1 million* profit, as we discuss in section 6 by comparing estimates of the expected payoffs in the model to the real-world data on deal sizes and expected payoffs in dollar units.

Equilibrium Values and Matching Payoffs. Table 3 shows the estimated average continuation values and expected conditional payoff from matching for startups and VCs in equilibrium. We report results for all estimation procedures, using startup-side experimental data only or both startup- and VC-side experimental data, and using revealed collaboration likelihoods vs. contact interests, as described in section 4. Estimates that use both startup- and VC-side experimental results have a larger standard error, likely because the number of subjects in our VC-side experiment is much less (roughly one-tenth) of the startup-side experiment. Nevertheless, in all specifications, an average VC has a higher continuation value than an average startup. This finding comes from the experimental results that, conditioned on matching profitability, the VC-level fixed effect terms in the specification (9) capture more variations than the startup fixed effects—that is, a VC is more determinant in setting the collaboration likelihood than a startup. Hence, VCs are attached with sizable outside options and continuation values through estimates of equations (16) and (17).

Insert Table 3 here

We highlight that for VCs the expected *conditional* payoff from matching is close to the continuation values. But this is not the case for startups. Upon matching, startups capture most of the matching *surplus* (matching value net of outside options) while VCs get close to their outside options, being their continuation values. Why do VCs get more equilibrium values on average than startups, although they get less of the matching surplus? The reason is, the environment is populated with much fewer VCs than is with startups. Hence, a given VC is much more likely to find a match than a given startup. Also, VCs are more patient than startups. Both forces increase the value of outside options of a VC in negotiating over the joint matching value with a startup, which allows the VC to get more payoff from matching and further supports a larger equilibrium value for an average VC than an average startup. The fact that the payoff from matching for VCs is mainly driven by their outside options (not the matching surplus, i.e., matching value net of outside options) has crucial implications for the source of variations in expected payoff from matching across (counterparty) types, which we explain later.

In the end, we find that existing VCs altogether capture only $M^{VC}\bar{v}/(M^S\bar{u} + M^{VC}\bar{v}) =$ 15-25% (depending on the specification) of the *total* present value of matching surplus generated over time. This is the case, as there are more startups in the search-and-matching environment. Hence, while an average VC gets more continuation value than an average startup ($\bar{v} > \bar{u}$), all startups combined capture the majority of the generated surplus in the environment that we study ($M^{VC}\bar{v} \ll M^{S}\bar{u}$).

To further demonstrate the role of patience and outside options for equilibrium payoffs in our search-and-matching environment we run several counterfactual experiments. Online Appendix table C1 shows the results. First, we make startups patient by closing the 5% wedge between the time discount rate of startups and VCs and set: $r^{S} = r^{VC} = 10\%$. Not surprisingly, startups' continuation value rises. Social surplus increases as well. Interestingly, the continuation value of an average VC falls by 15%. Startups are no longer desperate to make a deal and are willing to wait and search more for a productive match in future tries. As a result, the total number of realized matches per year *falls*. This result indicates that the number of deals—a sign that the market is on boom—is not necessarily a proxy for startups' well-being or total value-added. In the second counterfactual study, we double M^{VC} the mass of VCs. In this case, both the payoff of startups and the number of matches per year increases; while the payoff to an individual VC substantially falls—by 30%. Competition among VCs would reduce the chance to meet a startup for each VC in the search process, which lowers their outside option and decreases the equilibrium continuation value of VCs. The reverse happens for startups. Thirdly, we consider an improvement in the search technology ρ by 100%. As a result, the number of deals, as well as the payoff to both startups and VCs increase. Startups and VCs may find a match faster and indeed are more willing to wait to find a better match—draw a higher realization of the shock to the matching value. The total present value of the matching surplus then increases by about 10%.

Heterogeneity Across Types: The Role of Human vs. non-Human Attributes. We find significant heterogeneity in equilibrium values across types, especially on the startup side. See table 3. The mass-weighted standard deviation of the equilibrium continuation value across startups $std(u)$ is nearly 20% of the average level $\bar{u}$, and that of VCs $std(v)$ is of the order of 10% of the average $\bar{v}$. What are the determinant traits on either side for creating heterogeneity in equilibrium values? And what is the impact of each trait?

We find that both human and non-human traits matter for equilibrium values on both startup and VC side. We demonstrate the average impact of traits on continuation values through OLS fits of simulated continuation values on dummy indicators of human and non-human traits, across 16 types of startups and 8 types of VCs. Table 4 shows the results for all specifications with alternative experimental data sources.

Insert Table 4 here

Table 4, Panel A reports variations in continuation values for startups. Column 1 shows the results for the case in that we use the startup-side experiment data to estimate the continuation values of both startups and VCs. We find that having a business-to-business model, being a serial founder, and having prestigious education substantially impact the value of a startup—in the range of 25-35% of the value of the reference type (the constant term). The estimated impact of "positive traction" is negative but insignificant. Similar results are achieved in relative terms when using the revealed contact interest to infer perceived matching likelihoods (see Column 2). However, when using the VC-side experimental data to estimate the continuation values of startups (Columns 3-4) we find a much less (although positive and significant) impact of educational background and instead a positive and sizable impact of traction and business model on equilibrium value of startup types. These findings imply that startups of better education backgrounds may overestimate their startup value and competence in general. We highlight that the attribute "serial founder" which indicates the entrepreneurial experience of startups stays highly significant and sizable in all estimates. We conclude that both human assets (entrepreneurial experience and education background) and non-human assets (business model and traction) are determinant factors for the equilibrium continuation value of startups that seek funding from VCs.

Table 4, Panel B reports results for the average impact of traits on VC's equilibrium continuation values. We find that in all specifications the impact of historical performance and entrepreneurial experience of investors is sizable and highly significant—around 15 and 20% of the value of the reference type (the constant term), respectively. The impact of size is positive but only marginally significant and is around 5% of the reference value. We then report robust findings that both human capital (entrepreneurial experience) and non-human capital (historical performance and size) of investors and VCs are determinant factors for the equilibrium payoff of VCs in the entrepreneurial finance process.

Variation in Expected Matching Payoff Across Types. Attractive types: startups with traction, B2B model, prestigious education, and entrepreneurial experiences, and VCs of larger size, better historical performance, and with entrepreneurial experiences get a higher equilibrium value as reported in table 4 and so command a higher reservation payoff in negotiation over the joint matching value. Hence, they get a larger share of the total matching value. Figure 3 shows the VC's share of the conditional expected matching value $\Pi^{VC}/(\Pi^S + \Pi^{VC})$ between alternative startup and VC types. By definition, the startup's share $\Pi^S/(\Pi^S + \Pi^{VC})$ is one minus the VC share.

Insert Figure 3 here

The variation in the division of payoff is substantial. Figure 3, left Panel, shows that the VC share falls from .65 to .35 when dealing with the least and the most attractive startup type, respectively. Figure 3, right Panel, shows that the VC's share increases with the attractiveness of the VC type, or equivalently, the startup's share decreases when dealing with an attractive VC type. In particular, the startup's share of payoff falls by 5-10 percentage points when dealing with the most relative to the least attractive VC type—a result consistent with the findings documented in Hsu (2004). For both startups and VCs, we find that one unit increase in the attractiveness of the *counter*party type (continuation values, u_i for the startup and v_j for the VC) in our setup decreases the share in payoff for the startup and the VC by 5-10 percentage points. We note that in an average deal (between an average startup and VC type), the split of the matching payoff is close to 50:50, which is in line with the estimate in Ewens et al. (2022).

The fact that the *share* in the matching payoff falls when dealing with an attractive type implies that, while dealing with an attractive type increases the total payoff from matching, the payoff from matching for a startup and a VC in *absolute* terms may not increase much when dealing with an attractive counterparty type. On the other side, the likelihood to form a match with an attractive counterparty type is more, regardless, because an attractive type brings in more value and makes the matching more likely, which increases the expected payoff from collaboration through the extensive margin. To understand the underlying mechanism in creating variations in payoff across (counterparty) types, we decompose the expected payoff from collaboration for a given startup and a given VC, $\mathbb{E}[\Pi_{ij}^S] = p_{ij}\Pi_{ij}^S$ and $\mathbb{E}[\Pi_{ij}^{VC}] = p_{ij}\Pi_{ij}^{VC}$, in three terms. First, the likelihood to form a match p_{ij}. Second, the total payoff conditioned on matching $\Pi_{ij} = \mathbf{E}_\epsilon[z_{ij} + \epsilon | z_{ij} + \epsilon \geq u_i + v_j]$. And third, the share of startup and VC from the total matching value, $\Pi_{ij}^S/\Pi_{ij} = \frac{u_i + \pi \mathbf{E}_\epsilon[z_{ij}+\epsilon-u_i-v_j | z_{ij}+\epsilon \geq u_i+v_j]}{\mathbf{E}_\epsilon[z_{ij}+\epsilon | z_{ij}+\epsilon \geq u_i+v_j]}$ and $\Pi_{ij}^{VC}/\Pi_{ij} = \frac{v_j + (1-\pi)\mathbf{E}_\epsilon[z_{ij}+\epsilon-u_i-v_j | z_{ij}+\epsilon \geq u_i+v_j]}{\mathbf{E}_\epsilon[z_{ij}+\epsilon | z_{ij}+\epsilon \geq u_i+v_j]}$, respectively.

$$\text{expected payoff from matching for startup } i: \qquad \mathbb{E}[\Pi_{ij}^S] = p_{ij} * \Pi_{ij} * \Pi_{ij}^S/\Pi_{ij}$$
$$\text{expected payoff from matching for VC } j: \qquad \mathbb{E}[\Pi_{ij}^{VC}] = p_{ij} * \Pi_{ij} * \Pi_{ij}^{VC}/\Pi_{ij}$$

Table 5 shows the variations of each term in the expression for the expected payoff from matching for startups and VCs with respect to equilibrium continuation values u_i and v_j through OLS fits on the simulation results of the benchmark specification.[18]

[18] Online Appendix table C2 verifies that results on the sources of variation in the expected payoff is robust to using alternative experimental data sources in estimating the model.

Insert Table 5 here

Table 5, Column 1, shows that the matching likelihood p_{ij} positively correlates with the attractiveness of either startup or VC. Note that, fixing z_{ij}, a higher u_i or v_j would *decrease* the matching likelihood (see equation 1): An attractive type has a higher standard to make a deal, which shrinks the matching likelihood; however, at the same time, such types would bring in more value to a match on average (high z_{ij}) which increases the matching likelihood. In the end, the latter force dominates, hence p_{ij} significantly increases with both u_i and v_j. Because z_{ij} is more on average for attractive startup and VC types, the total payoff from matching Π_{ij} is also increasing with u_i and v_j as well. See table 5, Column 2.

While the matching likelihood and total payoff generated in matching increases with the attractiveness of the startup and the VC in a deal, the *share* in payoff from matching for a startup and for a VC decreases with the attractiveness of the *counter*party type. See table 5, Column 3. Such an impact would dampen the payoff for an average startup *conditional on matching* when dealing with an attractive VC type, and likewise, the payoff for an average VC *conditional on matching* when dealing with an attractive startup type, in absolute terms. Therefore, in the end, the variation in the extensive margin—the matching likelihood, captures most of the variations in the expected payoff from matching when dealing with an attractive counterparty type. See table 5, Column 4, and compare regression slopes with estimates in Column 1. For an average startup, 80% of the variation in expected payoff from matching with respect to v_j is explained by the variations in the matching likelihood, while for an average VC more than 95% of the variation in expected payoff with respect to u_i is explained by the variations in the matching likelihood. In other words, especially for VCs, whether to make a deal and form a match or not is the key source of variation in the final payoff. This finding is supported by the study in Gompers et al. (2020) that show deal selection is the most important margin for value creation from VCs' viewpoint.

Lastly, we highlight that all three forces: matching likelihood, total matching payoff, and share in payoff, for a startup and VC, are increasing with *self* attractiveness (u_i for the payoff of the startup: Π^S_{ij}, and v_j for the payoff of the VC: Π^{VC}_{ij}). Therefore, both extensive and intensive margins: matching likelihood and payoff conditional on matching, contribute to the expected payoff of an attractive startup and VC from matching when dealing with an average counterparty type. Indeed regression slopes show that variations in the intensive margins play a major role (roughly two-thirds) in explaining the increasing pattern of expected payoff from matching for attractive startup and VC types—i.e., those with higher u_i and v_j, respectively.

6 Discussion and External Validations

In this section, we discuss the testable implications of our model under our benchmark estimation. First, we test if pairs of startups and VCs with higher average conditional joint matching values in our estimation feature a larger deal size—a measure for the profitability of the match—in the Pitchbook data. Next, we study the link between the expected number of offers received by a startup type and the generated matching value on average for that startup type and confirm the positive relationship documented in Hsu (2004). Lastly, we discuss the role of endogenous sorting in the realized match qualities in equilibrium, as studied in Sørensen (2007). We further demonstrate the importance of sorting based on ex-ante unobservable shocks to the matching value in the model with search frictions.

Deal Size. We test if estimated matching values can predict the deal size in the data. In our estimation, the matching value is different in expectation across different pairs of startups and VCs in a deal. We consider the deal size in the Pitchbook data as an indicator of profitability and see if the pairs of startups and VCs with higher joint matching values in our simulation represent larger deal sizes in the real-world data.

We first establish a theoretical relationship between deal size and profitability. We consider a model with Cobb-Douglas technology in which cash-constrained startups raise capital from VCs. The optimal deal size solves $k^*_{ij} = \arg\max_k \pi_{ij}(k) = a_{ij}^{1-\theta} k^\theta - R^{VC} k$, where $a_{ij}^{1-\theta} k^\theta$ is the present value of resultant cash flows, in which a_{ij} is the productivity of the match between startup type i and VC type j, k is the endogenous investment amount—the deal size, and θ is the share of the physical capital in the production. $R^{VC} = 1 + r^{VC}$ is the gross return rate—the cost of capital for VCs. One may show that both the optimal investment k^*_{ij} and the resultant profit $\pi^*_{ij} := \pi_{ij}(k^*)$ scale linearly with a_{ij}, and then derive a linear relationship between the two as $k^*_{ij} = \frac{\theta}{1-\theta} R^{VC} \pi^*_{ij}$.

We consider the joint matching value between types i and j, $z_{ij} + \epsilon$, as a proxy for profitability π^*_{ij}, with a scaling factor κ that translates one unit of value in our reports into dollar terms. We then propose the following testable relationship:

$$k^*_{ij} = (\frac{\theta}{1-\theta} R^{VC})\ \kappa\ \mathbf{E}_\epsilon[z_{ij} + \epsilon \mid z_{ij} + \epsilon \geq u_i + v_j]$$

On the right-hand side, $\Pi_{ij} = \mathbf{E}_\epsilon[z_{ij} + \epsilon \mid z_{ij} + \epsilon \geq u_i + v_j]$ shows the matching value between type i startup and type j VC conditioned on that matching happens, which associates with the average matching values observed in the real world matches between the two types. We simulate $\mathbf{E}_\epsilon[z_{ij} + \epsilon \mid z_{ij} + \epsilon \geq u_i + v_j]$ in our model and then try to predict the observed deal sizes between pairs of startups and VCs in the Pitchbook.

Online Appendix figure C2, top Panel, plots the average log deal sizes (in million dollars) from the Pitchbook at the i/j type levels during 2015-2020 against the simulated conditional matching value.[19] We find a positive relationship between the two objects, that is statistically significant at 5% level. The constrained fit is based on the Cobb-Douglas model that implies section 6. The estimated slope (intercept in the log scale) identifies κ, given θ. For calibration of $\theta = .25$, we find $\kappa \simeq 1$, which implies that one unit of matching value in our normalization in the model and estimation is of the order of 1 million dollar profit.

Online Appendix figure C2, bottom Panel, studies the relationship between conditional payoff from matching for startups and VCs and deal size, on average at the startup- and VC-type level. Statistical power is not ideal; but, given the calibration $\theta = .25$ and the resulting $\kappa \simeq 1$ from the fit above for the total matching value, we find that 1 dollar deal size is associated with around 2 dollars expected profit on the VC side, which is consistent with the evidence on payoff per dollar investment in the VC industry. The fit is flatter for startups than what the Cobb-Douglas model predicts, which may be explained by the nonpecuniary aspects of running a business for startups.

Expected Number of Offers/Deals. We demonstrate the relationship between the likelihood of getting an offer/making a deal and the average conditional matching value for startups/VCs. In our model, attractive types generate a larger average joint matching value z_{ij}—hence, involve in matches of higher values. At the same time, such types are more likely to form a match, because of a higher p_{ij}. Hence, there exists a positive relationship between the likelihood of offers/deals and the conditional value of the match across startup/VC types.

Figure 4 depicts the link between matching likelihood and conditional value of matching that a startup and VC involves in. In our model, the expected number of funding offers that a startup of type i receives in a unit of time is $\rho^S \sum_j n_j p_{ij}$, and similarly, the number of deals that a VC of type j expects to make in a unit of time is $\rho^{VC} \sum_i m_i p_{ij}$. Figure 4, left Panel, shows that startup types that expect to receive more offers in a given time period get into matches with up to nearly twice the value compared to the rest. This result is in line with empirical findings in Hsu (2004), which shows that startups with multiple offers in the sample period feature better outcomes compared to those with single offers. We show that such a relationship exists across VCs as well. Figure 4, right Panel, shows that VCs that expect to make more deals over time are those who form matches of up to 20% more value. Online Appendix figure C3 verifies a one-to-one relationship between the attractiveness of a

[19]We plot variables in log scales to mitigate outliers in the data on the deal size.

type in our setup (estimated continuation values) and the expected number of offers/deals for startups and VCs over time.

Insert Figure 4 here

Endogenous Matching Formation and Conditional Matching Value. Below we discuss the role of endogenous matching on the conditional matching value between startups and VCs. The average matching value for a startup or VC in equilibrium depends on the likelihood that a given type is matched which various counterparty types. Attractive startup types may match with attractive VC types, which would generate a higher matching value, compared with a setting where matching with VCs was random. Sørensen (2007) identifies this mechanism and shows that the better outcome of startups that match with experienced VCs is in part due to the assortative matching of "high-type" startups with such VCs.

We further highlight the importance of ex-ante unobservable shocks to the matching value and search frictions in endogenous sorting for measuring variations in matching payoffs. Figure 5 shows that the gap in average conditional matching value in equilibrium and the matching value in a counterfactual setup with random matching indeed *shrinks* in case of attractive startup and VC types. Note that this gap stems from both weighting based on endogenous p_{ij} in measuring averages (the key force in the mechanism discussed above) and the incorporation of the expected conditional ϵ—the shock to the matching value. If one only takes the effect of weighting with p_{ij} into consideration, the gap is expected to be larger for attractive types (as shown in Sørensen, 2007). However, with the presence of the ϵ term, we find that the gap between the conditional and the unconditional matching value widens for *un*attractive types. In equilibrium, attractive types are more likely to form a match in a given period (because of higher z_{ij} and p_{ij}). In contrast, unattractive types (those with lower z_{ij} on average) search more to find a better draw of ϵ in order to get matched, which disproportionately raises the value *conditional on matching* for such types. This result demonstrates the role of search frictions and the shocks to the matching value when linking endogenous matching formation with realized matching values in equilibrium.

Insert Figure 5 here

7 Conclusion

This paper estimates a dynamic search-and-matching model with bargaining between VCs and startups based on data from two symmetric IRR experiments. Experimental subjects evaluate randomized profiles of potential collaborators and their evaluations are incentivized by real opportunities of being matched with their preferred partners. With these experimental behaviors and real-world portfolio data as inputs to our structural model, we are able to address several empirical challenges in estimating the search-and-matching model. We estimate the role of human and organizational capital on the side of investors and VC funds, and human and organizational assets on the side of founders and startup teams, for the continuation value of a VC and a startup, and the payoff from matching for startups and VCs in the equilibrium matching outcome.

Results from experiments discover several VC characteristics that influence startups' fundraising strategies and several startup characteristics that influence VCs' investment decisions. The startup-side experiment shows that both investors' human capital (investors' entrepreneurial experiences) and VC funds' organizational capital (previous financial performances, fund size) affect startups' intentions to approach VC funds. The investor-side experiment shows that startups' human assets (founders' entrepreneurial experience, educational background) and non-human assets (traction, business model) affect VCs' intentions to approach startups.

Based on the experimental results and frequency of observed matches between types in Pitchbook, our structural model estimates the effects of different startup and investor characteristics on the equilibrium continuation values, and payoffs from the matching for investors and startups when collaborating with alternative counterparty types. We find that an average VC gets more value than an average startup due to more outside options. However, substantial heterogeneity exists across startups and VCs with different human and organizational characteristics. Implied by heterogeneity in continuation values, we find substantial variations in the split of payoff in realized matches, depending on the attractiveness of the startup and the VC involved in the match. This variation in the split of payoff dampens the benefits of collaborating with an attractive counterparty type in absolute terms.

Overall, results from our experimental system and dynamic search-and-matching model provide thorough micro-level empirical foundations to understand the matching process and payoffs from matching—specifically, the split of payoff between VCs and startups in the US entrepreneurial finance context. Future research can replicate these experiments in different settings to study the impact of relevant attributes on the matching equilibrium outcomes.

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Tables and Figures

Table 1: Startups' Evaluation Results (Human Capital VS Organizational Capital)

Dependent Variable	Q1 Quality	Q2 Availability	Q5 Informativeness	Q3 Fundraising Plan	Q3 Fundraising Plan	Q4 Contact	Q4 Contact
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Top School	1.05*	1.11*	0.56	0.65	-0.53	0.85	-0.13
	(0.62)	(0.60)	(0.52)	(0.88)	(0.58)	(0.64)	(0.34)
Graduate Degree	-0.34	-0.58	-0.14	-0.12	0.36	-0.65	-0.25
	(0.64)	(0.63)	(0.56)	(0.95)	(0.67)	(0.67)	(0.40)
Years of Investment Experience	0.41**	0.22*	0.39***	0.47**	0.05	0.33**	-0.01
	(0.14)	(0.13)	(0.11)	(0.20)	(0.13)	(0.13)	(0.07)
Squared Years of Investment Experience	-0.01	-0.00	-0.01**	-0.01	-0.00	-0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)
Entrepreneurial Experience	3.87***	4.03***	2.75***	4.66***	0.12	3.86***	0.09
	(0.59)	(0.56)	(0.48)	(0.79)	(0.55)	(0.59)	(0.29)
First Time Fund	2.29***	1.25**	1.41**	2.97**	0.90	2.15**	0.45
	(0.67)	(0.63)	(0.59)	(1.00)	(0.70)	(0.69)	(0.39)
Better Historical Performance	4.99***	3.06***	3.11***	6.13***	1.45**	4.47***	0.62*
	(0.72)	(0.69)	(0.61)	(1.15)	(0.71)	(0.74)	(0.35)
Larger Fund	1.96***	1.21**	0.89**	3.40***	1.66**	1.45**	0.03
	(0.48)	(0.44)	(0.41)	(0.83)	(0.66)	(0.52)	(0.27)
Value Added Style	-0.14	0.87	-0.01	0.29	-0.07	0.37	0.05
	(0.58)	(0.58)	(0.50)	(0.88)	(0.60)	(0.65)	(0.33)
US Fund	0.98	0.77	-0.16	-0.09	-0.84	0.18	-0.44
	(0.83)	(0.76)	(0.68)	(1.20)	(0.87)	(0.84)	(0.48)
Q1					0.44***		0.34***
					(0.04)		(0.02)
Q2					0.49***		0.43***
					(0.04)		(0.03)
Q5					0.32***		0.26***
					(0.04)		(0.02)
Mean of Dep. Var.	62.63	58.98	66.98	89.86	89.86	59.90	59.90
Subject FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8180	8180	8180	8180	8180	8180	8180
R-squared	0.467	0.518	0.538	0.638	0.808	0.468	0.832

Notes. This table reports the OLS regression results of how startups' evaluation results respond to investors' characteristics. All regression results add subject fixed effects and cluster the standard errors within each startup founder. Standard errors are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 2: Investors' Evaluation Results (Human Capital VS Non-human Assets)

Dependent Variable	Q1 Quality (1)	Q2 Collaboration (2)	Q3 Contact (3)	Q3 Contact (4)	Q4 Investment (5)	Q4 Investment (6)
Serial Founder	5.23***	-0.81	5.64***	1.26	0.76***	0.13
	(1.08)	(0.88)	(1.28)	(0.91)	(0.19)	(0.15)
Ivy	5.36***	-1.06	7.44***	3.01***	0.87***	0.20
	(1.10)	(0.87)	(1.31)	(0.93)	(0.20)	(0.15)
Number of Founders	1.56	-1.21	1.17	-0.11	0.21	0.04
	(1.07)	(0.88)	(1.29)	(0.91)	(0.20)	(0.15)
US Founder	0.95	0.02	4.23***	3.69***	0.08	0.03
	(1.18)	(0.91)	(1.39)	(1.00)	(0.21)	(0.16)
# Comparative Adv	3.10***	-0.22	2.76***	0.34	0.55***	0.15**
	(0.54)	(0.43)	(0.64)	(0.43)	(0.10)	(0.07)
Has Positive Traction	12.70***	1.75**	13.35***	1.91*	1.81***	0.28*
	(1.07)	(0.86)	(1.28)	(0.99)	(0.20)	(0.16)
Number of Employees [0-10]	0.67	2.37**	-1.73	-2.57**	-0.19	-0.29
	(1.43)	(1.16)	(1.69)	(1.18)	(0.26)	(0.20)
Number of Employees [10-20]	-1.08	0.94	-3.26	-2.08	-0.46	-0.33
	(1.64)	(1.35)	(1.99)	(1.39)	(0.30)	(0.21)
Number of Employees [20-50]	-0.47	-0.02	-1.21	-0.72	-0.16	-0.12
	(1.45)	(1.17)	(1.71)	(1.17)	(0.27)	(0.19)
Company Age	-4.59*	-5.99***	-7.39**	-2.19	-1.26**	-0.54
	(2.72)	(2.19)	(3.19)	(2.26)	(0.49)	(0.37)
Company Age^2	0.75	1.12**	1.27**	0.42	0.23**	0.10
	(0.54)	(0.44)	(0.64)	(0.45)	(0.10)	(0.07)
Is B2B	3.90***	3.73***	6.10***	1.47	0.81***	0.32**
	(1.07)	(0.86)	(1.28)	(0.89)	(0.20)	(0.15)
Domestic Market	-0.10	-0.60	0.09	0.57	0.08	0.13
	(1.08)	(0.86)	(1.28)	(0.90)	(0.20)	(0.14)
Q1				0.88***		0.12***
				(0.03)		(0.01)
Q2				0.18***		0.01
				(0.03)		(0.01)
Investor FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,216	1,184	1,216	1,184	1,176	1,154
R-squared	0.44	0.55	0.56	0.80	0.44	0.70

Notes. This table reports the OLS regression results of how VCs' evaluation results respond to startups' characteristics. Regressions include subject fixed effects and cluster the standard errors within each investor. Standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 3: Simulation results—equilibrium values and expected conditional matching payoffs

	(S,p1)	(S,p2)	(S-VC,p1)	(S-VC,p2)
$\bar{u}$	1.89	2.178	1.936	1.93
	(0.048)	(0.048)	(0.083)	(0.116)
$std(u)$	0.326	0.434	0.487	0.666
	(0.032)	(0.051)	(0.1)	(0.134)
$ave(\Pi^S)$	2.726	3.143	2.793	2.783
	(0.069)	(0.069)	(0.121)	(0.17)
$\bar{v}$	3.384	2.507	2.938	5.963
	(0.721)	(0.685)	(1.327)	(1.908)
$std(v)$	0.252	0.294	0.283	0.577
	(0.043)	(0.07)	(0.125)	(0.202)
$ave(\Pi^{VC})$	3.485	2.582	3.026	6.143
	(0.743)	(0.706)	(1.368)	(1.97)
$M^S\bar{u} + M^{VC}\bar{v}$	111.4	121.5	111.5	126.3
	(2)	(2.6)	(2.8)	(4.2)
$\frac{M^{VC}\bar{v}}{M^S\bar{u}+M^{VC}\bar{v}}$	0.152	0.103	0.133	0.238
	(0.031)	(0.027)	(0.055)	(0.068)

Notes. In Columns (S,p1) and (S,p2) we use startup-side experimental data while in Columns (S-VC,p1) and (S-VC,p2) we use both startup-side and VC-side experimental data to estimate continuation values and conditional matching probabilities. In Columns (S,p1) and (S-VC,p1) we use the revealed collaboration likelihoods to set the conditional matching probabilities while in Columns (S,p2) and (S-VC,p2) we infer probabilities from the revealed contact interests. $\bar{u}$ and $\bar{v}$, and $std(u)$ and $std(v)$ are the mass-weighted average and standard deviation of continuation values for startups and VCs, respectively. $ave(\Pi^S) = \sum_i m_i \sum_j n_j p_{ij}\{u_i + \pi\mathbf{E}_\epsilon[z_{ij} + \epsilon - u_i - v_j|positive]\}/\sum_j n_j p_{ij}$ is the average expected payoff of startups *conditioned* on matching with various VC types and $ave(\Pi^{VC}) = \sum_j n_j \sum_i m_i p_{ij}\{v_j + (1-\pi)\mathbf{E}_\epsilon[z_{ij} + \epsilon - u_i - v_j|positive]\}/\sum_i m_j p_{ij}$ is the average expected payoff of VCs *conditioned* on matching with various startup types. The total present value of matching $M^S\bar{u} + M^{VC}\bar{v}$ is reported in the unit of 1,000. Numbers in parentheses show standard errors.

Table 4: Equilibrium values—premium attached to attributes

Panel A: Startups $[u_i]$	(S,p1)	(S,p2)	(S-VC,p1)	(S-VC,p2)
constant	1.466	1.646	0.93	0.454
	(0.126)	(0.163)	(0.255)	(0.3)
$\mathbf{1}\{\text{traction}\}_i$	−0.034	−0.059	0.944	1.39
	(0.107)	(0.133)	(0.194)	(0.223)
$\mathbf{1}\{\text{b2b}\}_i$	0.37	0.479	0.519	0.754
	(0.13)	(0.156)	(0.117)	(0.175)
$\mathbf{1}\{\text{serial founder}\}_i$	0.45	0.592	0.663	0.821
	(0.11)	(0.129)	(0.128)	(0.186)
$\mathbf{1}\{\text{prestig. education}\}_i$	0.492	0.636	0.04	0.088
	(0.089)	(0.129)	(0.022)	(0.043)

Panel B: VCs $[v_j]$	(S,p1)	(S,p2)	(S-VC,p1)	(S-VC,p2)
constant	2.97	2.029	2.463	5.01
	(0.675)	(0.596)	(1.156)	(1.637)
$\mathbf{1}\{\text{size}\}_j$	0.132	0.149	0.168	0.215
	(0.073)	(0.089)	(0.102)	(0.194)
$\mathbf{1}\{\text{hist. performance}\}_j$	0.367	0.428	0.422	0.915
	(0.093)	(0.125)	(0.202)	(0.328)
$\mathbf{1}\{\text{entr. experience}\}_j$	0.439	0.514	0.468	0.961
	(0.1)	(0.14)	(0.214)	(0.368)

Notes. The average impact of attributes on equilibrium continuation values is estimated from simulation outcomes using models estimated via alternative experimental data sources in Columns (S,p1), (S,p2), (S-VC,p1), and (S-VC,p2), as defined in table 3. In Panel A we run the OLS regressions of startups' continuation values $\{u_i\}$ on dummy variables of attributes over 16 types of startups, using the underlying mass of startup types $\{m_i\}$ as regression weights. In Panel B we run the OLS regressions of VCs' continuation values $\{v_i\}$ on dummy variables of attributes over 8 types of VCs, using the underlying mass of VC types $\{n_j\}$ as regression weights. Numbers in parentheses show standard errors.

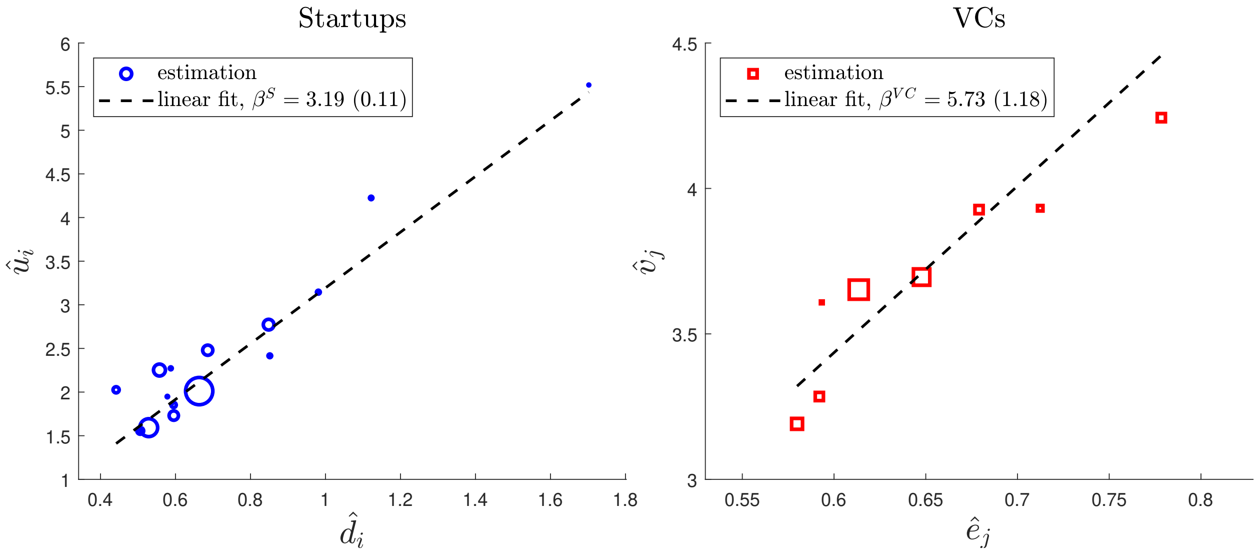
Table 5: Expected payoff from matching—economic decomposition

Panel A: Startups' expected payoff				
	$\log(p_{ij})$	$\log(\Pi_{ij})$	$\log(\Pi_{ij}^S/\Pi_{ij})$	$\log\left(\mathbb{E}[\Pi_{ij}^S]\right)$
$\log(u_i)$	0.53	0.379	0.46	1.369
	(0.022)	(0.066)	(0.064)	(0.019)
$\log(v_j)$	0.58	0.63	−0.488	0.722
	(0.022)	(0.066)	(0.064)	(0.022)

Panel B: VCs' expected payoff				
	$\log(p_{ij})$	$\log(\Pi_{ij})$	$\log(\Pi_{ij}^{VC}/\Pi_{ij})$	$\log\left(\mathbb{E}[\Pi_{ij}^{VC}]\right)$
$\log(u_i)$	0.53	0.379	−0.364	0.544
	(0.022)	(0.066)	(0.066)	(0.021)
$\log(v_j)$	0.58	0.63	0.354	1.564
	(0.022)	(0.066)	(0.065)	(0.022)

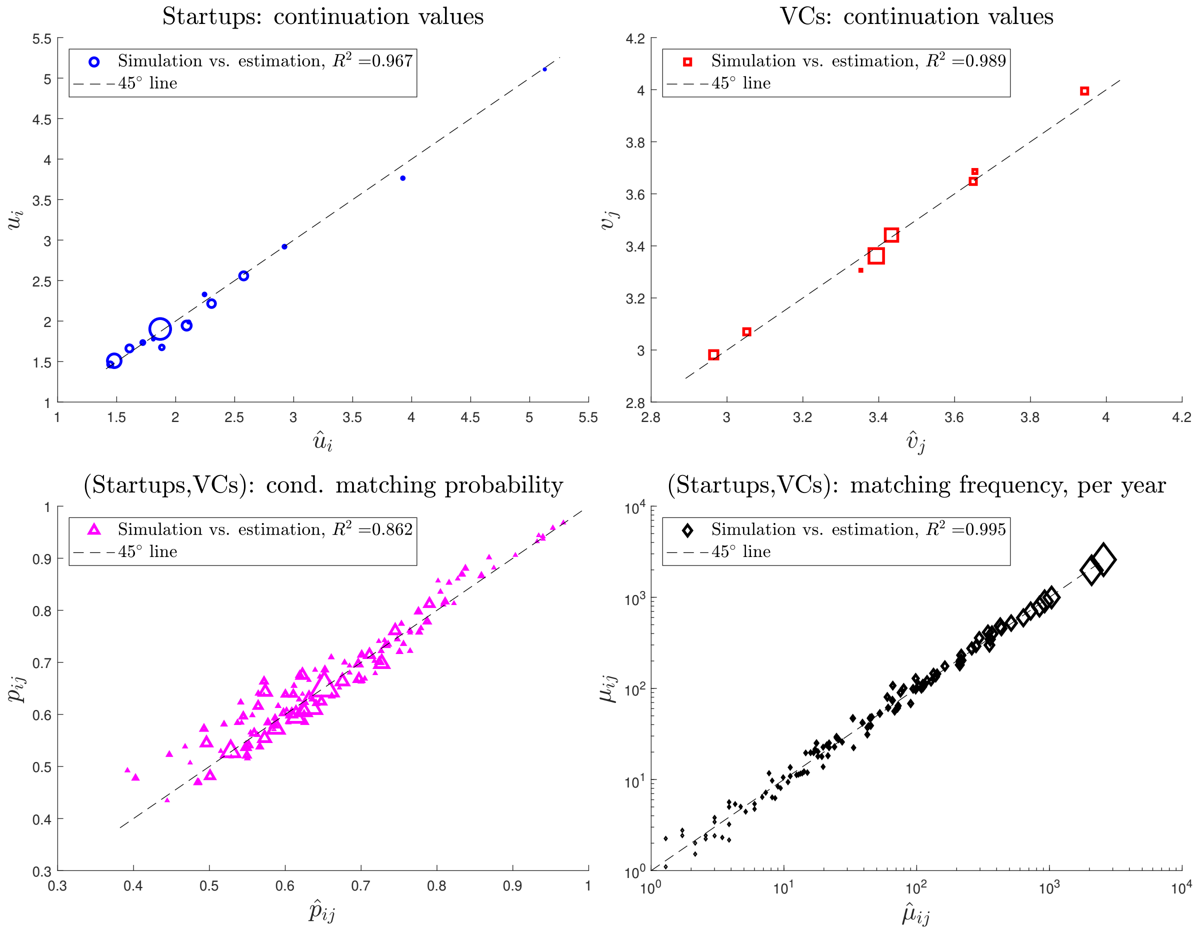
Notes. The relationship between components of the expected payoff from matching for startups and VCs $\mathbb{E}[\Pi_{ij}^S] = p_{ij} * \Pi_{ij} * \Pi_{ij}^S/\Pi_{ij}$ and $\mathbb{E}[\Pi_{ij}^{VC}] = p_{ij} * \Pi_{ij} * \Pi_{ij}^{VC}/\Pi_{ij}$, respectively, and continuation values of startups and VCs, u_i and v_j, respectively, is shown via multivariate OLS regressions on 16∗8=128 points at the startup-by-VC type level data. We use simulation results of the benchmark specification and run weighted regressions via the mass of underlying startup and VC types, $\{m_i\}$ and $\{n_j\}$.

Figure 1: Estimation results—continuation values vs. expected matching payoffs



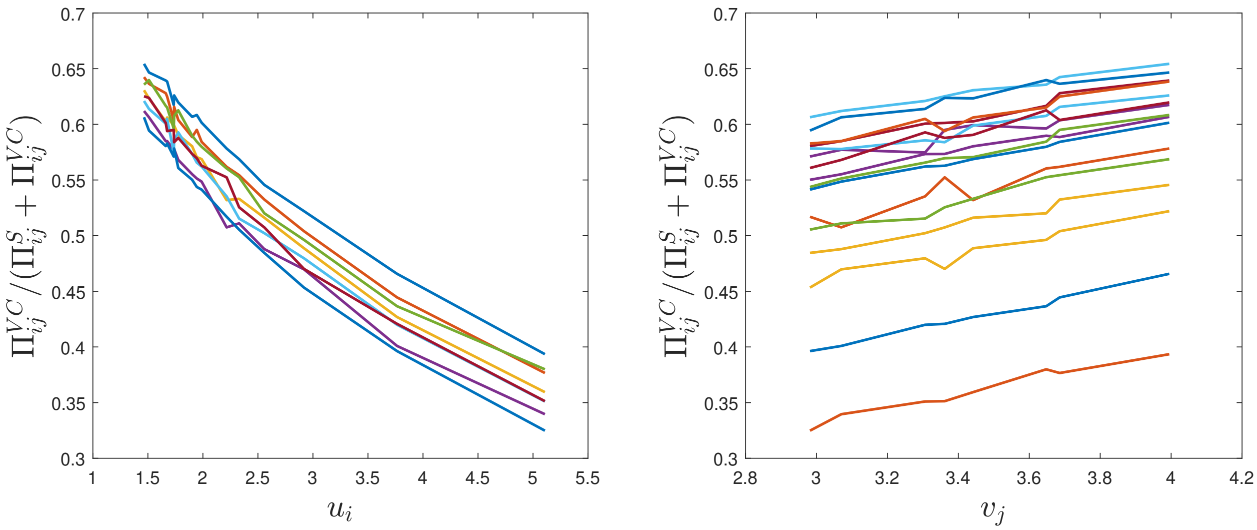
Notes. The size markers represent the estimated mass of startup and VC types, $\{m_i\}$ and $\{n_j\}$ in the left and right panel, respectively. Numbers in parentheses show the standard error of the estimated slopes.

Figure 2: Model fit—continuation values, cond. matching likelihoods, and matching frequencies



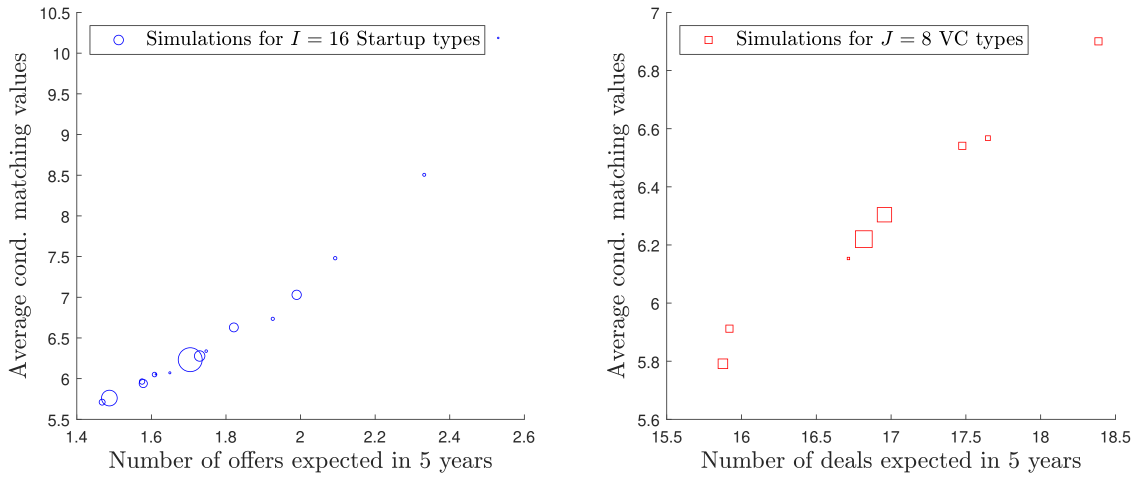
Notes. In bottom panels we depict the pooled data of $\{p_{ij}\}$ and μ_{ij} for all startup and VC types, consisting 16x8=128 points. The size of dots reflect the estimated mass of startup and VC types, $\{m_i\}$ and $\{n_j\}$ in the top left and top right panels, respectively, and $\{m_i * n_j\}$ in the bottom left and bottom right panels.

Figure 3: VCs' share of the matching value



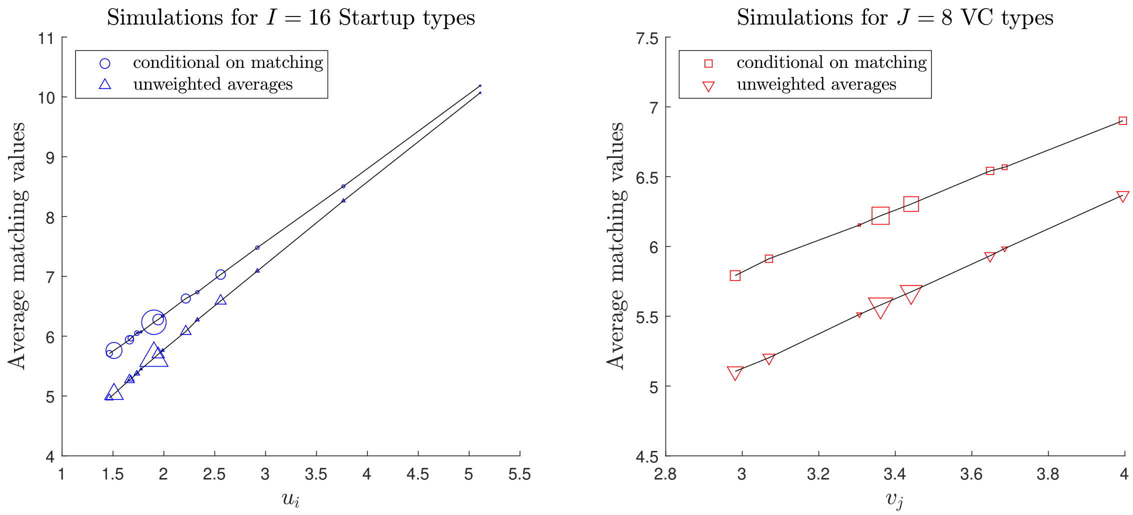
Notes. This graph shows the share of the VC from the joint matching value $\Pi_{ij}^{VC}/(\Pi_{ij}^{S}+\Pi_{ij}^{VC}) = \frac{v_j+(1-\pi)\mathbf{E}_\epsilon[z_{ij}+\epsilon-u_i-v_j|positive]}{\mathbf{E}_\epsilon[z_{ij}+\epsilon|z_{ij}+\epsilon\geq u_i+v_j]}$ versus continuation values of the startup and VC, u_i in the left Panel, and v_j in the right Panel, respectively. Plots are based on the simulation outcomes of the benchmark estimation and are reported at the startup-by-VC type level, consisting 16x8=128 data points. Each color line represents a given VC type in the left Panel and a given startup type in the right Panel.

Figure 4: Expected number of offers/deals and value of realized matches for startups and VCs



Notes. The left panel shows for each startup type the average conditional value in matches with VCs $\sum_j n_j \cdot p_{ij} \cdot \mathbf{E}_\epsilon[z_{ij} + \epsilon \, |z_{ij} + \epsilon \geq u_i + v_j]/\sum_j n_j \cdot p_{ij}$ versus the expected number of funding offers received in a 5-year period $5 * \rho^S \sum_j n_j \cdot p_{ij}$. The right panel shows for each VC type the average conditional value in matches with startups $\sum_i m_i \cdot p_{ij} \cdot \mathbf{E}_\epsilon[z_{ij} + \epsilon \, |z_{ij} + \epsilon \geq u_i + v_j]/\sum_i m_i \cdot p_{ij}$ versus the expected number of deals made in a 5-year period $5 * \rho^{VC} \sum_i m_i \cdot p_{ij}$. Marker sizes indicate the mass of startup and VC types.

Figure 5: Average matching values—unconditional and conditioned on matching



Notes. The average conditional matching value is $\sum_j n_j \cdot p_{ij} \cdot \mathbf{E}_\epsilon[z_{ij} + \epsilon \;|z_{ij} + \epsilon \geq u_i + v_j]/\sum_j n_j \cdot p_{ij}$ for startups and $\sum_i m_i \cdot p_{ij} \cdot \mathbf{E}_\epsilon[z_{ij} + \epsilon \;|z_{ij} + \epsilon \geq u_i + v_j]/\sum_i m_i \cdot p_{ij}$ for VCs. The unconditional averages of matching values are $\sum_j n_j z_{ij}$ for startups and $\sum_i m_i z_{ij}$ for VCs. The left panel shows results based on startups' continuation value u_i. The right panel shows results based on VCs' continuation value v_j.

Appendix—for Online Publication

A Startup-Side IRR Experiments

A.1 Reduce Noise

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

a. Use Attention Check Questions. We insert one attention check question and several other background questions requiring participants to manually enter the answer. If participants fail the attention check question, the Qualtrics system will terminate their evaluation process and inform them that they are unqualified for this study. If participants type in some irrelevant answers, their responses are also removed from our formal data analysis.[20]

b. Enough Evaluation Time. We only include evaluation results from participants who satisfy the following criteria based on evaluation time: 1) spend at least 15 minutes on this study.[21] 2) spend at least 50 (15) seconds on evaluating the first (second) profile.

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

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

[21]In our soft launch process, only 10% participants spend less than 15 minutes on this study. Such participants also give more sloppy evaluation results and always prefer money to higher quality investor recommendation lists in the payment game. Hence, we decided to remove them in our formal study.

that participants give the same evaluation to these questions.[22]

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

d. Reasonable Answers to Text Entry Questions. When the tool asks participants to enter their industry background, amount of funding needed, or general comments about the study, any answers containing gibberish lead to removal of subjects' evaluations.

e. Other Subsidiary Criteria In addition to the criteria mentioned above, we also take the following subsidiary criteria into consideration when identifying "noisy participants". These criteria include i) a reasonable amount of required funding; ii) time spent on evaluating profiles (i.e., "Timing - Last Click", "Timing - Page Submit", "Duration (in seconds)"); iii) distribution of rating variations; iv) the list of low-quality responses identified by Qualtrics team based on their designed "data scrub" algorithms.[23]

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

A.2 Distributional Effects across Market Conditions

When the capital supply is abundant (limited) on the market, startups have more (less) outside options for their fund-raising purposes and generally increase (decrease) their internal thresholds of choosing future collaboration partners. In this situation, the VC market becomes more (less) competitive for different VC funds. To understand how startups' preferences vary in different market conditions as measured by startups' internal thresholds of selecting investors, Figure A2 investigates the distributional effects of investor characteristics across startups' contact interest ratings. Panels A, C, and E provide the empirical cumulative density function (CDF) for the investor's entrepreneurial experience, the VC fund's size,

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

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

and the VC fund's historical financial performances across startups' contact interest ratings, respectively. Panels B, D, and F provide the OLS coefficient estimates and the corresponding 95% confidence intervals for the investor's entrepreneurial experience, the VC fund's size, and the VC fund's historical financial performances across startups' contact interest ratings, respectively.

Figure A2 shows that the direction of startups' preferences is very stable in different market conditions. However, the magnitude of these preferences varies dramatically depending on the position of startups' internal thresholds, which is similar to the findings of the investor-side IRR experiment. For the impact of an investor's entrepreneurial experience, its magnitude is smallest in extreme market conditions where investors' thresholds are too high or too low. When startups' internal thresholds fall in the range between 40% and 80% contact interest ratings, the magnitude of its impact is relatively stable and slightly stronger than other market conditions. For the impact of a VC fund size, the magnitude is largest when startups' internal thresholds fall around the threshold of 80% contact interest ratings. This indicates that a larger VC fund size can bring investors stronger comparative advantages when startups become more picky about investors. As for the impact of a VC fund's historical performances, its magnitude becomes the strongest when startups' internal thresholds are between 50% and 70% contact interest rating. It should be noted that the direction of these preferences about attractive investor characteristics is very positive across different market conditions. This suggests that investors' entrepreneurial experience, VC funds' outperforming financial performances, and fund size help to attract startups in most market conditions.

A.3 Heterogeneous Effects across the Spectrum of Investors' Quality

One of this paper's purposes is to provide practical guidance to venture capitalists on improving VC funds' financial performances through attracting better deals. Therefore, we further examine the heterogeneous effects of investor characteristics across the spectrum of investors' quality. Depending on investors' self-positioning of their quality, practitioners can optimally choose different investor characteristics to emphasize when communicating with their preferred startups. To achieve this goal, we estimate quantile regressions to study investor characteristics' impact on the conditional quantile of startups' evaluation results.

Table A3 reports the quantile regression results about different investor characteristics' impact across the investor's quality spectrum. The dependent variable is the investor's received ability rating (i.e., Q_1). In each of Columns (1)–(9), the reported coefficient of each investor characteristics stands for the effect of the characteristic on the kth conditional percentile ($k \in 10, 20, 30, ..., 90$) of the investor's received rating (i.e., Q_1). In Column (10), the reported coefficients using OLS regressions stand for the effects on the conditional mean of Q_1. Standard errors in parentheses are clustered at the subject level, and reported in parentheses.

Results of Table A3 show that different investor characteristics have different heterogeneous effects across the spectrum of investors' quality. Although the impact of VC funds' historical financial performances dominates the impact of other investor characteristics at almost all quantiles of investor quality, its impact is stronger for relatively low-quality investors compared to relatively high-quality investors. For the bottom 10th quantile investors (i.e., low-quality investors) in terms of quality, the magnitude of financial performances' impact (i.e., 10.86%) is almost twice as large as the magnitude of investors' entrepreneurial experience's impact (i.e., 4.95%). However, for the 80th quantile investors (i.e., high-quality investors), the magnitude of financial performances' impact (i.e., 1.68%) is smaller than the magnitude of investors' entrepreneurial experience's impact (i.e., 2.35%). This indicates that worse historical financial performances hurt low-quality investors more compared to high-quality investors. Other investor characteristics follow similar patterns in terms of the magnitudes of their impact. For example, the coefficients of "Larger Fund" is 2.81% for the 40th quantile investors and decreases to 1.68% for the 80th quantile investors. All results are statistically significant.

Table A1: Summary Statistics of Startup Founders

Panel A: Founder Demographic Information

Demographic Information	N	Fraction (%)
Female Founder	167	40.83%
Minority Founder	91	22.25%
Serial Founder	168	41.08%
Educational Background		
High school graduate, diploma or the equivalent	89	21.76%
Bachelor's degree	136	33.25%
Master's degree	84	20.54%
Doctorate degree	23	5.62%
Professional degree	39	9.54%
Other	38	9.29%
Political Attitudes		
Democratic	206	50.37%
Republican	98	23.96%
Constitution Party	6	1.47%
Green Party	7	1.71%
Libertarian Party	15	3.67%
I do not want to say	35	8.56%
Others	42	10.27%

Panel B: Startup Background Information

Category	N	Fraction (%)
Standard Classification		
B2B	89	21.76%
B2C	279	68.22%
Healthcare	16	3.91%
Others	25	6.11%
Detailed Classification		
Information technology	90	22.00%
Consumers	117	28.61%
Healthcare	25	6.11%
Clean technology	22	5.38%
Finance	53	12.96%
Media	22	5.38%
Energy	10	2.44%
Education	16	3.91%
Life sciences	8	1.96%
Transportation & Logistics	23	5.62%
Manufacture & Construction	68	16.63%
Others	93	22.74%

Continued

Category	N	Fraction (%)
Stage		
Seed Stage (developing products or services)	91	22.25%
Seed Stage (mature products, no revenue)	116	28.36%
Seed Stage (mature products, positive revenue)	158	38.63%
Series A	17	4.16%
Series B	12	2.93%
Series C or later stages	9	2.20%
Others	6	1.47%
Number of Employees		
0-5 employees	191	46.70%
5-20 employees	63	15.40%
20-50 employees	67	16.38%
50-100 employees	49	11.98%
100+ employees	39	9.54%
Startup Team Composition		
Both male and female founders	248	60.64%
Only female founders	82	20.05%
Only male founders	79	19.32%
Startup Philosophy		
Financial Gains	360	88.02%
Promote Diversity	242	59.17%
ESG Criteria	261	63.81%

Notes. This table reports descriptive statistics for the startup founders who participate in this experiment. In total, 409 startup founders from the U.S. provide evaluations of 8180 randomly generated investor profiles. Panel A reports the demographic information of recruited founders. "Female Founder" is an indicator variable that equals one if the founder is female, and zero otherwise. "Minority Founder" is an indicator variable that equals one if the investor is Asian, Hispanic, Middle Eastern, Native American, Pacific Islander, or African Americans, and zero otherwise. Founders who prefer not to disclose their race are not included in this variable. "Serial Founder" is equal to one if the founder is a serial startup founder, and zero otherwise. Panel B reports background information on participants' startups. Based on the standard classification methods of industries, founders report their startups' general business categories and each founder can only choose one unique classification from B2B, B2C, Healthcare, and others. Based on the detailed classification methods of startups' industry backgrounds, founders can select multiple industries as their startups' industry backgrounds. "Others" includes HR tech, Property tech, infrastructure, etc. Sector *Stage* reports the stage distribution of the participants' startups, where each founder can only choose one unique stage. Sector *Number of Employees* reports startups' current total number of employees, and founders can only choose one of the categories that fit them the best. Sector *Startup Team Composition* reports the gender composition of startups' co-founders. Sector *Startup Philosophy* provides the startups' goals, which contain whether they aim for any financial returns, promote diversity of the entrepreneurial community, and care about ESG impact. Each founder can choose multiple startup goals.

Table A2: Randomization of Investor Profile Components

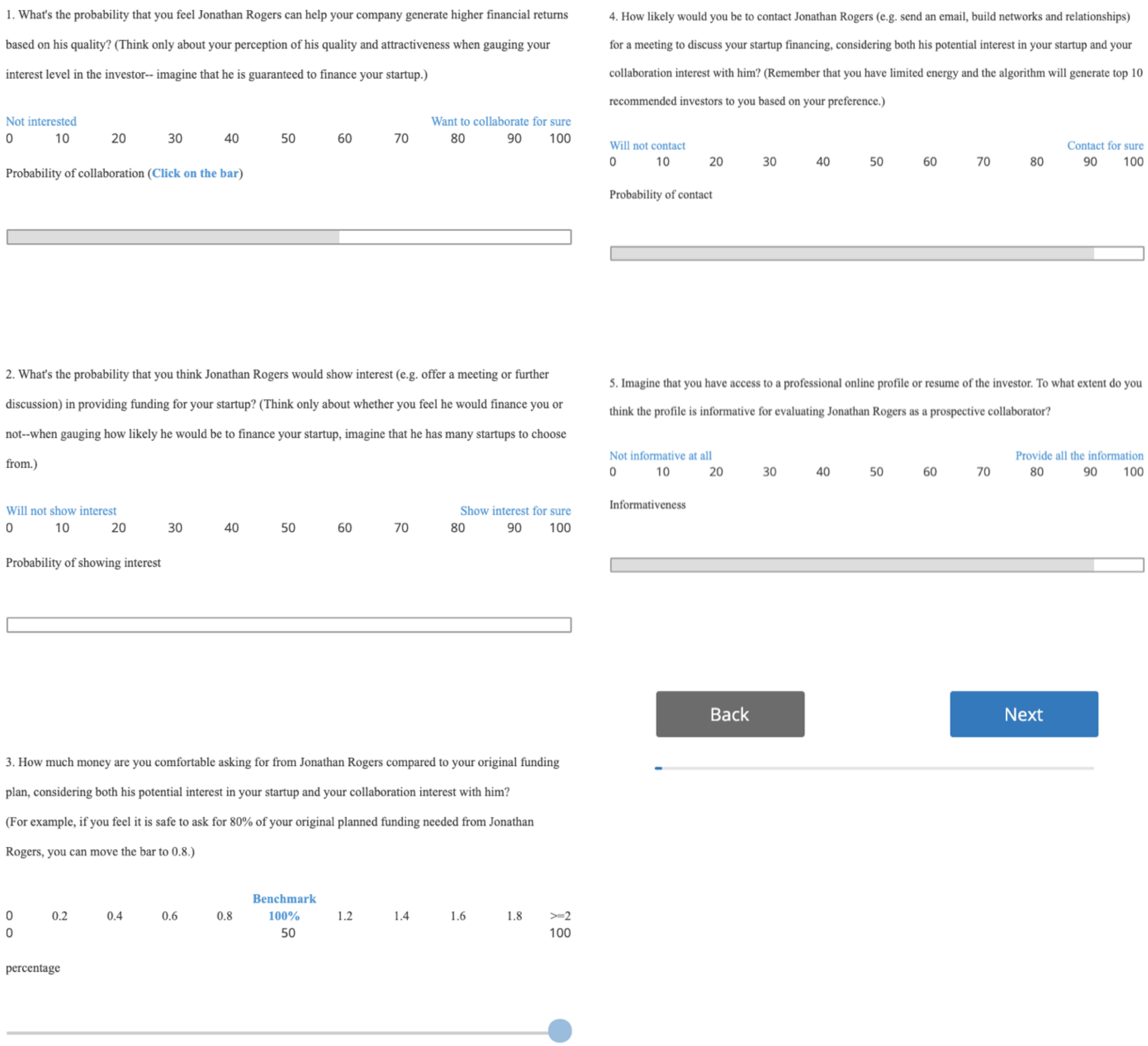
Profile Component	Randomization Description	Analysis Variable
Investor's individual-level demographic information		
First and last name	Drawn from list of 50 candidate names given randomly assigned race and gender (for names, see Online Appendix Section A.2). To maximize the experimental power, Race randomly drawn (50% Asian, 50% White), Gender randomly drawn (50% Female, 50% Male)	Female, white (25%) Male, white (25%) Female, Asian (25%) Male, Asian (25%)
Educational background		
Degree	Degree drawn randomly (50% Bachelor (BA/BS), 50% graduate school degrees (JD/MBA/Master/PhD))	Bachelor Degree (10/20)
College	College drawn randomly (50% prestigious universities, 50% common universities)	Prestigious College (10/20)
Investment experience		
Years of investment experience	Drawn Unif [0,30] to integers	Years of Investment
Number of deals involved	3×Years of experience + Drawn Unif [-2,2] to integers	Deals
Entrepreneurial experience	Drawn randomly (50% with entrepreneurial experience, 50% without entrepreneurial experience)	With Entrepreneurial experience (10/20)
Investor's fund-level information *(Sensitive characteristics)*		
Fund type	Drawn randomly (50% profit-driven fund, 50% ESG fund)	ESG Fund (10/20)
Investment philosophy	Drawn randomly (50% profit-driven fund, 20% ESG fund, 10% ESG fund focusing on environmental issues, 10% ESG fund focusing on social issues, 10% ESG fund focusing on governance issues)	Investment Philosophy
Senior management composition	Drawn Unif [0%,20%] to integers. "relatively high" if the fraction of women is more than 10%, "relatively low" if the fraction of women is less than 10%.	Fraction of Women
(Non-sensitive characteristics)		
Previous performance	Drawn randomly (20% first-time fund, 80% funds with historical performance). For funds with historical performance, its internal rate of return (i.e., irr) drawn from Normal distribution N(19.8%, 34%) to the second decimal place.	IRR
Fund size	Drawn randomly (50% small fund, 50% large fund). AUM is drawn Unif [1,130] to integers for small funds, and drawn Unif [130,1500] to integers for large funds. Dry powder is calculated as 0.27×AUM.	Large Fund (10/20)
Investment style	Drawn randomly (80% Value-added, 20% Spray and pray)	Value-added style (16/20)
Location	Drawn randomly (90% US, 10% Foreign)	US Funds (18/20)

Notes. This table provides the randomization process of each investor profile's component and the corresponding analysis variables.

Table A3: Quantile-Regression Estimates for Startups' Evaluations on Investors' Quality

	Quality (i.e., Q_1)									
	10th [1]	20th [2]	30th [3]	40th [4]	50th [5]	60th [6]	70th [7]	80th [8]	90th [9]	Mean [10]
Top School	1.49	1.91	1.86*	0.84	0.90	1.46**	0.50	0.46	0.33	1.05*
	(1.51)	(1.40)	(1.07)	(0.96)	(0.84)	(0.67)	(0.58)	(0.72)	(0.58)	(0.62)
Graduate Degree	0.19	-0.93	-1.52	-0.91	0.41	-0.40	-0.00	-0.00	0.04	-0.34
	(1.56)	(1.44)	(1.19)	(1.08)	(0.92)	(0.68)	(0.61)	(0.74)	(0.56)	(0.64)
Years of Investment Experience	0.54*	0.67*	0.47**	0.38	0.29	0.23	0.17	0.19	0.35**	0.41**
	(0.32)	(0.41)	(0.24)	(0.25)	(0.19)	(0.16)	(0.15)	(0.16)	(0.15)	(0.14)
Squared Years of Investment Experience	-0.01	-0.01	-0.01	-0.01	-0.00	-0.00	-0.00	-0.00	-0.01	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)
Entrepreneurial Experience	4.95***	7.49***	5.77***	5.22***	4.73***	2.81***	2.19***	2.35***	1.00	3.87***
	(1.26)	(1.34)	(0.98)	(0.93)	(0.77)	(0.62)	(0.54)	(0.61)	(0.62)	(0.59)
First Time Fund	4.37**	6.62***	3.58**	2.77**	3.01**	2.40**	1.33**	1.02	0.86	2.29***
	(1.71)	(1.85)	(1.18)	(1.21)	(1.00)	(0.78)	(0.68)	(0.87)	(0.65)	(0.67)
Better Historical Performance	10.86***	11.88***	8.06***	7.99***	6.14***	4.61***	3.31***	2.65**	1.23*	4.99***
	(1.83)	(1.94)	(1.37)	(1.20)	(1.03)	(0.82)	(0.69)	(0.89)	(0.72)	(0.72)
Larger Fund	-0.40	1.70	2.52**	2.81**	2.73***	2.53***	2.13***	1.68**	1.44**	1.96***
	(1.28)	(1.34)	(0.93)	(0.96)	(0.80)	(0.65)	(0.63)	(0.74)	(0.67)	(0.48)
Value Added Style	0.02	0.30	0.24	0.73	0.26	0.03	-0.61	-0.68	-0.19	-0.14
	(1.24)	(1.43)	(0.89)	(1.07)	(0.73)	(0.65)	(0.61)	(0.66)	(0.53)	(0.58)
US Fund	1.37	2.28	1.03	0.18	1.04	0.46	1.15	1.30	0.49	0.98
	(1.95)	(1.71)	(1.57)	(1.19)	(1.15)	(0.86)	(0.77)	(0.97)	(0.76)	(0.83)
Mean of Dep. Var.	20	40	51	60	68	74	80	86	95	62.63
Observations	8,180	8,180	8,180	8,180	8,180	8,180	8,180	8,180	8,180	8,180

Notes. This table reports the effects of different investor characteristics on the conditional quantiles and the conditional mean of startups' provided quality evaluations. The dependent variable is the investor's received ability rating (i.e., Q_1). In each of Columns (1)–(9), the reported coefficient of each investor characteristic stands for the effect of the characteristic on the kth conditional percentile ($k \in 10, 20, 30, ..., 90$) of the investor's received rating (i.e., Q_1). In Column (10), the reported coefficients using OLS regressions stand for the effects on the conditional mean of Q_1. Standard errors in parentheses are clustered at the subject level and reported in parentheses. $*p < 0.10, **p < 0.05, ***p < 0.01$



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

Not interested — Want to collaborate for sure

0 10 20 30 40 50 60 70 80 90 100

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

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

Will not show interest — Show interest for sure

0 10 20 30 40 50 60 70 80 90 100

Probability of showing interest

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

Benchmark

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

0 50 100

percentage

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

Will not contact — Contact for sure

0 10 20 30 40 50 60 70 80 90 100

Probability of contact

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

Not informative at all — Provide all the information

0 10 20 30 40 50 60 70 80 90 100

Informativeness

Back Next

Figure A1: Sample Evaluation Questions of Startup-side Experiments

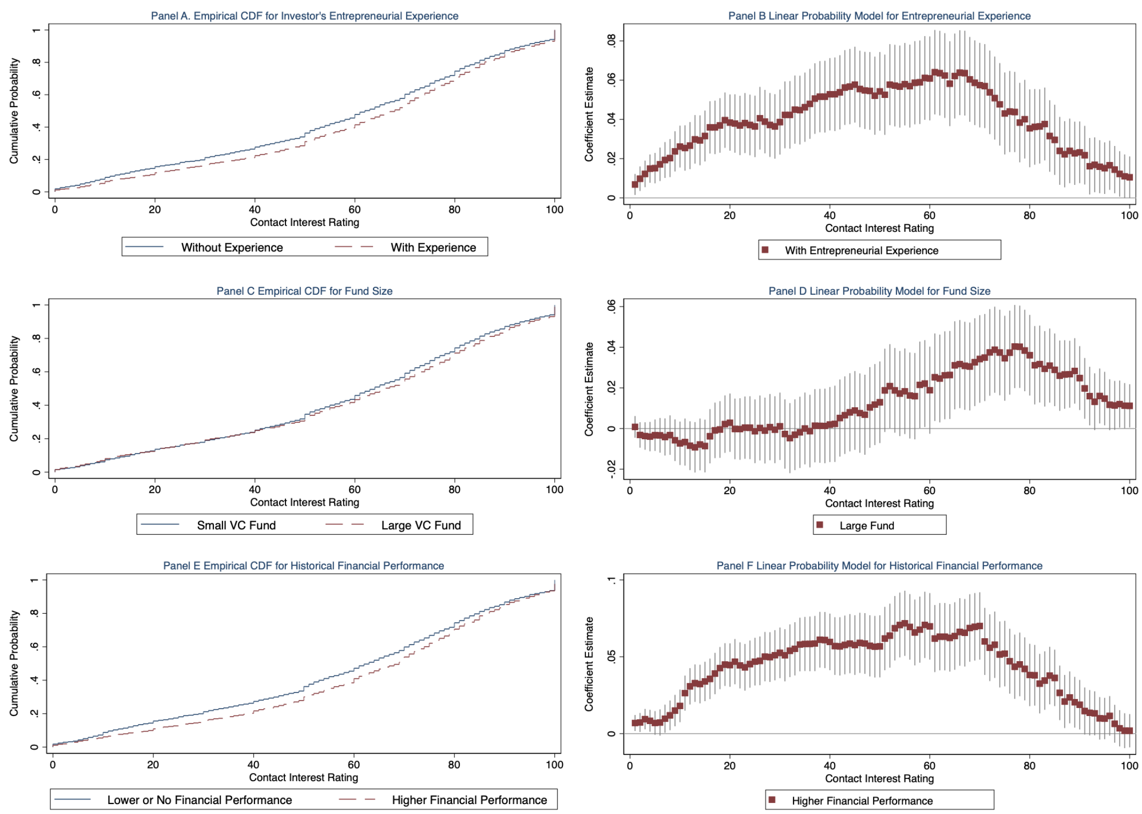


Figure A2: Distributional Effect across Startups' Contact Ratings

Notes. This figure demonstrates the effect of an investor's individual-level and fund-level characteristics across startups' contact rating distribution using the investor profiles evaluated in the startup-side IRR experiment.

B Investor-Side IRR Experiments

B.1 Distributional Effects Across Market Conditions

The previous regression specifications only provide the average treatment effect of the startup team and project characteristics on investors' decisions. However, as pointed out by Kessler et al. (2019) and Zhang (2020), the magnitude and direction of evaluators' preferences can vary with market conditions and across investors' internal thresholds. Understanding this distributional effect is helpful to predict how generalized these experimental results are in different market conditions and with different fundraising settings. For example, when the economy is booming and abundant capital flows into the VC industry, investors' preferences can be shifted to the relatively left part of the distribution of startups' quality as their investment bars get lower. However, when the economy is experiencing recession and venture capitalists have to increase their investment thresholds, their preferences can be shifted to the right tail of the distribution. Moreover, since other experimental papers in entrepreneurial finance usually implement correspondence test methods, these results are unavoidably affected by investors' internal thresholds in the corresponding experimental settings. Therefore, checking distributional effects also helps to understand the external validity of the identified investors' preferences in different experimental settings.[24]

Figure B7 shows that investors' preferences about certain important team characteristics (e.g., educational backgrounds and entrepreneurial experiences) and project characteristics (e.g., traction and business models) are causally important along the whole distribution of investors' contact ratings. When investors' internal thresholds fall in the range between 60% to 80% likelihood of contacting the startup, the magnitude of their preferences is the strongest. However, for the right tail of the investment ratings, these preferences are no longer salient. This happens potentially because investors' internal thresholds are generally lower than their normal investment benchmark level (i.e., lower than the middle point if the investment ratings). Figure B8 shows that a similar pattern exists along the distribution of investors' investment interest rating. To sum up, startups with these attractive team and project characteristics enjoy more advantages in most market conditions and fundraising settings. Specifically, having positive traction plays an important role across investors' contact ratings and investment ratings.

[24] For discussions on the comparison of correspondence test and IRR experiments, please read Kessler et al. (2019) and Zhang (2020).

B.2 Heterogeneous Effects across the Spectrum of Quality

Considering that one of the paper's purposes is to provide guidance on startups' fundraising process, we further investigate the heterogeneous effects of various startup team and project characteristics on investors' evaluations across the spectrum of startups' quality. Depending on the startup's self-positioning, the founding team can "customize" their optimal startup pitching strategies. Classical OLS regressions mainly identify the population average treatment effects and test the effect of startup characteristics on the conditional mean of investors' profitability evaluations. Hence, to achieve our purpose of providing customized fundraising advice, we exploit quantile regressions, which identify startup characteristics' impact on the off-central conditional quantiles of the response variable (i.e., the distribution of investors' evaluations in our setting).

Table B5 reports the quantile regression results that investigate how different startup characteristics affect investors' judgments on their quality across their quality spectrum. The dependent variable is the startup's received profitability rating (i.e., Q_1). In each of Columns (1)–(9), the reported coefficient of each startup characteristic stands for the effect of the characteristic on the kth conditional percentile ($k \in 10, 20, 30, ..., 90$) of the startup's received rating (i.e., Q_1). In Column (10), the reported coefficients using OLS regressions stand for the effects on the conditional mean of Q_1. Standard errors in parentheses are clustered at the subject level, and reported in parentheses.

Results of Table B5 find that the direction of investors' preferences about startup characteristics focused on by this paper are very stable across the spectrum of startup quality. However, the relative magnitude of these preferences sometimes varies depending on the perceived startup quality. For example, the coefficient for "Serial Founder" in the conditional-20th quantile model is 4.09 percentile ranks, which is much lower than the coefficient (i.e., 7.48 percentile ranks) in the conditional-60th quantile model. In particular, the positive effect of having entrepreneurial experience is strongest between the 30th quantile and 80th quantile of startup's quality. Similarly, although prestigious educational background of the founding team also improves investors' profitability evaluations, this positive effect is also strongest for the middle-quality startups. Specifically, these attractive team characteristics are not helpful for the bottom 10th quantile startups.

Compared to the impact of startup team characteristics, having positive traction has stronger positive impact on investors' profitability evaluations in terms of both the magnitude and the coverage of this impact. Across the whole spectrum of startup quality, the impact of positive traction is more than twice as important as the impact of prestigious educational background or the impact of previous educational background. Moreover, startups with positive traction receive 8.58 higher percentile ranks of profitability evaluations compared to startups without any traction even when these startups belong to the lowest-quality startups. As for the impact of startups' business models, being a B2B startup (i.e., business to business startup) mainly benefits the high-quality startups whose quality lies above the 50th percentile rank. Results are statistically significant at the 1% level, which support the suggestion of Kaplan et al. (2009) by confirming the importance of startups' project characteristics.

Table B1: Summary Statistics of Recruited Investors in Experiment A

Panel A: Investor Stated Interest Across Sectors

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

Panel B: Investor Stated Interest Across Stages

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

Panel C: Investor Stated Demographic Information

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

Panel D: Investor Stated Investment Philosophy

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

Continued

Panel E: Available Venture Capital Companies' Financial Performance

				Percentile		
	N	Mean	S.D	10	50	90
Recruited Sample						
Total Active Portfolio	54	41.40	44.51	10	24	102
Total Exits	46	32.74	48.39	1	9	110
VC Company Age	52	11.75	8.95	3	8.5	25
AUM (Unit: $1 Million)	33	547.46	1029.10	30	111.7	1700
Dry Powder (Unit: $1 Million)	33	163.86	307.04	6.43	44.35	313.59
Fraction of Female Founders in Portfolio Companies	66	0.12	0.13	0.02	0.10	0.21
Fraction of Asian Founders in Portfolio Companies	66	0.30	0.21	0.05	0.27	0.64
Pitchbook Sample (US VC Funds)						
Total Active Portfolio	5,015	21.16	47.71	1	9	47
Total Exits	3,725	22.75	57.07	1	6	52
VC Company Age	3,898	9.67	11.02	1	6	21
AUM (Unit: $1 Million)	1,802	2419.19	30574.22	10	100	1300
Dry Powder (Unit: $1 Million)	2,017	137.54	615.08	0.12	15.24	250
Fraction of Female Founders in Portfolio Companies	3,864	0.13	0.18	0	0.09	0.33
Fraction of Asian Founders in Portfolio Companies	3,864	0.25	0.24	0	0.21	0.53

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

Table B2: **Randomization of Profile Components**

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

Notes. This table provides the randomization of each startup profile's components and the corresponding analysis variables. Profile components are listed in the order that they appear on the hypothetical startup profiles. Weights of characteristics are shown as fractions when they are fixed across subjects (e.g., each subject saw exactly 8/16 resumes with all-female team members) and percentages when they represent a draw from a probability distribution (e.g., for startups with positive revenue records, the revenue follows a uniform distribution between [5K - 80 K]). Variables in the right-hand column are randomized to test how investors respond to these analysis variables.

Table B3: Investors' Evaluation Results — q-value

Dependent Variable	Q1 Quality (1)	Q2 Collaboration (2)	Q3 Contact (3)	Q3 Contact (4)	Q4 Investment (5)	Q4 Investment (6)
Serial Founder	5.23***	-0.81	5.64***	1.26	0.76***	0.13
	(1.08)	(0.88)	(1.28)	(0.91)	(0.19)	(0.15)
Ivy	5.36***	-1.06	7.44***	3.01***	0.87***	0.2
	(1.10)	(0.87)	(1.31)	(0.93)	(0.20)	(0.15)
Number of Founders	1.56	-1.21	1.17	-0.11	0.21	0.04
	(1.07)	(0.88)	(1.29)	(0.91)	(0.20)	(0.15)
US Founder	0.95	0.02	4.23***	3.69***	0.08	0.03
	(1.18)	(0.91)	(1.39)	(1.00)	(0.21)	(0.16)
# Comparative Adv	3.1***	-0.22	2.76***	0.34	0.55***	0.15
	(0.54)	(0.43)	(0.64)	(0.43)	(0.10)	(0.07)
Has Positive Traction	12.7***	1.75*	13.35***	1.91	1.81***	0.28
	(1.07)	(0.86)	(1.28)	(0.99)	(0.20)	(0.16)
Number of Employees [0-10]	0.67	2.37*	-1.73	-2.57*	-0.19	-0.29
	(1.43)	(1.16)	(1.69)	(1.18)	(0.26)	(0.20)
Number of Employees [10-20]	-1.08	0.94	-3.26	-2.08	-0.46	-0.33
	(1.64)	(1.35)	(1.99)	(1.39)	(0.30)	(0.23)
Number of Employees [20-50]	-0.47	-0.02	-1.21	-0.72	-0.16	-0.12
	(1.45)	(1.17)	(1.71)	(1.17)	(0.27)	(0.19)
Company Age	-4.59	-5.99**	-7.39**	-2.19	-1.26**	-0.54
	(2.72)	(2.19)	(3.19)	(2.26)	(0.49)	(0.37)
Company Age^2	0.75	1.12**	1.27*	0.42	0.23**	0.1
	(0.54)	(0.44)	(0.64)	(0.45)	(0.10)	(0.07)
Is B2B	3.90***	3.73***	6.1***	1.47	0.81***	0.32
	(1.07)	(0.86)	(1.28)	(0.89)	(0.20)	(0.15)
Domestic Market	-0.10	-0.60	0.09	0.57	0.08	0.13
	(1.08)	(0.86)	(1.28)	(0.90)	(0.20)	(0.14)
Q1				0.88***		0.12***
				(0.03)		(0.01)
Q2				0.18***		0.01
				(0.03)		(0.01)
Constant	49.75***	78.2***	66.2***	-4.19	5.62***	-0.33
	(6.56)	(6.02)	(4.93)	(7.50)	(1.43)	(0.63)
Investor FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,216	1,184	1,216	1,184	1,176	1,154
R-squared	0.44	0.55	0.56	0.80	0.44	0.70

Notes. This table reports regression results of how the evaluation results respond to other startup team characteristics and startup project characteristics. It's the same as Table 2 except that we report the q-value adjusted by the Bonferroni method and Simes method (red *) to implement the multiple hypothesis testing. Since the Simes method is less conservative than the Bonferroni method, we use * to indicate the significance level of the q-value generated by the Simes method whenever the significance level of the Simes method q-value is smaller than that of the Bonferroni method q-value. Standard errors are in parentheses. *** q-value<0.01, ** q-value<0.05, * q-value<0.1 indicate statistical significance at 1%, 5%, and 10%

Table B4: Standardized Coefficients of Investors' Evaluation Results

Dependent Variable	Q1 Quality (1)	Q2 Collaboration (2)	Q3 Contact (3)	Q3 Contact (4)	Q4 Investment (5)	Q4 Investment (6)
Serial Founder	0.109***	-0.019	0.087***	0.019	0.089***	0.015
	(0.022)	(0.021)	(0.020)	(0.014)	(0.023)	(0.017)
Ivy	0.111***	-0.025	0.114***	0.046***	0.101***	0.023
	(0.023)	(0.021)	(0.020)	(0.014)	(0.023)	(0.017)
Number of Founders	0.033	-0.029	0.018	-0.002	0.024	0.005
	(0.023)	(0.021)	(0.020)	(0.014)	(0.023)	(0.017)
Located in US	0.018	0.000	0.061***	0.053***	0.009	0.003
	(0.022)	(0.020)	(0.020)	(0.014)	(0.023)	(0.017)
# Comparative Adv	0.131***	-0.010	0.087***	0.011	0.132***	0.036
	(0.022)	(0.020)	(0.020)	(0.014)	(0.023)	(0.017)
Has Positive Traction	0.265***	0.041*	0.207***	0.030	0.211***	0.033
	(0.022)	(0.021)	(0.020)	(0.015)	(0.023)	(0.018)
Number of Employees [0-10]	0.012	0.048*	-0.023	-0.034*	-0.020	-0.030
	(0.026)	(0.024)	(0.023)	(0.016)	(0.027)	(0.020)
Number of Employees [10-20]	-0.018	0.018	-0.040	-0.026	-0.043	-0.031
	(0.027)	(0.025)	(0.024)	(0.017)	(0.027)	(0.020)
Number of Employees [20-50]	-0.009	0.000	-0.016	-0.010	-0.016	-0.012
	(0.026)	(-0.317)	(0.023)	(0.016)	(0.027)	(0.020)
Company Age	-0.214	-0.317**	-0.256**	-0.076	-0.330**	-0.142
	(0.127)	(0.116)	(0.112)	(0.078)	(0.129)	(0.097)
Company Age^2	0.177	0.301**	0.224*	0.074	0.300**	0.128
	(0.127)	(0.116)	(0.112)	(0.078)	(0.129)	(0.097)
Is B2B	0.081***	0.088***	0.095***	0.023	0.095***	0.037
	(0.022)	(0.020)	(0.020)	(0.014)	(0.023)	(0.017)
Domestic Market	-0.002	-0.014	0.001	0.009	0.009	0.015
	(0.022)	(0.020)	(0.020)	(0.014)	(0.023)	(0.017)
Q1				0.639***		0.659***
				(0.018)		(0.023)
Q2				0.121***		0.040
				(0.020)		(0.025)
Investor FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,216	1,184	1,216	1,184	1,176	1,154
R-squared	0.44	0.55	0.56	0.80	0.44	0.70

Notes. $Y_{ij}^{(k)} = X_{ij}\beta_i^{(k)} + \alpha_i + \epsilon_{ij}^{(k)}$ Investor i evaluates the k^{th} question of the j^{th} profile. This table reports the q-value (multiple hypothesis testing), which is adjusted by the Bonferroni method or Simes method (blue *, use more information). Standardization applies to all the independent variables except for the indicator variables used for the fixed effect. In Columns (1)-(6), the dependent variable is the evaluation results of Q1 (profitability evaluation), Q2 (collaboration interest), Q3 (contact interest), and Q4 (investment interest). "Serial Founder", "Ivy", "US Founder", "Has Positive Traction", "Is B2B" and "Domestic Market" are indicative variables that equal to one if the founder is a serial entrepreneur, graduated from an Ivy League College, lives in the U.S., the project has positive traction, is a Business-to-Business startup, and focuses on the domestic market. These variables are equal to 0 if the startup does not have any such characteristics. Number of founders is either 1 or 2; Number of Comparative Advantages and Company Age can be {1,2,3,4}; Company Age^2 is the square of the company age. Q1 is the evaluation results of startup quality. Q2 is the evaluation results of the collaboration likelihood. All the regression results add investor fixed effect and use the robust standard errors reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1 indicate statistical significance at 1%, 5%, and 10% levels, respectively.

Table B5: Quantile-Regression Estimates for Investors' Evaluations on Startups' Profitability

	Quality (i.e., Q_1)									
	10th [1]	20th [2]	30th [3]	40th [4]	50th [5]	60th [6]	70th [7]	80th [8]	90th [9]	Mean [10]
Serial Founder	0.47	4.09**	6.41***	6.05***	6.35***	7.48***	6.98***	6.00***	3.12	5.23***
	(1.67)	(1.97)	(1.75)	(1.85)	(2.03)	(1.99)	(1.98)	(1.98)	(2.40)	(1.08)
Ivy	2.18	3.47*	7.41***	7.96***	7.37***	6.67***	7.40***	7.31***	5.43***	5.36***
	(1.65)	(1.91)	(1.75)	(1.61)	(1.61)	(1.54)	(1.55)	(1.99)	(1.70)	(1.10)
Number of Founders	-0.71	0.92	1.87	1.62	1.49	1.55	0.77	1.35	0.83	1.56
	(1.34)	(1.46)	(1.60)	(1.67)	(1.64)	(1.69)	(1.74)	(1.34)	(1.44)	(1.07)
Located in US	-0.39	-0.17	1.80	1.48	0.44	-0.48	0.62	2.64	1.74	0.95
	(1.89)	(2.04)	(1.90)	(1.86)	(1.73)	(1.82)	(1.85)	(1.65)	(2.11)	(1.18)
# Comparative Adv	1.32	2.16***	2.52***	3.67***	3.89***	3.71***	3.19***	3.45***	4.83***	3.1***
	(0.81)	(0.55)	(0.67)	(0.83)	(0.91)	(0.77)	(0.78)	(0.98)	(1.24)	(0.54)
Has Positive Traction	8.58***	11.36***	14.24***	15.00***	15.60***	16.43***	16.06***	15.57***	11.82***	12.7***
	(2.53)	(2.84)	(2.46)	(2.52)	(2.56)	(2.42)	(2.63)	(2.35)	(3.02)	(1.07)
Number of Employees [0-10]	-1.37	-4.35**	-3.49*	0.14	1.22	0.48	0.00	-0.43	0.00	0.67
	(1.91)	(1.92)	(2.00)	(2.59)	(2.17)	(2.46)	(2.15)	(2.16)	(2.32)	(1.43)
Number of Employees [10-20]	-2.38	-5.56**	-5.00*	-5.56**	-4.19	-3.12	-2.04	-3.68	-2.46	-1.08
	(2.27)	(2.56)	(2.65)	(2.61)	(3.03)	(3.00)	(2.76)	(2.33)	(3.28)	(1.64)
Number of Employees [20-50]	-1.19	-4.25*	-3.53	-2.05	-1.01	-0.57	-0.65	-0.85	-1.51	-0.47
	(2.55)	(2.45)	(2.39)	(2.41)	(2.22)	(1.94)	(2.18)	(2.23)	(2.76)	(1.45)
Company Age	1.15	-2.53	-7.78	-9.92**	-5.01	-3.79	-3.97	-2.42	-1.16	-4.59
	(4.05)	(4.36)	(4.77)	(4.69)	(4.00)	(3.95)	(4.06)	(3.99)	(5.08)	(2.72)
Company Age^2	-0.32	0.40	1.27	1.78*	0.86	0.55	0.73	0.32	0.05	0.75
	(0.76)	(0.80)	(0.94)	(0.93)	(0.79)	(0.79)	(0.82)	(0.80)	(0.99)	(0.54)
Is B2B	1.88	2.66	2.37	2.53	3.89**	5.64***	6.72***	5.95***	5.34**	3.90***
	(1.38)	(1.98)	(1.89)	(1.75)	(1.82)	(1.78)	(1.83)	(1.98)	(2.38)	(1.07)
Domestic Market	1.37	-0.94	-1.68	0.75	0.21	-0.74	-0.68	-0.18	-0.01	-0.10
	(1.43)	(1.74)	(1.56)	(1.70)	(1.79)	(1.55)	(1.52)	(1.60)	(1.82)	(1.08)
Mean of Dep. Var.	10	20	30	36	42	50	60	70	79	44
Observations	1216	1216	1216	1216	1216	1216	1216	1216	1216	1216

Notes. This table reports the effects of different startup team and project characteristics on the conditional quantiles and the conditional mean of investors' profitability evaluations. The dependent variable is the startup's received profitability rating (i.e., Q_1). In each of Columns (1)–(9), the reported coefficient of each startup characteristic stands for the effect of the characteristic on the kth conditional percentile ($k \in 10, 20, 30, ..., 90$) of the startup's received rating (i.e., Q_1). In Column (10), the reported coefficients using OLS regressions stand for the effects on the conditional mean of Q_1. Standard errors in parentheses are clustered at the subject level, and reported in parentheses. $*p < 0.10, **p < 0.05, ***p < 0.01$

Dear [Investor Name],

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

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

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

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

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

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

If you have any questions or would like more detailed information about how the tool will enhance your portfolio construction process, please contact the tool developer and project investigator, Ye (Iris) Zhang (yz2865@columbia.edu).

Thank you very much and have a nice day!

Sincerely,
Ye

--
Ye Zhang
Ph.D. Candidate
Economics Department, Columbia University
Email: yz2865@columbia.edu

Figure B1: Recruitment Email (Version 1)

Notes. Version 1 provides both matching incentive and monetary incentive to randomly selected 11183 U.S. venture capitalists.

Dear [Investor Name],

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

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If you have any questions or would like more detailed information about how the tool will enhance your portfolio construction process, please contact the tool developer and project investigator, Ye (Iris) Zhang (yz2865@columbia.edu).

Thank you very much and have a nice day!

Sincerely,
Ye

--
Ye Zhang
Ph.D. Candidate
Economics Department, Columbia University
Email: yz2865@columbia.edu

Figure B2: Recruitment Email (Version 2)

Notes. Version 2 provides only a matching incentive to randomly selected 4000 U.S. venture capitalists.

Figure B3: Recruitment Poster (Version 1)

Notes. Version 1 provides both matching incentive and monetary incentive to randomly selected 11183 U.S. venture capitalists.

Figure B4: Recruitment Poster (Version 2)

Notes. Version 2 provides only matching incentive to randomly selected 4000 U.S. venture capitalists.

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

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

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

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

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

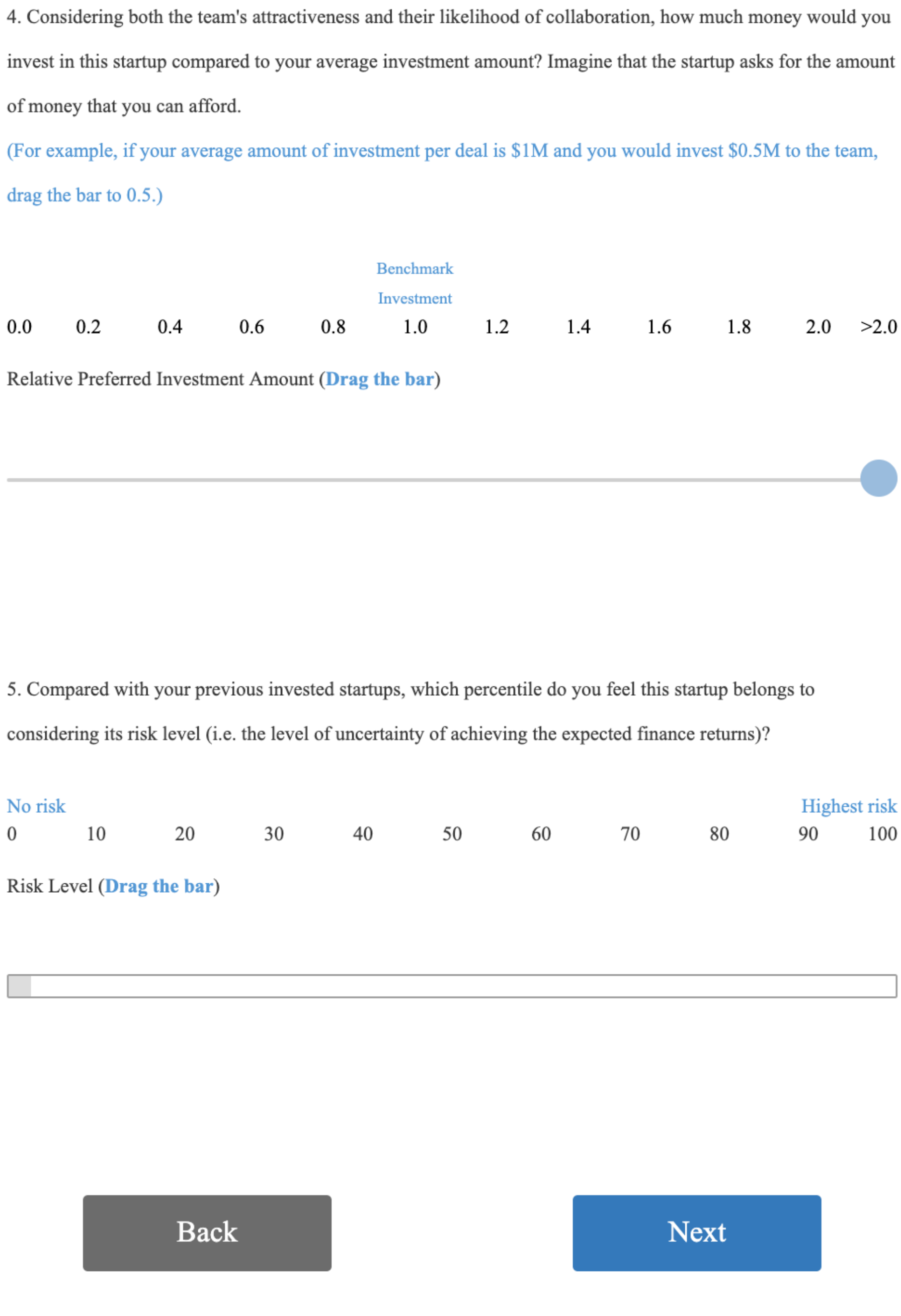
Probability of Accepting Your Offer (**Drag the bar**)

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

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

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

Figure B5: Evaluation Questions (Part 1)


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

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

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

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

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

No risk 0	10	20	30	40	50	60	70	80	90	Highest risk 100

Risk Level (**Drag the bar**)

Back

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Figure B6: Evaluation Questions (Part 2)

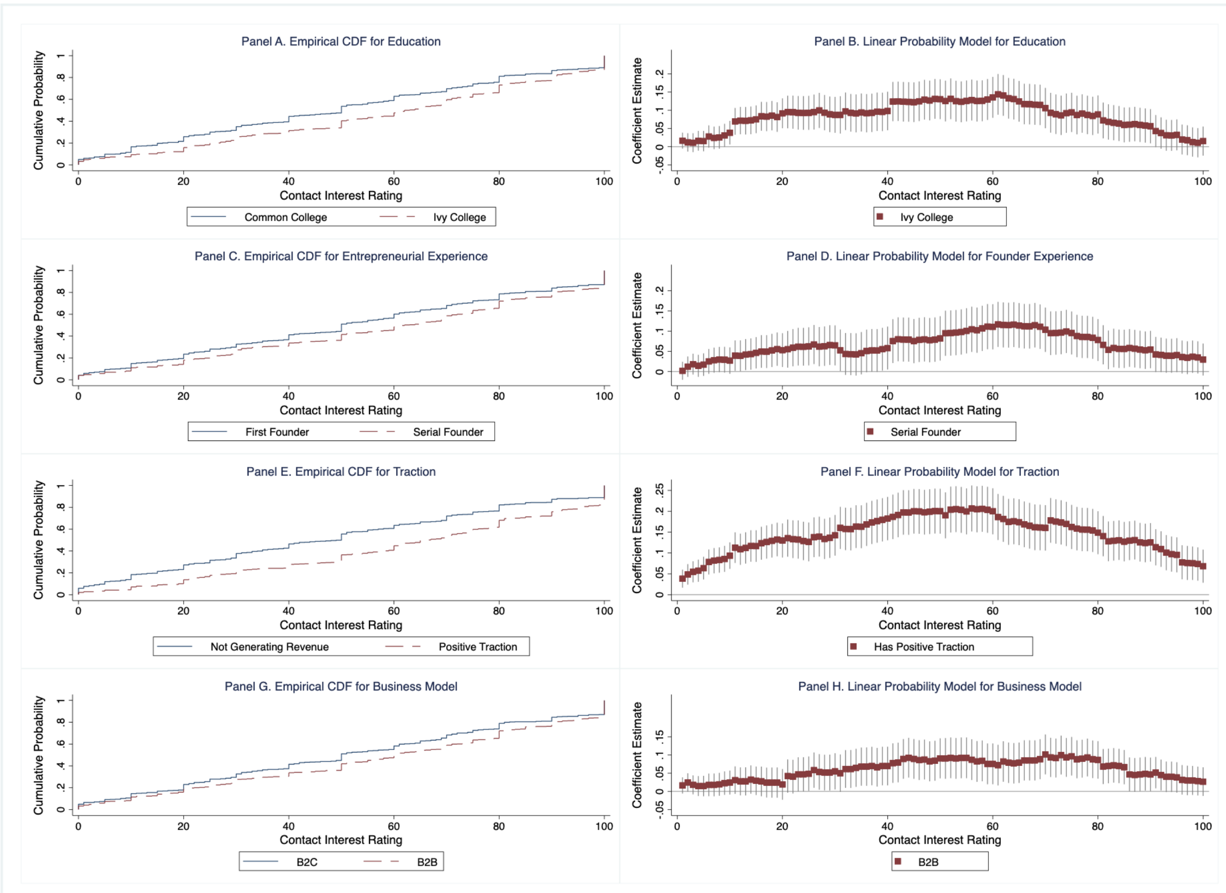


Figure B7: Distributional Effect across Investors' Contact Interest

Notes. This figure demonstrates the effect of a startup's team and project characteristics across the contact interest distribution using the total profiles evaluated in the investor-side IRR experiment. Panel A provides the empirical CDF for founders' educational background of investors' contact interest rating (i.e., $Pr(\text{Contact Interest} > x|$ Graduate from Ivy League College) and $Pr(\text{Contact Interest} > x|$ Graduate from Common College)). Panel B provides the OLS coefficient estimates (i.e., $Pr(\text{Contact Interest} > x|$ Graduate from Ivy League College) $-$ $Pr(\text{Contact Interest} > x|$ Graduate from Common College)) and the corresponding 95% confidence level. Similarly, Panels C, E and G provide the empirical CDF for the founder's entrepreneurial experiences, the project's traction, and the business model. Panels D, F and H provide the OLS coefficient estimates for the founder's entrepreneurial experiences, the project's traction, and the business model.

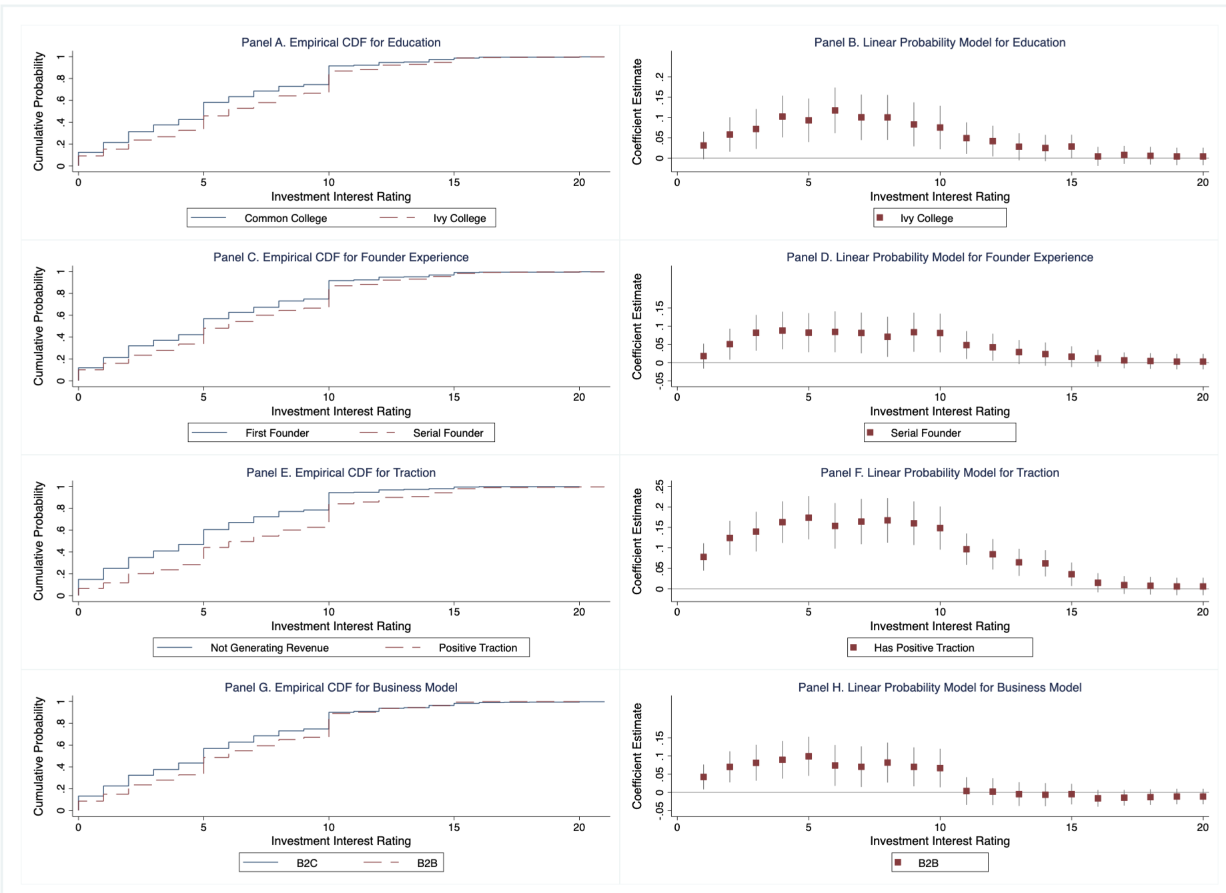
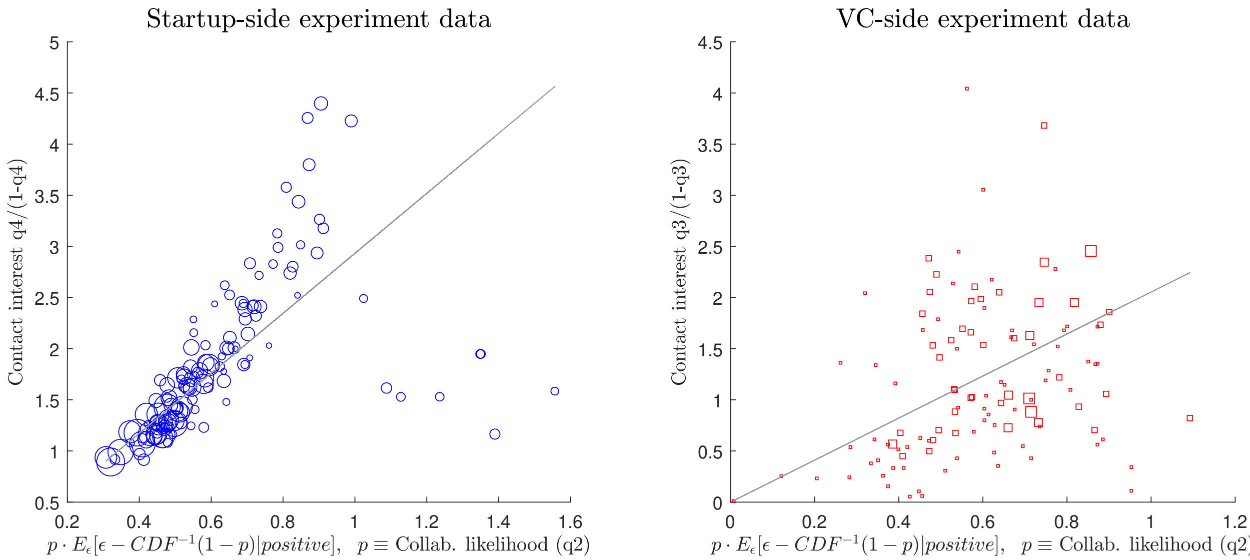


Figure B8: Distributional Effect across Investors' Investment Interest

Notes. This figure demonstrates the effect of startup team and project characteristics across the investment interest distribution using the total profiles evaluated in the investor-side IRR experiment. Panel A provides the empirical CDF for founder's educational background of investors' investment interest rating (i.e., $Pr(\text{Investment Interest} > x|\text{ Graduate from Ivy League College})$ and $Pr(\text{Investment Interest} > x|\text{ Graduate from Common College})$). Panel B provides the OLS coefficient estimates (i.e., $Pr(\text{Investment Interest} > x|\text{ Graduate from Ivy League College}) - Pr(\text{Investment Interest} > x|\text{ Graduate from Common College})$) and the corresponding 95% confidence level. Similarly, Panels C, E and G provide the empirical CDF for founder's entrepreneurial experiences, project's traction, and business model. Panels D, F and H provide the OLS coefficient estimates for the founder's entrepreneurial experiences, the project's traction, and the business model.

C Supplementary Simulation Results

Figure C1: Contact interest—direct reports vs. indirect derivation from collaboration likelihoods



Notes. Y-axis shows revealed contact interests from experiment data, and X-axis shows the inferred contact interest using the model-implied equation for expected gains from matching: $p_{ij} \cdot \mathbf{E}_\epsilon[\epsilon - CDF^{-1}(1 - p_{ij}) \mid positive]$, with p_{ij} set from revealed collaboration likelihoods in the experiment data. Panel (A) depicts the relationship in the startup-side experiment and Panel (B) depicts the relationship in the VC-side experiment data. Data is collapsed and reported at the startup type-i by VC type-j level, which consists $16 * 8 = 128$ points. Marker sizes indicate the number of observations in the experiments at the i/j type levels.

Table C1: Equilibrium values, payoffs, and matching frequencies—counterfactual results

	Benchmark	$r^S = r^{VC}$	$100\% \uparrow M^{VC}$	$100\% \uparrow \rho$
$\bar{u}$	1.89	2.473	2.785	2.062
$std(u)$	0.326	0.357	0.36	0.358
$ave(\Pi^S)$	2.726	3.262	3.638	2.725
$\bar{v}$	3.384	2.924	2.449	3.714
$std(v)$	0.252	0.249	0.235	0.267
$ave(\Pi^{VC})$	3.485	3.018	2.55	3.794
$\frac{M^{VC}\bar{v}}{M^S\bar{u}+M^{VC}\bar{v}}$	0.152	0.107	0.082	0.152
$ave(\frac{\Pi^{VC}}{\Pi^S+\Pi^{VC}})$	0.576	0.494	0.425	0.595
$sum(\mu)$	16.8	15.6	24.4	23.2
$M^S\bar{u} + M^{VC}\bar{v}$	111.4	138.3	151.5	121.7

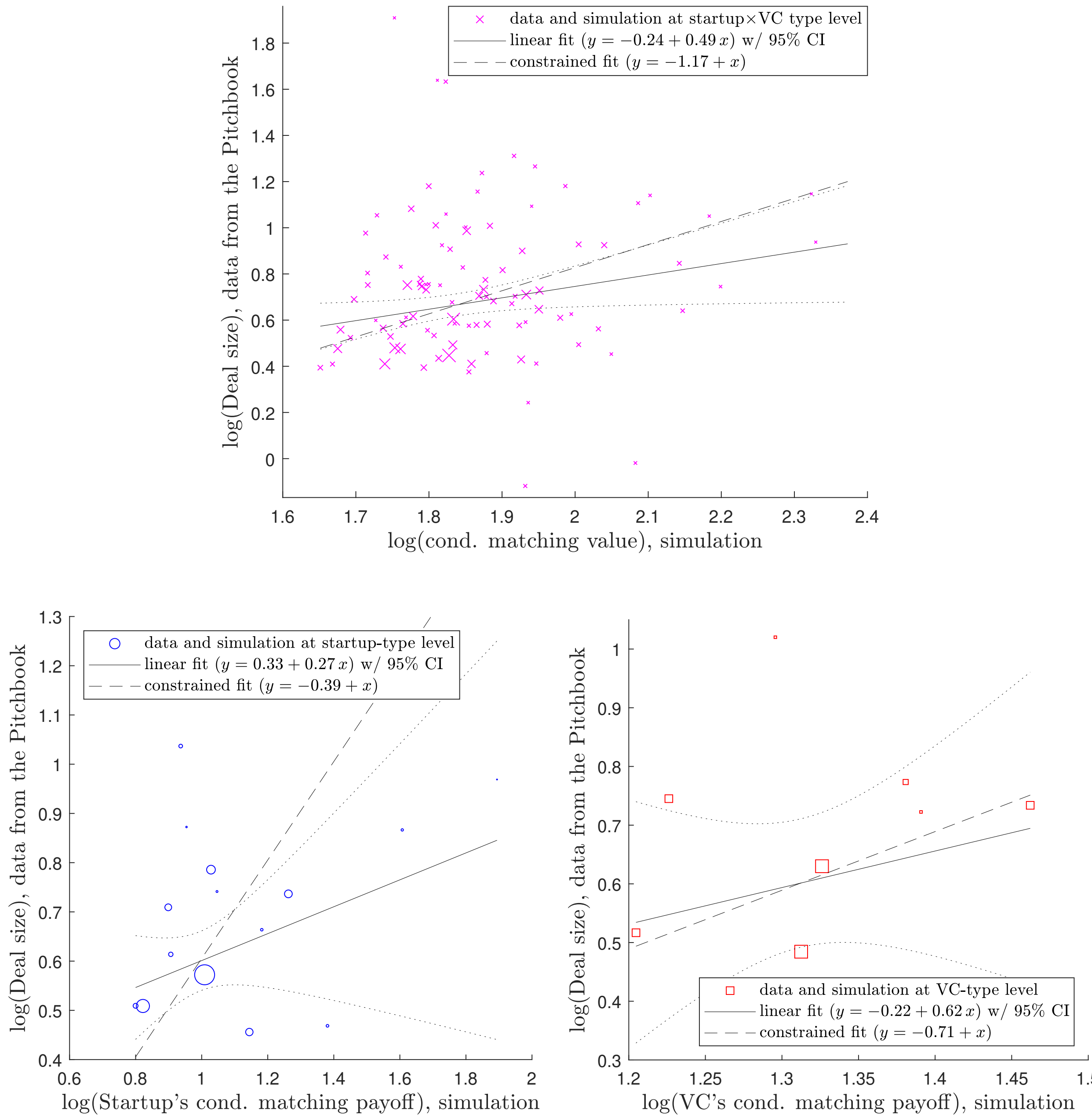
Notes. In these counterfactual experiments, we keep the mean joint matching values $\{z_{ij}\}$ unchanged, and change primitive parameters of the search and matching environment, which would correspond to counterfactual β^S and β^{VC}. We do counterfactual analysis using the model estimated via the startup-side experiment and data on revealed collaboration likelihoods. Averages and standard deviations of outcome statistics are calculated using the mass of types, $\{m_i\}$ and $\{n_j\}$ for startups and VCs, respectively, as weights. The total number of matches $sum(\mu)$ is reported on a per annum basis and is reported in the unit of 1,000. The total net present value of matching values $M^S\bar{u} + M^{VC}\bar{v}$ is reported in the unit of 1,000.

Table C2: Robustness check: Expected payoff from matching—economic decomposition

			Startups'		VCs'	
	$\log(p_{ij})$	$\log(\Pi_{ij})$	$\log(\frac{\Pi^S_{ij}}{\Pi_{ij}})$	$\log\left(\mathbb{E}[\Pi^S_{ij}]\right)$	$\log(\frac{\Pi^{VC}_{ij}}{\Pi_{ij}})$	$\log\left(\mathbb{E}[\Pi^{VC}_{ij}]\right)$
			—(S,p1)—			
$\log(u_i)$	0.53	0.379	0.46	1.369	−0.364	0.544
	(0.022)	(0.066)	(0.064)	(0.019)	(0.066)	(0.021)
$\log(v_j)$	0.58	0.63	−0.488	0.722	0.354	1.564
	(0.022)	(0.066)	(0.064)	(0.022)	(0.065)	(0.022)
			—(S,p2)—			
$\log(u_i)$	0.473	0.485	0.373	1.331	−0.468	0.49
	(0.024)	(0.073)	(0.071)	(0.02)	(0.073)	(0.023)
$\log(v_j)$	0.513	0.543	−0.386	0.671	0.442	1.499
	(0.024)	(0.071)	(0.069)	(0.022)	(0.071)	(0.024)
			—(S-VC,p1)—			
$\log(u_i)$	0.589	0.342	0.463	1.394	−0.331	0.6
	(0.03)	(0.11)	(0.084)	(0.011)	(0.109)	(0.029)
$\log(v_j)$	0.563	0.605	−0.465	0.703	0.38	1.547
	(0.042)	(0.098)	(0.095)	(0.046)	(0.098)	(0.042)
			—(S-VC,p2)—			
$\log(u_i)$	0.594	0.182	0.606	1.382	−0.172	0.604
	(0.059)	(0.102)	(0.058)	(0.036)	(0.1)	(0.057)
$\log(v_j)$	0.547	0.751	−0.592	0.706	0.235	1.533
	(0.071)	(0.085)	(0.077)	(0.079)	(0.084)	(0.071)

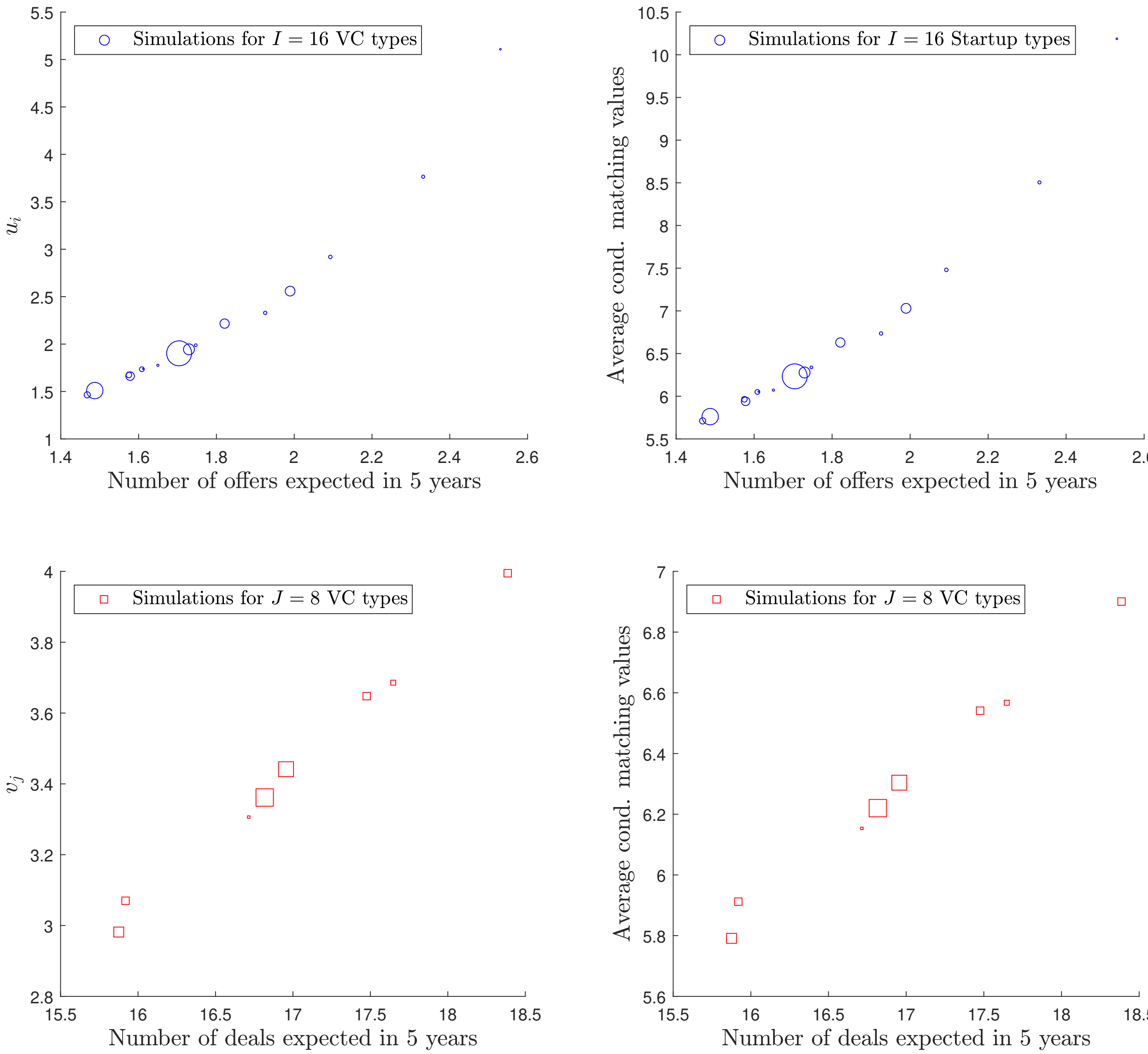
Notes. The relationship between components of the expected payoff from matching for startups and VCs $\mathbb{E}[\Pi^S_{ij}] = p_{ij} * \Pi_{ij} * \Pi^S_{ij}/\Pi_{ij}$ and $\mathbb{E}[\Pi^{VC}_{ij}] = p_{ij} * \Pi_{ij} * \Pi^{VC}_{ij}/\Pi_{ij}$, respectively, and continuation values of startups and VCs, u_i and v_j, respectively, is shown via multivariate OLS regressions on 16∗8=128 points at the startup-by-VC type level data. We use simulation results of specifications with alternative experimental data and run weighted regressions via the mass of underlying startup and VC types, $\{m_i\}$ and $\{n_j\}$. In specifications (S,p1) and (S,p2) we use startup-side experimental data while in specifications (S-VC,p1) and (S-VC,p2) we use both startup-side and VC-side experimental data to estimate continuation values and conditional matching probabilities. In specifications (S,p1) and (S-VC,p1) we use the revealed collaboration likelihoods to set the conditional matching probabilities while in specifications (S,p2) and (S-VC,p2) we infer probabilities from the revealed contact interests.

Figure C2: Deal size (data) vs. conditional matching payoffs (simulation)



Notes. Y-axis shows the log deal size (in million dollars) from the Pitchbook data during 2015-2020. In the top Panel, X-axis shows the log average conditional matching payoffs $\mathbf{E}_\epsilon[z_{ij} + \epsilon \mid z_{ij} + \epsilon \geq u_i + v_j]$ from simulation. Data and simulation results are reported at the startup-by-VC type level. Marker sizes indicate the estimated underlying mass of types at the i/j level, $\{m_i * n_j\}$. In the bottom-left Panel, results are collapsed at the startup-type level. X-axis shows the average payoff of a startup from matching: $u_i + \pi \sum_j n_j \cdot p_{ij} \cdot \mathbf{E}_\epsilon[z_{ij} + \epsilon - u_i - v_j | \, positive]/\sum_j n_j \cdot p_{ij}$. In the bottom-right Panel, results are collapsed at the VC-type level. X-axis shows the average payoff of a VC from matching: $v_j + (1-\pi)\sum_i m_i \cdot p_{ij} \cdot \mathbf{E}_\epsilon[z_{ij} + \epsilon - u_i - v_j | \, positive]/\sum_i m_i \cdot p_{ij}$. Marker sizes indicate the estimated underlying mass of types, $\{m_i\}$ in the bottom-left Panel and $\{n_j\}$ in the bottom-right Panel.

Figure C3: Continuation values and average conditional value of matching for startups and VCs



Notes. The top panels show simulation results for startup types on equilibrium continuation values u_i (top-left) and average average conditional values in matches with VCs $\sum_j n_j \cdot p_{ij} \cdot \mathbf{E}_\epsilon[z_{ij} + \epsilon \; |z_{ij} + \epsilon \geq u_i + v_j] / \sum_j n_j \cdot p_{ij}$ (top-right) on the y-axis versus the expected number of funding offers received in a 5-year period $5 * \rho^S \sum_j n_j \cdot p_{ij}$ on the x-axis. The bottom panels show simulation results for VC types on equilibrium continuation values v_j (bottom-left) and average average conditional values in matches with startups $\sum_i m_i \cdot p_{ij} \cdot \mathbf{E}_\epsilon[z_{ij} + \epsilon \; |z_{ij} + \epsilon \geq u_i + v_j] / \sum_i m_i \cdot p_{ij}$ (bottom-right) on the y-axis versus the expected number of deals made in a 5-year period $5 * \rho^{VC} \sum_i m_i \cdot p_{ij}$ on the x-axis. Marker sizes indicate the estimated underlying mass of types, $\{m_i\}$ in the top panels and $\{n_j\}$ in the bottom panels.