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

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Abstract

We estimate a dynamic search-and-matching model with bargaining between venture capitalists (VCs) and startups using two symmetric incentivized resume ranking (IRR) experiments implemented with real US VCs and startups. Experimental subjects evaluate randomized profiles of potential collaborators and these evaluation results are incentivized by real opportunities of being matched with their preferred cooperative partners. Taking these experimental behaviors and real-world portfolio data as inputs to our structural model, we find that both investors' human capital (i.e., entrepreneurial experiences) and funds' organizational capital (i.e., previous financial performance, fund size) and startups' human assets (i.e., educational background, entrepreneurial experiences) and non-human assets (i.e., traction, business model) affect matching payoff and continuation values of startups and VCs. We find that an average VC gets more value in equilibrium than an average startup because of better outside options. However, startups altogether get four-fifth of the total present value of all matches in our environment.

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

JEL Classification: C78, C93, D83, G24, G40, J71

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1 Introduction

The venture capital industry (VC) spurs innovations in the US by providing crucial funding and monitoring to high-impact startups. However, the entrepreneurial financing process in the VC industry often involves a two-sided matching process between VC investors and startups. According to Sørensen (2007), the effect of sorting is almost twice as important as the direct influence of investors in explaining startups' IPO rates. Therefore, understanding the matching process between VCs and startups is of first-order importance in explaining both startups' fundraising outcomes and VCs' financial performance. Following the literature, this paper studies the matching process between VCs and startups, especially by focusing on the role of various human and non-human assets, and the corresponding welfare consequences.

Economists face several empirical challenges to study the matching process in the entrepreneurial finance industry. Most standard databases only record realized matching pairs, and perhaps proxies of matching outcomes for the realized matches, making it difficult to identify deep parameters governing the value of a match versus endogenous determinants of forming a match. Specifically, the conditional matching probabilities depend on the outside option of VCs and startups, both of which are unobservable and endogenous in this framework. To address these empirical challenges, we provide a structural estimation of a search and matching between entrepreneurs and VCs based on results from two symmetric incentivized resume rating (IRR) experiments. To run experiments we recruit real US VCs and real US startup founders. Created by Kessler, Low and Sullivan (2019), the IRR experimental method can examine evaluators' preferences on a rich set of candidate characteristics in a high-skilled labor market. As different candidate characteristics share similar "signal-to-noise" ratios in the IRR experimental setting, researchers can further explore the relative importance of these characteristics. We use experimental results on the perceived value of a match, and the expected collaboration likelihood to estimate the matching model and find the matching payoff for startups and VCs with different characteristics.

In the startup-side IRR experiment, we invite real US startup founders, who are seeking funding from the VC industry, to evaluate several dimensions (i.e., ability, availability, informativeness) of multiple randomly generated VC investor profiles. Recruited founders also need to indicate their fundraising plans and the likelihood of contacting each investor. To incentivize founders to reveal their true preferences, we collect a unique, comprehensive global VC database and develop a symmetric 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 investors.

The results from the startup-side experiment show that, first, both VCs' human capital and organizational capital affect startups' willingness to collaborate. Relevant individual-level investor characteristics (i.e., human capital) 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 rich investment experience. Startups also prefer investors who work for larger VC funds and funds with better historical financial performances. Among these investor characteristics, the impact of historical financial performances dominates, which helps to explain the unique "performance persistence" of VC funds from the perspective of matching. Secondly, startups' fundraising plans also get adjusted based on investors' characteristics. Entrepreneurs on average ask for 90% of the funding amount in their original fundraising plans. However, they have more courage to ask for a larger amount of funding from investors with the previously mentioned attractive characteristics. Lastly, results show that startups especially care about investors' availability (i.e., the potential to invest in the startup) for collaboration decisions and fundraising plans.

In the investor-side IRR experiment, we invite real US VCs to evaluate several dimensions (i.e., profitability, availability, risk) of multiple randomly generated startup profiles. Investors also need to indicate their willingness to contact and invest in each startup. To incentivize investors to reveal their true preferences, we collaborate with several real US incubators and develop a matching algorithm that helps investors to match startups in our collaborating incubators. Although investors know the startup profiles are hypothetical, they are willing to provide truthful evaluations so that the algorithm works better to help them identify real matched investment opportunities. This "matching incentive" serves as the main incentive used. We also add a "monetary incentive" to a randomly selected subgroup of investors to increase the sample size.

The results of the investor-side experiment show the following main findings. Firstly, both startups' human assets and non-human assets influence early-stage VCs' intentions to contact and invest in the startup. Relevant startup team characteristics (i.e., human assets) include entrepreneurs' educational backgrounds and previous entrepreneurial experience. Relevant startup project characteristics (i.e., non-human assets) include the firm's business model, comparative advantages, previous traction, and company age. These characteristics affect investors' decisions by influencing investors' judgments on startups' profitability, availability, and risk. Importantly, perceived startups' profitability most highly correlates with investors' decisions, including both the likelihood of contacting the startup and the willingness to invest. Secondly, we find that project traction plays the most important role among all the startup characteristics in investors' evaluations. Its effect is more than twice as important as startups' educational backgrounds in terms of increasing investors' profitability ratings and investment interest ratings. This result confirms the insight of Kaplan, Sensoy and Strömberg (2009) by demonstrating the importance of startup projects by using experimental methods.

Building on these experimental findings, we develop and estimate a search-and-matching model with bargaining between startups and VCs to understand the equilibrium outcomes on matching payoffs, for various types of startups and VCs. We study the role of human and organizational capital on the side of investors and VCs, and human and organizational assets on the side of founders and startups, for the value of a startup and a VC in equilibrium. 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 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 (through financial transfers and various contract terms in reality). If the matching value surpasses the continuation values of the startup and the VC a matching takes place and parties divide the matching surplus according to their bargaining power and outside options. Otherwise, agents keep searching for a better match. In equilibrium, the continuation values of startups and VCs are determined by the average expected conditional value generated in possible matches times the probability of forming a match, which itself depends on the continuation values of both startups and VCs in a recursive format, times the probability of meeting a counterparty in the search process and the bargaining power, divided by the time discount rate for each party.

The paper estimates the model using responses from the IRR experiments. First, we assign startups into $I = 16$ types, using attributes that appear as determinants in the evaluations: traction, business model, founder's education background, and founder's entrepreneurial experience, all as dummy variables determining organizational and human assets on the startup side. We assign VCs into $J = 8$ types, again using attributes that appear as determinant in our reduced-form evaluation results: size, historical performance, and investor's entrepreneurial experience, all as dummy variables determining organizational and human capital on the VC side. We then use the quality evaluation question (Q1, which asks to ignore strategic considerations in its framing) to infer the expected matching value between two startup and VC types, and we use the strategic question of the perceived collaboration likelihood (Q2) to set the matching probabilities between startup and VC types. The perceived collaboration likelihood identifies the continuation values in relative terms.

If, for example, a startup type i considers a particular VC profile of type j as valuable (high Q_1), a larger matching value is identified; but, if at the same time, she doesn't consider a matching to be likely to happen (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, which, together with the estimated expected values of matching, allows us to estimate the bargaining power and equilibrium payoffs for each startup and VC type.

Results show that in equilibrium an average VC gets more continuation value than an average startup. The point is, 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—she is more willing to wait then, which raises her reservation payoff in equilibrium. Using model-based counterfactual analysis, we find that doubling the number of VCs indeed raises the equilibrium value of an average startup by 50% and *reduces* the value of an individual VC by 30%. We also show that reducing the time discount factor of startups by 5% (from 15% to 10%) would substantially reduce the matching frequency—by a factor of 2, and would increase (reduce) the equilibrium value of startups (VCs) by 33% (14%). Startups are more willing to wait for a better realization of matching value, which hurts VC's bargaining power in equilibrium. We highlight that, while an average VC gets more equilibrium value than an average startup in our benchmark estimations, all VCs combined get only 15-25% of the present value of the matching value (depending on the specification). Startups get the majority share of the generated value of matches, because the environment is populated with more startups.

Our estimation discovers a substantial variation in equilibrium payoffs exists across both startups and VCs. When using the startup-side experimental results in estimation, we find that on average, startups with a business-to-business model get about 25% more value relative to the reference group. The average impact of being a serial founders, and having a prestigious education on equilibrium value is also substantial at 30-35%. The impact of "positive traction" is, however, insignificant. When we use VC-side experimental results in our estimation of the continuation values of startups, however, we find that the role of education background on equilibrium values of startups is less, while the impact of traction becomes substantial. This disparity highlights the misperception of startup types on the value of their startups. Regardless of the experiment data source, however, 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 historical performance and having investors with entrepreneurial experiences have an average positive impact of about 15% and 20% (relative to the reference group), respectively, across all specifications, while the impact of size is about 5% and only marginally significant. Our findings, therefore, confirm the role of both human and organizational characteristics for the equilibrium payoff of both startups and VCs in the entrepreneurial finance market.

We discuss testable results of our estimates, by comparing the simulation outcomes at the startup- and VC-type level with the observable real-world data and empirical findings in the literature. First, we show that the predicted expected conditional matching value across startup-VC pairs can predict variations in deal size in the data. A Cobb-Douglass technology for generated discounted revenue with respect to the capital invested in the startup, with the share of capital equal to .25, would explain a payoff of 2 dollars for VCs per dollar invested in startups. Second, we show that "attractive types" in our model expect to receive more offers and make more deals in a given period of time. Attractive types are startups with traction and b2b model, and with serial founders and a prestigious education; and VCs of larger size, better historical performance, and with investors with entrepreneurial experiences; We show that such types involve in matches of substantially higher expected values. This result confirms the findings of Hsu (2004) which documents better outcomes over startups with multiple offers. Third, we show that endogenous matching indeed would overestimate the underlying value of matches for *unattractive* types, a result that is in contrast with Sørensen (2007). Unattractive types need to search more in the market for a better draw of the matching value; this would hurt their equilibrium continuation values, but it would imply that the gap in the expected value *conditioned* on matching and the unconditional average of the matching value that is more for unattractive types compared to attractive types. Sørensen (2007) does not have search friction and uncertainty in matching values.

The contribution of this paper is both empirical and methodological. 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 startups' team characteristics or project characteristics, and suggest project characteristics should be more important. Later, Bernstein, Korteweg and Laws (2017) implement the first field experiment with real US early-stage investors, which generates rigorous causal evidence of venture capitalists' startup selection strategies. They find that investors mainly care about startup teams' educational backgrounds. Block, Fisch, Vismara and Andres (2019) implement the conjoint analysis method with real private equity investors and documents that revenue growth is the most important investment criterion. Zhang (2021) exploit the IRR experimental method with real venture capitalists and discover that startups' ESG characteristics also influence investors' decisions.[1] Following this literature, our paper confirms previous papers' findings and also provides experimental evidence on how other startup characteristics, such as founders' entrepreneurial experiences, startups' locations, business models (i.e., B2B vs B2C), and company age influence investors' preferences. Taking advantage of several unique features of the IRR experimental method, we can further investigate mechanisms that drive these preferences. Furthermore, we feed experimental results on VCs' selection criteria into a search and matching model between startups and VCs to estimate the equilibrium implications of startups' preferences for the payoff of startups with heterogeneous attributes in the market for fund-seeking from VCs.

Secondly, our paper contributes to the literature studying startups' preferences for VCs. Hsu (2004) discover that startups are willing to be acquired by high-reputation VCs at a 10-14% discount in exchange for the certification and other value-added benefits provided by prestigious VCs. Mayer and Scheck (2018) implement the conjoint analysis method with social entrepreneurs and discover that social entrepreneurs value several non-financial features of potential funders. Following this literature, our experiment discovers several other important investor characteristics that influence startups' fund-seeking behaviors, including both investors' human capital (i.e., previous entrepreneurial experiences, investment experiences) and funds' organizational capital (i.e., previous financial performances, fund size). Similar to the investor-side IRR experiment, the startup-side IRR experiment also enables researchers to go beyond estimating average treatment effects. We test mechanisms that drive startups' preferences and investigate how these investor characteristics influence both startups' fundraising plans and the likelihood of collaboration. We further study the implications of startups' preferences for the payoff of VCs with heterogeneous characteristics in the market equilibrium via structural estimation.

Thirdly, this paper contributes to the literature explaining the financial performances of PE/VC funds. VC funds' financial performances depend on the value added of VCs (i.e., the direct influence channel) and the ability to attract great deal flows (i.e., the sorting channel). Most papers in this area focus on the value-added role of investors (Bottazzi, Da Rin and Hellmann (2008), Hellmann and Puri (2002), Bernstein, Giroud and Townsend (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 to explain companies' outcomes. Therefore, understanding founders' preferences for investors is of first-order importance to explain funds' financial performances. This paper focuses on this crucial

[1] There are also some excellent survey papers to help understand how investors make their decisions (e.g., Gompers, Gornall, Kaplan and Strebulaev (2020)).

sorting channel and studies the detailed mechanisms that affect the matching process between investors and startups in the US. Our experimental results on the importance of detailed investors' human capital characteristics and funds' organizational capital characteristics help to explain the findings identified in Ewens and Rhodes-Kropf (2015). The result that startups prefer VC funds with better historical financial performances provides novel causal evidence that explains the well-documented persistent out-performance of top-performing VC funds (Robinson and Sensoy (2016), Harris, Jenkinson, Kaplan and Stucke (2020), Chung (2012), Kaplan and Schoar (2005)).

Methodologically, we adopt a different approach to estimating a dynamic search-and-matching model by using field experimental data, which helps to relax structural assumptions in estimation. Ewens, Gorbenko and Korteweg (2022) estimate a dynamic search-and-matching model to study the role of VC contract terms in splitting value between VCs and startups. Our paper complements their work by using experimental data to directly identify the underlying matching values across startup types and VC types; we use revealed preferences to estimate not only the bargaining power of startups and VCs and the division of surplus in the matching market equilibrium, but also the role of observable attributes, human and organizational capital, on the equilibrium payoff of startups and VCs.

This paper also contributes 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 (2020a), Zhang (2021), Colonnelli, Li and Liu (2022)). The idea of running an experimental system is 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. We use micro-level empirical foundations to estimate a theoretical model with search friction and study welfare in matching equilibrium outcomes.[2]

This paper is organized as follows. Section 2 presents the set-up of our structural model and discusses the empirical challenges of estimating the search-and-matching model using solely observable matching outcomes. Section 3 presents the design, implementation details, and reduced-form results of the symmetric IRR experiments. Section 4 introduces the es-

[2]A concurrent work of Colonnelli et al. (2022) estimates a search and matching model between LPs and GPs using experimental data. In their framework, the matching value is not transferable between parties and each party gets her own private value in a match. We instead consider a transferable and perfectly divisible matching value between entrepreneurs and VCs, which reflects bargaining and negotiations in our context, and makes the division of surplus and payoff from matching an endogenous outcome in our model.

timation procedures of the structural model and discusses the identification of the model. Section 5 shows our main results, including the estimated bargaining power, welfare implications, and counterfactual analysis. Section 6 discusses the testable implications of the model and compares our simulation results with 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 frequency, 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 matching outcomes recorded by 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 bargaining over the matching value 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 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). Upon a meeting, the startup proposes a take-it-or-leave-it offer to the VC with probability π and the VC proposes a take-it-or-leave-it offer to the startup with probability $1-\pi$. As will be clear below, π represents the bargaining power of startups versus VCs over the matching *surplus*: the fraction of the matching surplus that a party expects to capture, on top of her outside option. If a proposal is made and accepted by the counterparty, we call it a matching. Matching takes place if the joint value $z_{ij}+\epsilon$ is greater than the sum of the outside option of the two parties. Otherwise, both parties leave the meeting and keep searching for another match. 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. 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 offering/accepting strategies and the corresponding 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 a startup of type i with a VC of type j, conditioned on a meeting happening 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 proposer offers the outside option of the counterparty, which is going to be accepted. The matching surplus is then captured by the proposer, who is going to be the startup with probability π and the VC with probability $1-\pi$. The expected payoff of a startup and of a VC conditioned on matching is

$$\text{expected cond. payoff of type } i \text{ startup:} \quad u_i + \pi * \mathbf{E}_\epsilon[z_{ij}+\epsilon-u_i-v_j \mid \textit{positive}]$$
$$\text{expected cond. payoff of type } j \text{ VC:} \quad v_j + (1-\pi) * \mathbf{E}_\epsilon[z_{ij}+\epsilon-u_i-v_j \mid \textit{positive}]$$

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 written 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 chance that a party offers the terms of the contract; and 4) the frequency of a meeting with various counterparty types over time. In short, the right-hand side represents the expected *flow* of payoff. 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., 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 $1-\pi$ 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 $\bar{v} = \sum_j n_j v_j$ is 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 $r^{VC} = \rho/M^{VC}$. 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 js 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, which need to be inferred from the equilibrium relationships implied by HJB equations (2) and (3) by imposing structural assumptions on z_{ij} and 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) considers an environment with no search frictions. Therefore, all types by construction are matched in equilibrium, which 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 assumption 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 bargaining power parameter 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 continuation values $\{u_i\}$, $\{v_j\}$ separately.

Unlike Sørensen (2007), 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 VC id observed in a given period of time in the data. In their setup, investors always set the contract term (i.e., $\pi = 0$). Contract terms (observed in the data) offered by VCs affect both the continuation values (i.e., $\{u_i\}$ and $\{v_j\}$) and the joint values (i.e., $\{z_{ij}\}$ by considering moral hazard friction and the fact that startups need to have skin in the game. Finally, structural assumptions are imposed to estimate a deterministic joint value $\{z_{ij}\}$, which are inferred from observable matching outcomes based on the likelihood of IPO and high-value acquisitions.

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 perceived by startups and VCs. 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 and implement the counterfactual analysis.

3 Two-Sided IRR Experiments

3.1 Data

To implement symmetric IRR experiments on both the investor side and the startup side, we construct a comprehensive individual-level global venture capitalists' database. This database contains more than 17,000 global venture capitalists' updated demographic information and contact information before 03/2020. All the email addresses had been verified before our experiments started.

This database serves multiple functions. For the startup-side IRR experiment, a comprehensive VC database enables us to provide a valuable data-driven investor recommendation service to startups. Hence, it is the key to providing the "matching incentive" and increasing the stakes involved in the experiment. For the investor-side IRR experiment, the collected VCs' contact information enables us to recruit real US VCs to generate enough experimental power. Furthermore, the collected VCs' demographic information helps to check the sample representativeness. The detailed data construction process is provided in the Online Appendix of Zhang (2020a).

3.2 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.

3.2.1 Recruitment Process and Sample Selection

To recruit a large number of real US startup founders who fit the research purpose, I 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

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

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%, and 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 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.

3.2.2 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, 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.

[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.

[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), please see Feng, Zhang and Zhong (2022) and Zhang (2022)

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, Kovner and Lerner, 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 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 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, Nanda and Rhodes-Kropf (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

[7] Graduate degrees include MBA, JD, master, and Ph.D. 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.

[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.

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.

3.2.3 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 A2 for an example of designed evaluation questions).

Mechanism Questions. Three mechanism questions are designed to test the following three standard, belief-driven sub-mechanisms explaining 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") theoretically also affect their decisions (Heckman, 1998; Neumark, 2012) 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. Option 2 is to receive (\$500 - price) and a more comprehensive investor recommendation list containing the 200 most matched real venture capitalists' information. 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).

3.2.4 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 (2020b)). In our experimental setting, we choose to provide this standard "matching incentive" to all experimental participants.

Specifically, after evaluating 20 hypothetical investor profiles, each startup founder will receive 10 real VCs' contact information recommended by the matching algorithm. This recommendation service relies on the availability of a large comprehensive global VC investor database. Startup founders generally need to purchase licenses to get access to this information on Pitchbook. Hence, we provide valuable benefits to experimental participants. To justify the validity of the provided incentive, we show that reduced-form results are similar when focusing on the subgroup participants who choose to pay real money for this recommendation service.

3.2.5 Relevant Human Capital and Organizational Capital Characteristics

Ewens and Rhodes-Kropf (2015) discovers strong VC partner and firm fixed effects in explaining VC firms' performance, emphasizing the importance of investors' human capital and the VC firm's organizational capital. These strong fixed effects motivate further study of detailed individual investor characteristics and VC fund characteristics to explain VC performances. Following their work, we investigate detailed individual-level investor characteristics, such as educational background, entrepreneurial experiences, and investment experiences, and fund-level firm characteristics, such as fund location, historical performances, fund size, investment strategy, and being a first-time fund or not, that affect VC outcomes. Our experimental results are consistent with Ewens and Rhodes-Kropf (2015) by documenting the importance of human capital and organizational capital in explaining VC firms' performance. However, this paper mainly focuses on the sorting channel instead of the direct influence channel by investigating how various investor characteristics affect the investor's ability to attract potential high-quality deals.

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 Q1 (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 Q2 (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 Q5 (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, 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, 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.

Column (1) finds that startups give higher quality 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 point, 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 quality 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.

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.

Performance Persistence. Several papers 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)). General explanations mainly focus on the importance of investors' skills and networks (i.e., accessing to proprietary deals) for successful VC investing. In this paper, we document that outperforming VC funds have more advantages of attracting startups given the same level of investor skills and networks. Similarly, historically underperforming VC funds get punished by their worse financial performance because startups are less willing to collaborate with them compared to first-time VC funds and outperforming VC funds. Since sorting plays a dominant role in explaining portfolio companies' outcomes, failing to attract high-quality startups can hurt VC funds' future financial performances seriously. Different from mutual funds and hedge funds, this special two-sided matching nature of the entrepreneurial financing process can contribute significantly to VC funds' persistent performances.

Investment Style. While Mayer and Scheck (2018) shows that social entrepreneurs value the traditional value-added investment strategy commonly used by VC, adopting this investment strategy does not affect startups' collaboration interest compared to adopting the diversified investment strategy (i.e., the "spray and pray" investment strategy) in our experimental setting. Two potential reasons help to explain this inconsistency. First of all, the majority of our experimental subjects are profit-driven startups rather than social entrepreneurs. This is consistent with the finding that the financial features of VC funds affect our experimental subjects' evaluations the most. Hence, social entrepreneurs and profit-driven entrepreneurs might have different fund-seeking behavior patterns. Second, as we include richer investor characteristics in our experimental setting, the impact of more influential investor characteristics might dominate the impact of less influential investor characteristics. That is to say, compared to VC funds' financial features and investors' various experience, adopting the value-added investment strategy serves as a less important investor characteristic in startups' entrepreneurial financing process.

3.3 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 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.

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

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.

3.3.1 Recruitment Process and Sample Selection

This IRR experiment was mainly implemented between 03/2020 and 07/2020. We sent invitation emails and instructional posters to the 15,000+ US-based VCs, whose information is collected by Zhang (2020a). Both the recruitment emails and posters emphasized the matching purpose of this tool (see Online Appendix Figures B5 and B6 for the recruitment emails, Figures B7 and B8 for the instruction posters). Nonetheless, we also notify them that their anonymized data will be used for some research purposes as required by IRB. In total, 69 VCs from 68 different VC funds chose to participate in this experiment, providing 1,216 total startup profile evaluation results.[10] The number of recruited experimental participants is comparable to Kessler et al. (2019).

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

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

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

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.

3.3.2 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.[11]

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.[12] We only provide startup information which is publicly available

[11]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.

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

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 plan, we exclude them from our experiments. Randomization of different startup components is provided in Table B2.

3.3.3 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. Given that venture capitalists are generally well-educated and sophisticated investors, we choose to use probability or percentile ranking questions instead of Likert scale questions.[13] 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. Our evaluation question design allows us to implement infra-marginal analysis, distributional analysis, and welfare implications in Section 5. This provides a more nuanced picture of the matching process. Screenshots of evaluation questions are provided in Figure B3 and Figure B4.

Mechanism Questions. Three mechanism questions are designed to test the following three standard belief-based mechanisms influencing investors' preferences. First, some startup characteristics may serve as indicators of the startup's quality. To test this channel, investors need to evaluate a quality 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. Third, certain startup characteristics are signals of the startup's risk level. Therefore, investors also evaluate a risk evaluation question (Q_5) and provide the risk percentile rank of each startup profile compared to their previously invested startups.[14]

[13] Similarly, Brock and De Haas (2020) uses probability questions to replace Likert Scale questions when they recruit real Turkish bankers to evaluate different loan profiles in their lab-in-the-field experiment.

[14] The risk evaluation question was added when we were recruiting investors with only the "matching incentive" for a robustness test purpose. During the recruitment process, we received feedback from investors suggesting to add this question. Therefore, when recruiting the rest investors using only "matching incentive", this risk evaluation question was added at the end of all the other questions to minimize its impact on previously existing questions. An alternative way is to implement a new field project as Bartoš, Bauer, Chytilová and Matějka (2016) does. However, it cannot guarantee to collect information from the same group of investors. Hence, we still decide to add Q_5 after adjusting the pre-registration plan and submitting modifications to Columbia IRB.

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 about whether preferences in the contact stage can be fully transformed into preferences in the 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 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.

3.3.4 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, Fuster and Zafar (2019). Details and justifications of both incentives are provided below.[15]

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 our collaborating incubators. Matched startups will contact investors for a potential

[15]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 extra noises to this experiment. Later, we show that these noises do not distort the preferences systematically.

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 five evaluation questions are incentivized and the description of the algorithm is provided in the consent form.

Monetary Incentive. To increase the sample size, we provide both a "matching incentive" and a "monetary incentive" to a randomly selected 14000 investors who receive the recruitment email (Version B). 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.[16] 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.

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.

Another concern is that the "monetary incentive" essentially elicits each subject's judgment of how the market evaluates each startup's profitability. This might be different from the subject's own judgment of each startup's profitability as incentivized by the "matching incentive." To address these concerns, we have compared the evaluation results of investors who receive only the "matching incentive" and those who receive both incentives. Results show that these two incentive structures do not cause systematically different evaluations, especially the profitability ratings.

[16]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.

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)	Q5 Risk (7)
Serial Founder	5.23***	-0.81	5.64***	1.26	0.76***	0.13	-0.65
	(1.08)	(0.88)	(1.28)	(0.91)	(0.19)	(0.15)	(3.05)
Ivy	5.36***	-1.06	7.44***	3.01***	0.87***	0.20	-6.44**
	(1.10)	(0.87)	(1.31)	(0.93)	(0.20)	(0.15)	(3.26)
Number of Founders	1.56	-1.21	1.17	-0.11	0.21	0.04	-5.32*
	(1.07)	(0.88)	(1.29)	(0.91)	(0.20)	(0.15)	(3.06)
US Founder	0.95	0.02	4.23***	3.69***	0.08	0.03	-0.91
	(1.18)	(0.91)	(1.39)	(1.00)	(0.21)	(0.16)	(3.48)
# Comparative Adv	3.10***	-0.22	2.76***	0.34	0.55***	0.15**	0.91
	(0.54)	(0.43)	(0.64)	(0.43)	(0.10)	(0.07)	(1.48)
Has Positive Traction	12.70***	1.75**	13.35***	1.91*	1.81***	0.28*	-9.51***
	(1.07)	(0.86)	(1.28)	(0.99)	(0.20)	(0.16)	(3.15)
Number of Employees [0-10]	0.67	2.37**	-1.73	-2.57**	-0.19	-0.29	-1.18
	(1.43)	(1.16)	(1.69)	(1.18)	(0.26)	(0.20)	(3.94)
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	-1.28
	(1.45)	(1.17)	(1.71)	(1.17)	(0.27)	(0.19)	(3.59)
Company Age	-4.59*	-5.99***	-7.39**	-2.19	-1.26**	-0.54	-3.41
	(2.72)	(2.19)	(3.19)	(2.26)	(0.49)	(0.37)	(7.74)
Company Age^2	0.75	1.12**	1.27**	0.42	0.23**	0.10	0.77
	(0.54)	(0.44)	(0.64)	(0.45)	(0.10)	(0.07)	(1.52)
Is B2B	3.90***	3.73***	6.10***	1.47	0.81***	0.32**	-4.91
	(1.07)	(0.86)	(1.28)	(0.89)	(0.20)	(0.15)	(3.01)
Domestic Market	-0.10	-0.60	0.09	0.57	0.08	0.13	-3.32
	(1.08)	(0.86)	(1.28)	(0.90)	(0.20)	(0.14)	(3.19)
Q1				0.88***		0.12***	
				(0.03)		(0.01)	
Q2				0.18***		0.01	
				(0.03)		(0.01)	
Constant	49.75***	78.20***	66.20***	-4.19	5.62***	-0.33	67.01***
	(6.56)	(6.02)	(4.93)	(7.50)	(1.43)	(0.63)	(11.66)
Investor FE	Yes	Yes	Yes	Yes	Yes	Yes	
Observations	1,216	1,184	1,216	1,184	1,176	1,154	176
R-squared	0.44	0.55	0.56	0.80	0.44	0.70	0.34

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

3.3.5 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)-(7), the dependent variable is the evaluation results of Q_1 (quality evaluation), Q_2 (availability evaluation), Q_3 (contact decision), Q_4 (investment decision) and Q_5 (risk evaluation), 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 and q-value in Table B3 to implement the multiple hypothesis testing.

In columns (1), (3), and (5) of Table 2 and Table B3, we find multiple startup characteristics and project characteristics that are causally important to investors' quality evaluation results, contact decisions, and investment decisions. 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 its business models. Specifically, Column (1) shows that while founders' previous entrepreneurial experiences and impressive educational backgrounds both increase investors' quality judgment by 5 percentile ranks, the positive traction of startup projects is almost twice as important as educational backgrounds, increasing investors' quality judgments by 12.7 percentile ranks.[17]

It should be noted that in Table 2, coefficients of the project traction are the largest among all coefficients of other startup characteristics. This confirms the hypothesis of Kaplan et al. (2009), which suggests that investors should bet more on projects rather than teams. Similarly, Table B4 shows that after all coefficients are standardized, project traction is still the most influential characteristic among all the other influential factors. Actually, the coefficients of these project characteristics can also be interpreted as the lower bound of the real effects if someone is concerned about the impact of potential noises.

[17] In our investor-side IRR experiment, we do not find the number of existing investors affects venture capitalists' decisions. However, it does not mean that the endorsement of prestigious investors does not matter. For relevant discussions, please see Bernstein, Mehta, Townsend and Xu (2022).

4 Estimation

In this section, we estimate the search and matching model with bargaining between startups and VCs presented in section 2. 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 run in **??** 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 in detail and counterfactual analysis.

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 levels and count realized matches for $16 * 8 = 128$ pairs of startup and VC types.

4.2 Identification

We use the quality 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 attenuation biases implied by measurement errors. We first describe a version of the estimation in which we use startup-side experiment results regarding matching values and collaboration likelihood with VCs. Then we extend the methodology to use experiment results from both sides—startups evaluating VC profiles and VCs evaluating startup profiles—in estimating model primitives. Using experiment 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 experiment 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 in the previous section. Furthermore, we set $\hat{p}_{ij}$ from the revealed matching likelihood, taken directly from the answers to the experiment survey Question 2. Note that we collapse all data and responses at the i/j type level by taking averages: $p_{ij} \to \hat{p}_{ij} = \overline{ans(Q_2)_{ij}}$. We achieve an estimate for the underlying distribution 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. 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 by our 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). Now we perform the following fit to equation (8), by assuming that the conditional matching odds p_{ij} is revealed from the answers to the survey Question 2 directly:

$$p_{ij} \rightarrow \hat{p}_{ij} = ans(Q_2)_{ij}$$

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 to be estimated later, $\bar{u}$ and $\bar{v}$:

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

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 mean values $\bar{u}$ 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 value—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 $p_{ij} \rightarrow \hat{p}_{ij} = \overline{ans(Q_2)_{ij}}$ 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 payoffs 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 payoff to continuation values, being meeting intensity times bargaining power 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 implies a linear fit with zero intercept between continuation values in *absolute* terms and expected flow of matching payoffs. 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/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 bargaining power 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, bargaining power, 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 $p_{ij} \rightarrow \hat{p}_{ij} = \overline{ans(Q_2)_{ij}}$, 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 of counterfactual 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 ρ, M^S, M^{VC}, 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 is 36,579, and during 2018-2020 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, Jones and Rhodes-Kropf, 2013; Harris, Jenkinson and Kaplan, 2014; Korteweg and Nagel, 2022).[18] We calibrate $r^{VC} = 10\%$ (on a per annum basis) as a median estimate 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 the startup types that we consider in the 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,

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

our robustness checks show that changing discount rates affect estimated values in absolute terms, but not much in the *relative* sense (i.e., the equilibrium payoff of a given startup type *relative* to the average startup and to an average VC remains 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 estimation errors. The direction of bias is not clear though (and whether there is a bias, to begin with) as the error in $\hat{u}^r$ and $\hat{v}^r$ is not in form of classical measurement error. We run Monte Carlo simulations to assess and correct for bias in our objects of estimates. We consider the deviation from average reports collapsed at the i/j type level of individual answers to experiment questions as statistical errors. We 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 consider the correlation in error terms in answers to survey questions in our re-draws of error terms. We replicate all estimation steps described above for each set of noise draws. We use Monte Carlo results from 100 replicates to correct for the bias in our estimation reports. We also use these Monte Carlo results to obtain and report standard errors of our objects of estimates.[19]

4.2.4 Alternative Sources of Experiment Data

First, we highlight that the estimation approach that we explained above can be implemented using only the startup-side experiment data. The variation in matching values (Q1) across VC profiles revealed by startups can identify variations in the index j of z_{ij} and therefore the variation in VCs' continuation values v_js in the specification (8). And the variation across startups of their revealed perceived values (Q1) can identify variations in the index i of z_{ij} and so variations in Startups' continuation values u_is in the same specification (8).

One critique, however, is that in the startup-side experiment startups reveal variations in perceived values (Q1) 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, as *each* startup may rank VCs based on her priors. Specification (8) is then 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

[19]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 experiment data and X_s is the estimation in the simulation number s, and $S = 100$ is the total number of simulations. We also report the standard error of our final estimate of X via $\sum_{s=1}^{S} X_s^2/S - (\sum_{s=1}^{S} X_s/S)^2$.

only VC-side experiment reports, especially because, in an attempt to reduce the noise in reports, in the framing of the question to solicit matching values we specifically ask VCs to rank startup profiles relative to the pool of startups that they have experienced before.

To address this critique, we use information from both startup-side and VC-side experiments. We run specification (8) using the startup-side experiment data on revealed values and perceived matching likelihoods to estimate the variations in VCs' continuation values $\{v_j\}$. And we run the same specification (8) using the VC-side experiment 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 $\hat{p}_{ij}$ and thereby 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). Finally, we use the same specifications (14) and (15) to estimate average continuation values, $\bar{u}$ and $\bar{v}$, and parameters of search and bargaining, β^S and β^{VC}.

Second, we mention that we may use alternative data to set the matching likelihood p_{ij} in the estimation. In the estimation approach that we presented above, we directly use the revealed collaboration likelihood (Q2). Alternatively, we may use the revealed contact interest on either side (Q4 in the startup-side experiment and Q3 in the VC-side experiment) to back out the perceived matching likelihoods. The revealed contact interest maps to the expected matching *surplus* 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 via $p_{ij} \cdot \mathbf{E}_\epsilon[\epsilon - CDF^{-1}(1 - p_{ij}) \mid \textit{positive}]$, 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.

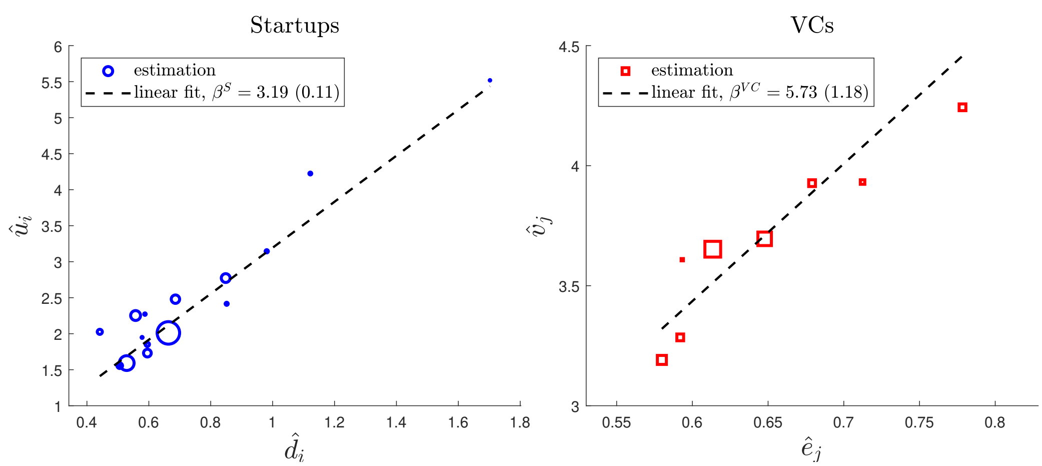
In an alternative estimation, we back out p_{ij} from the revealed contact interest (Q4 in the startup-side experiment and Q3 in the VC-side experiment) by inverting the function $p_{ij} \cdot \mathbf{E}_\epsilon[\epsilon - CDF^{-1}(1 - p_{ij}) \mid \textit{positive}]$. We first check the consistency in the experiment results regarding the contact interests. Online Appendix figure C11 shows the relationship between the revealed contact interests in the experiment data and the model-implied measure $p_{ij} \cdot \mathbf{E}_\epsilon[\epsilon - CDF^{-1}(1 - p_{ij}) \mid \textit{positive}]$ in which we set p_{ij} from the revealed collaboration likelihoods in the data. A positive covariation is verified. The mapping is not precise though, especially on the VC-side experiment 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 Q2, and indirectly by inferring from the revealed contact interest—Q4 in the startup-side experiment and Q3 in the VC-side experiment (after appropriate scaling via the implied slopes in Online Appendix figure C11).

In what follows, we demonstrate parameter estimates and model fit using only startup-side experiment data in the estimation. Plus, we use the revealed collaboration likelihoods (Q2) directly to set the matching likelihoods. We also report counterfactual results in the next section via the model estimated by startup-side experiment data and data on revealed collaboration likelihoods as the benchmark. Meanwhile, we report continuation values and expected matching payoffs for startup and VC types estimated using all alternative sources of experiment data on the startup-side, and on the startup and the VC side combined.

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 value of a type equals the expected matching payoff, 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 bargaining power, 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

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

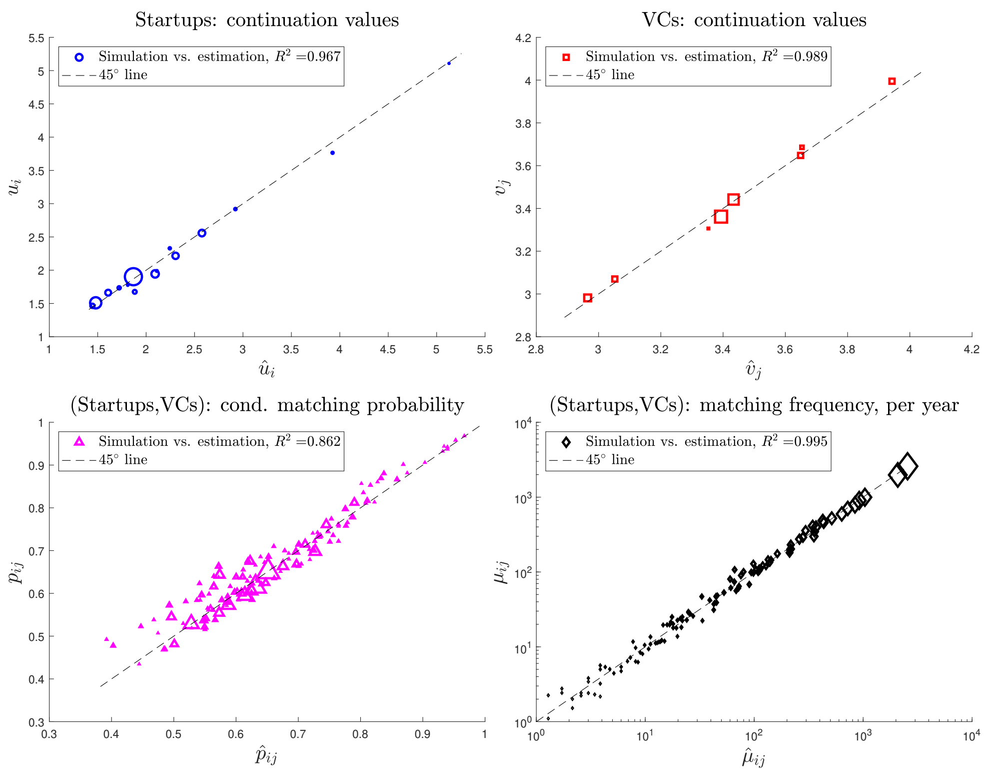


Notes. The size markers represent the estimated mass of startup and VC types, $\{m_i\}$ and $\{n_j\}$ in the left and right panel, respectively. Numbers in parentheses show the standard error of the estimated slopes.

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 values and payoffs in section 5.

The gap between point estimates for continuation values from experiment data using equation (9) and the linear fit (dashed lines) in figure 1 shows the error in the model prediction. Given the estimates of β^S and β^{VC} and the estimated $\{z_{ij}\}$ 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 and matching probabilities from the experiment data and observed matching frequencies from the Pitchbook. Simulation results align with the estimations and data quite well. We further discuss the simulation performance in section 5.

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.

5 Results

In this section, we provide estimation results for continuation values and expected payoffs of the matching values for an average startup and an average VC, as well as the role of human and non-human attributes for variations in values across startups and VCs. We report results on the present value of total surplus as well. Next, we run the following counterfactual analyses: i) an increase in the patience of startups; ii) an equal split of the matching surplus between startups and VCs; and iii) an increase in the mass of VCs. 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 by comparing values and payoffs in the model to the real-world data on deal sizes in section 6.

Equilibrium Values and Conditional Matching Payoffs. Table 3 shows the estimated average continuation values and expected conditional matching payoffs for startups and VCs. We report results for all estimation procedures, using startup-side experiment data only or both startup- and VC-side experiment data, and using revealed collaboration likelihoods vs. contact interests, as described in section 4. Estimates that use both startup- and VC-side experiment 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 experiment results that, conditioned on joint matching values, 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).

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* while VCs usually get their outside options, being their continuation values. Why 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 outside option of a given VC in negotiating over the joint matching value with a given startup, which supports a larger equilibrium value for an average VC than an average startup.

Lastly, we find that VCs overall 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 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, startups altogether capture the majority of the generated surplus in the environment that we study.

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 (0.048)	2.178 (0.048)	1.84 (0.098)	1.918 (0.115)
$ave(u + \pi \frac{d}{\sum_j n \cdot p})$	2.726 (0.069)	3.143 (0.069)	2.656 (0.143)	2.766 (0.167)
$\bar{v}$	3.384 (0.721)	2.507 (0.685)	4.222 (1.613)	6.364 (1.946)
$ave(v + (1-\pi)\frac{e}{\sum_i m \cdot p})$	3.485 (0.743)	2.582 (0.706)	4.348 (1.663)	6.556 (2.007)
$M^S\bar{u} + M^{VC}\bar{v}$	111.4 (2)	121.5 (2.6)	113.1 (3.4)	127.7 (4.4)
$\frac{M^{VC}\bar{v}}{M^S\bar{u}+M^{VC}\bar{v}}$	0.152 (0.031)	0.103 (0.027)	0.188 (0.065)	0.251 (0.069)

Notes. Statistics from simulation outcomes are reported based on models estimated via alternative experiment data sources. In Columns (S,p1) and (S,p2) we use startup-side experiment data while in Columns (S-VC,p1) and (S-VC,p2) we use both startup-side and VC-side experiment 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. See further details on estimation procedures in section 4. Averages statistics are calculated using the mass of types, $\{m_i\}$ and $\{n_j\}$ for startups and VCs, respectively, as weights. $u+\pi\frac{d}{\sum_j n \cdot p}$ shows the average expected payoff of a startup *conditioned* on matching with various VC types and $v+(1-\pi)\frac{e}{\sum_j n \cdot p}$ shows the average expected payoff of a VC *conditioned* on matching with various startup types. $d = \sum_j n \cdot p \cdot \mathbf{E}_\epsilon[z+\epsilon-u-v|positive]$ and $e = \sum_i m \cdot p \cdot \mathbf{E}_\epsilon[z+\epsilon-u-v|positive]$ show the expected matching *surplus* for a startup and for a VC, respectively, as defined in equations (12) and (13). The total present value of matching values $M^S\bar{u}+M^{VC}\bar{v}$ is reported in the unit of 1,000. Numbers in parentheses show standard errors.

Heterogeneity Across Types: The Role of Human vs. non-Human Attributes. We find significant heterogeneity in equilibrium payoffs across types, especially on the startup side. See table 4, Column 1. The mass-weighted standard deviation of the equilibrium value across startups is nearly 20% of the average, and that of VCs is of the order of 10% of the average level. What are the determinant attributes on either side for creating heterogeneity in equilibrium payoffs? To answer this question, we run counterfactual analyses in which we eliminate the dependency of the matching values $\{z_{ij}\}$ with respect to a specific attribute of startups or of VCs. Specifically, we collapse $\{z_{ij}\}$ to the mass-weighted mean values along a specific attribute, conditioned on the rest of the attributes on either side.[20] Given counterfactual matching values we solve the recursive equations (1) to (4), to get the counterfactual continuation values and matching likelihoods and frequencies. In this exercise we fix βs.

Table 4, Columns 2-5 show the variation in equilibrium values in counterfactual settings. Row 3 in each panel documents the fall in the variance of values, relative to the benchmark. We find that both human and non-human attributes contribute to the creation of heterogeneity in equilibrium values on either side. However, human attributes are dominant. On the startup side, human assets: education and entrepreneurial experience, are more determinant than organizational assets: traction and business model. In the absence of either prestigious education or serial founder as observable factors, the variance in the continuation values across startups falls by about 50%, while in the absence of positive traction and the business model the heterogeneity in value measured by the variance falls by 10-30%. On the VC side, we also find both the human capital of investors in the VC fund: entrepreneurial experience, and the organizational capital of the fund: size and historical performance, are determinant factors in creating heterogeneity in values; although the most single informative factor is yet human capital—the entrepreneurial experience of investors, which explain more than 40% of the variance of the equilibrium continuation values across VC types. We note that results in this table are based on the model estimated via startup-side experiment data. As we show below, estimations based on the VC-side experiment indicate an opposite trend,

[20] More specifically, take an attribute of either startups or VCs; for example, a startup's education background, denoted by A_i^{educ}. Denote the rest of the attributes of startups by the vector $A_i^{\neg educ}$. We consider a set of counterfactual matching values, $z_{ij}^{\neg educ}$, in which, having controlled for the rest of attributes, startups of different education backgrounds would rather command the same matching value, being equal to the conditional mean matching values across startups of different education background:

$$z_{ij} \to z_{ij}^{\neg educ} = \sum_{i' \in \mathcal{I}(A_i^{\neg educ})} m_{i'} z_{i'j} \ / \sum_{i' \in \mathcal{I}(A_i^{\neg educ})} m_{i'}$$

The sum is over all startup types that share the same *non*-education attributes as the given startup type i:

$$\mathcal{I}(A_i^{\neg educ}) := \ i' \in \{1, 2, ..., I\} \mid A_{i'}^{\neg educ} = A_i^{\neg educ}, \ \textit{in all elements}$$

Likewise, for an arbitrary characteristic j of VCs, for example size, being indicated by C_j^{size}, where the non-size-related characteristics are denoted by the vector of $C_j^{\neg size}$, we construct the counterfactual values

$$z_{ij} \to z_{ij}^{\neg size} = \sum_{j' \in \mathcal{J}(C_j^{\neg size})} n_{j'} z_{ij'} \ / \sum_{j' \in \mathcal{J}(C_j^{\neg size})} n_{j'}$$

where the sum is over all VC types that share the same *non*-size-related characteristics as a given VC type j:

$$\mathcal{J}(C_j^{\neg size}) := \ j' \in \{1, 2, ..., J\} \mid C_{j'}^{\neg size} = C_j^{\neg size}, \ \textit{in all elements}$$

in that the role of traction and business model is much more than the role of the educational background for startups. Nevertheless, regardless of the estimation inputs, entrepreneurial experience as a factor that represents human assets stays a determinant attribute. Lastly, note that average continuation values (Row 1) almost do not change as we eliminate heterogeneity in z in a specific dimension while keeping the mean of z (conditional on the rest of attributes) unchanged.

Table 4: Variation in equilibrium payoffs and matching frequencies—the role of attributes

Panel A: Startups

	Benchmark	¬traction	¬b2b	¬serial founder	¬prestig. education
$\bar{u}$	1.89	1.89	1.889	1.889	1.889
$std(u)$	0.326	0.306	0.276	0.246	0.205
$1 - \dfrac{var(u^{\neg})}{var(u)}$	-	0.119	0.283	0.431	0.605
$sum(\mu^S)$	16.8	16.9	16.9	16.9	16.9
$hhi(\mu^S)$	0.257	0.257	0.26	0.265	0.246
$\Delta hhi(\mu^S)$	-	0	0.003	0.008	-0.011

Panel B: VCs

	Benchmark	¬size	¬hist. performance	¬entr. experience
$\bar{v}$	3.384	3.384	3.384	3.384
$std(v)$	0.252	0.246	0.204	0.189
$1 - \dfrac{var(v^{\neg})}{var(v)}$	-	0.047	0.345	0.438
$sum(\mu^{VC})$	16.8	16.9	16.8	16.8
$hhi(\mu^{VC})$	0.218	0.218	0.214	0.221
$\Delta hhi(\mu^{VC})$	-	0	-0.004	0.003

Notes. Underlying parameters and joint matching values are based on the model estimated via startup-side experiment and data on revealed collaboration likelihoods—(S,p1) in table 3. Each column presents simulation results in a counterfactual setting that matching values $\{z_{ij}\}$ are collapsed to the mean level over a specific attribute on the startup side (index i) or VC side (index j). Averages and standard deviations of variables of interests are calculated using the mass of types, $\{m_i\}$ and $\{n_j\}$ for startups and VCs, respectively, as weights. $1 - \frac{var(u^{\neg})}{var(u)}$ and $1 - \frac{var(v^{\neg})}{var(v)}$ show the fall in the variance of continuation values of startups and VCs, respectively, in either counterfactual scenarios in Columns 2-5 relative to the benchmark simulation in Column 1. The Herfindahl indexes are defined as follows. $hhi(\mu^S) := \sum_i (\mu_i^S)^2$, where $\mu_i^S = \sum_j \mu_{ij} / \sum_{i,j} \mu_{ij}$, and $hhi(\mu^{VC}) := \sum_j (\mu_j^{VC})^2$, where $\mu_j^{VC} = \sum_i \mu_{ij} / \sum_{i,j} \mu_{ij}$. The last row reports the change in the Herfindahl index under counterfactual scenarios in Columns 2-5, relative to the benchmark simulation in Column 1. The total number of matches $sum(\mu) = sum(\mu^S) = sum(\mu^{VC}) = \sum_{i,j} \mu_{ij}$ is reported on a per annum basis and is reported in the unit of 1,000.

Table 4 also reports the *Herfindahl* index measuring the variety of matching representations by various attributes on either side. For startups: $hhi(\mu^S) := \sum_i (\mu_i^S)^2$, where $\mu_i^S = \sum_j \mu_{ij} / \sum_{i,j} \mu_{ij}$ is the share of a given startup type in realized matches. In our model $\mu_{ij} \propto m_i n_j p_{ij}$, where p_{ij} is the equilibrium conditional matching probability. A random matching implies $\mu_{ij} \propto m_i n_j$, hence, $hhi(\mu^S) = \sum_i m_i^2$, which equals 0.258 according to estimated masses $\{m_i\}$. Likewise, for VCs, the *Herfindahl* index measuring the variety of matching representation is defined as $hhi(\mu^{VC}) := \sum_j (\mu_j^{VC})^2$, where $\mu_j^{VC} = \sum_i \mu_{ij} / \sum_{i,j} \mu_{ij}$ is the share of a given VC type in realized matches. A random allocation implies $hhi(\mu^{VC}) = \sum_j n_j^2$, which equals 0.218 according to the estimated masses $\{n_j\}$. Comparing results of the random matching with results in table 4 shows that the representation of types in realized matches is mainly driven by heterogeneity in the underlying masses for either side, not the variation in the conditional matching probabilities $\{p_{ij}\}$.

Which startup and VC types get a higher value in equilibrium? We demonstrate the *average* impact of attributes on continuation values of startups and VCs through OLS fits of simulated continuation values on dummy indicators of attributes, across all 16 types of startups and 8 types of VCs. Table 5 shows the results. We report results for all specifications with alternative experiment data sources. Panel A reports results for startups. Column 1 shows the results for the case in that we use 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 estimate the perceived matching likelihoods (see Column 2). However, when using the VC-side experiment data to estimate the continuation values of startups (Columns 3-4) we find a much less (although positive) impact of educational background and instead a positive and sizable impact of traction and business model on equilibrium payoff of startup types. These findings imply that startups of better education backgrounds (with graduate degrees/Ivy League graduates) 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 maybe education background) and non-human assets (business model and perhaps traction) are determinant factors for the equilibrium value of startups who seek funding from VCs.

Table 5, Panel B reports results for the average impact of attributes on VC's equilibrium

Table 5: Equilibrium values—premium attached to attributes

	(S,p1)	(S,p2)	(S-VC,p1)	(S-VC,p2)
Panel A: u_i				
constant	1.466	1.646	1.089	1.061
	(0.126)	(0.163)	(0.244)	(0.254)
$\mathbf{1}\{\text{traction}\}_i$	−0.034	−0.059	0.56	0.622
	(0.107)	(0.133)	(0.122)	(0.125)
$\mathbf{1}\{\text{b2b}\}_i$	0.37	0.479	0.922	1.098
	(0.13)	(0.156)	(0.273)	(0.25)
$\mathbf{1}\{\text{serial founder}\}_i$	0.45	0.592	0.518	0.567
	(0.11)	(0.129)	(0.133)	(0.138)
$\mathbf{1}\{\text{prestig. education}\}_i$	0.492	0.636	0.121	0.158
	(0.089)	(0.129)	(0.027)	(0.033)
Panel B: v_j				
constant	2.97	2.029	3.606	5.333
	(0.675)	(0.596)	(1.414)	(1.718)
$\mathbf{1}\{\text{size}\}_j$	0.132	0.149	0.189	0.245
	(0.073)	(0.089)	(0.128)	(0.192)
$\mathbf{1}\{\text{hist. performance}\}_j$	0.367	0.428	0.563	0.987
	(0.093)	(0.125)	(0.245)	(0.314)
$\mathbf{1}\{\text{entr. experience}\}_j$	0.439	0.514	0.607	1.02
	(0.1)	(0.14)	(0.274)	(0.355)

Notes. The average impact of attributes on equilibrium continuation values is estimated from simulation outcomes using models estimated via alternative experiment data sources. In Columns (S,p1) and (S,p2) we use startup-side experiment data while in Columns (S-VC,p1) and (S-VC,p2) we use both startup-side and VC-side experiment 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. See further details on estimation procedures in section 4. 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.

continuation values. We find that in all specifications the impact of historical performance and entrepreneurial experience of investors is sizable and highly significant—around 15-20% of the value of the reference type (the constant term), respectively. The impact of size is positive only marginally significant and is around 5% of the reference value. We then report a robust findings that both human capital (entrepreneurial experience) and non-human capital (historical performance) of investors and VCs are determinant factors for the equilibrium payoff of VCs in the entrepreneurial finance industry.

Counterfactual Analyses. We study the impact of the primitive parameters of the search-and-matching model on equilibrium payoffs. We consider closing the wedge between the time discount rate of startups and VCs, an equal split of the matching surplus between startups and VCs, an increase in the mass of VCs, and an improvement in the matching technology. In these counterfactual experiments, we keep the structure of the mean matching values $\{z_{ij}\}$ unchanged. Each scenario is though associated with a different β^S and β^{VC} than the benchmark. We then simulate the model using equations (1) to (3). Table 6 presents the results. In Column 2 we confirm that simulation results in the benchmark setup closely match the variations in estimated values across startups and VCs (reported in Column 1). Columns 3-6 show simulation results for counterfactual analyses, which we discuss below.

First, we consider closing the wedge between the time discount rate (the cost of capital) for startups and VCs: $r^S = r^{VC} = 10\%$, which corresponds to a 50% increase in β^S. Table 6, Column 3 presents the counterfactual results. Not surprisingly, the continuation value of an average startup rises. Interestingly, the continuation value of an average VC falls by 15%. Startups are no longer desperate to make a deal and are more willing to wait for a better match in future tries. This is why the total number of realized matches $sum(\mu)$ *falls*. In the end the outside option of startups and thereby their payoff out of the bargaining increase, which hurts VCs. The share of all VCs from the total value of matching reduces from .15 to .10 This result indicates that the number of realized matches—a sign that the market is on boom—is not necessarily a proxy for startups' well-being. Startups wish to stay more in the market in search for a productive match if their time discount rate is low.

Second, we change the share in the matching surplus from the benchmark estimate $\pi \simeq .9$, which is in favor of startups, to a scenario with an equal split of the pie $\pi = .5$. This counterfactual scenario corresponds to a reduction in β^S by a factor of 4/9 and an increase in β^{VC} by a factor of 5. Table 6, Column 4 shows the results. The average of the continuation values of startups sharply falls, by much more than proportionate to the change in π. In this case, as opposed to Column 2, the outside option and willingness to wait for VCs goes up, which reflects in a much lower matching frequency $sum(\mu)$. Interestingly, the overall present value $M^S\bar{u} + M^{VC}\bar{v}$ substantially falls as well, while the share of all VCs in the total present value of matches rises to more than half. Startups are impatient (and in need of capital), while VCs are now more hesitant to make a deal, and are more willing to stay in the search process for an ideal match, as they earn more surplus from a match.

Next, we consider an increase in the mass of VCs by 100%. This change corresponds to an increase in β^S by a factor of $\sqrt{2}$ and a decrease in β^{VC} by the same factor $\sqrt{2}$. Table 6, Column 5 presents the counterfactual results. The average value of a startup increases by

50%. The average value of a given VC is also affected and decreases substantially by 30%, while the total present value of the matching of startups and VCs increases by 36%. At the same time, the share of all VCs from the present value of all matches is cut in half. The standard deviation of matching values across both startups and VCs remains almost unchanged. Competition among VCs would reduce the chance to meet a startup for each VC in the search process, which lowers the outside option and equilibrium continuation value of VCs. On the other hand, the chance to find a match for each startup increases which increases their continuation values on average.

Lastly, we consider a 100% increase in ρ the efficiency of the matching technology. Counterfactual results are presented in table 6, Column 6. Startups and VCs would have a higher bar to make a deal. Given a higher chance of finding a counterparty in a given time interval startups and VCs wait to find a better match—draw a higher realization of ϵ the shock to the matching value. While ρ doubles, because $\{p_{ij}\}$ falls, in the end, the number of matches $sum(\mu) = \rho\sqrt{M^S M^{VC}} \sum_{ij} m_i n_j p_{ij}$ in equilibrium goes up by 40%. Continuation values of both startups and VCs and the total present value of matching values increase by close to 10%. The share of all VCs from total matching values remains the same.

Table 6: Equilibrium values and matching frequencies—counterfactual results

	Estimation	Simulation				
		Benchmark	$r^S = r^{VC}$	$\pi = 1/2$	$100\% \uparrow M^{VC}$	$100\% \uparrow \rho$
$\bar{u}$	1.89 (0.047)	1.89	2.473	0.381	2.785	2.062
$std(u)$	0.348 (0.038)	0.326	0.357	0.202	0.36	0.358
$\bar{v}$	3.384 (0.721)	3.384	2.924	5.716	2.449	3.714
$std(v)$	0.246 (0.039)	0.252	0.249	0.277	0.235	0.267
$sum(\mu)$	16.8 –	16.8	15.6	8.5	24.4	23.2
$M^S\bar{u} + M^{VC}\bar{v}$	111.4 (2)	111.4	138.3	47.6	151.5	121.7
$\frac{M^{VC}\bar{v}}{M^S\bar{u}+M^{VC}\bar{v}}$	0.152 (0.031)	0.152	0.107	0.6	0.082	0.152

Notes. Averages and standard deviations 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. Numbers in parentheses show standard errors.

6 Case Studies 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 expected conditional 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 and compare our findings with results in Sørensen (2007).

6.1 Deal Size

In this section, 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. 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 matching values in our simulation represent larger deal sizes in the real world.

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 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 to dollar terms. We then propose the following testable relationship:

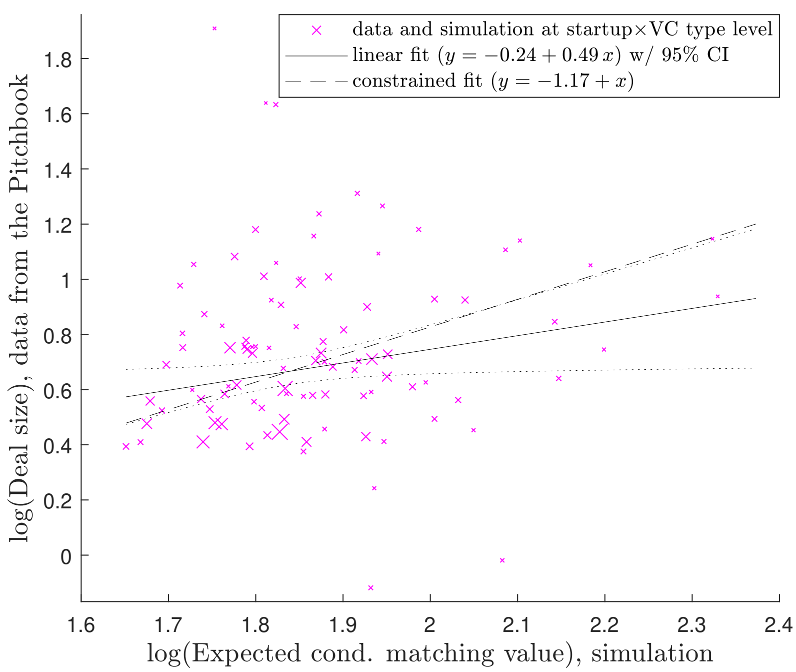
$$k^*_{ij} = (\frac{\theta}{1-\theta} R^{VC})\ \kappa\ \mathbf{E}_\epsilon[z_{ij} + \epsilon \mid z_{ij} + \epsilon \geq u_i + v_j] \tag{19}$$

On the right-hand side, $\mathbf{E}_\epsilon[z_{ij}+\epsilon \mid z_{ij}+\epsilon \geq u_i+v_j]$ shows the expected 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 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.

Figure 3 plots the average log deal sizes (in million dollars) from the Pitchbook at the i/j type levels during 2015-2020 against the simulated expected conditional matching values.[21] We find a positive covariation between the two objects, that is statistically significant at 5% level. The constrained fit is based on the Cobb-Douglas model that implies equation (19). The estimated slope (intercept in the log scale) identifies κ, given θ. For a calibration of $\theta = .25$, we find $\kappa \simeq 1$, which implies that one unit of matching value in our normalization is of the order of \$1 million dollar profit. Online Appendix figure C12 studies the relationship between average expected conditional payoff from matching and deal size for startups and VCs separately. Statistical power is not ideal; but, given the calibration $\theta = .25$ and the resulting $\kappa \simeq 1$ from the fit in figure 3 we find that 1 dollar deal size is associated with around 2 dollars expected profit on the VC side, which is consistent with anecdotal evidence 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.

Figure 3: Deal size (data) versus expected conditional matching value (simulation)



Notes. Y-axis shows the average log deal size (in million dollars) from the Pitchbook data during 2015-2020 and X-axis shows the log expected conditional matching value $\mathbf{E}_\epsilon[z_{ij} + \epsilon \mid z_{ij} + \epsilon \geq u_i + v_j]$ from the 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, $\{m_i * n_j\}$.

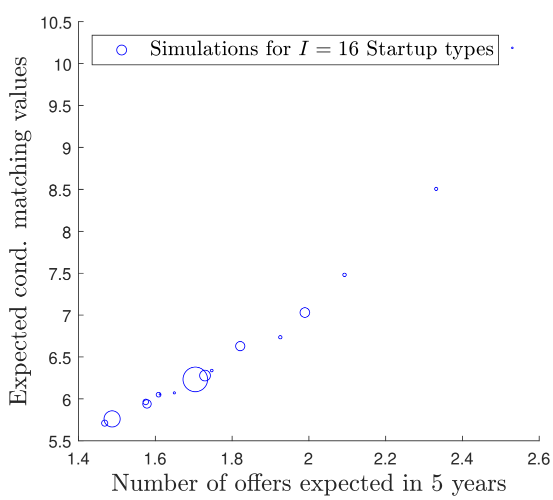
[21] We plot variables in log scales to mitigate outliers in the data on the deal size.

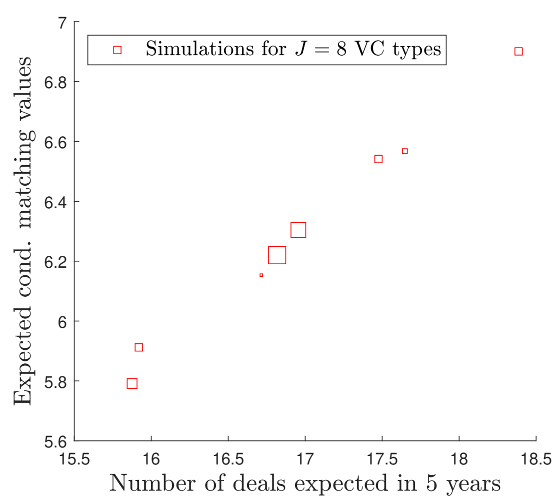
6.2 Expected Number of Offers/Deals

In this section, we demonstrate the relationship between likelihood of getting an offer/making a deal and the expected conditional matching value for startups/VCs. In our model, "attractive" types generate more matching value z_{ij}—hence, are more likely to form a match, because of a higher p_{ij}. As a result, they have a higher continuation value. According to estimations in table 3, attractive types—those with higher continuation values—are startups with traction, b2b model, prestigious education, and entrepreneurial experiences; and VCs of larger size, better historical performance, and with entrepreneurial experiences.

Figure 4 depicts the link between matching likelihood and expected conditional matching value. 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 $\rho^{VC} \sum_i m_i p_{ij}$. 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; Likewise, VCs that expect to make more deals over time are those who form matches of up to 20% more value. 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. Online Appendix figure C13 verifies a one-to-one relationship between continuation values and the expected number of offers/deals over time.

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





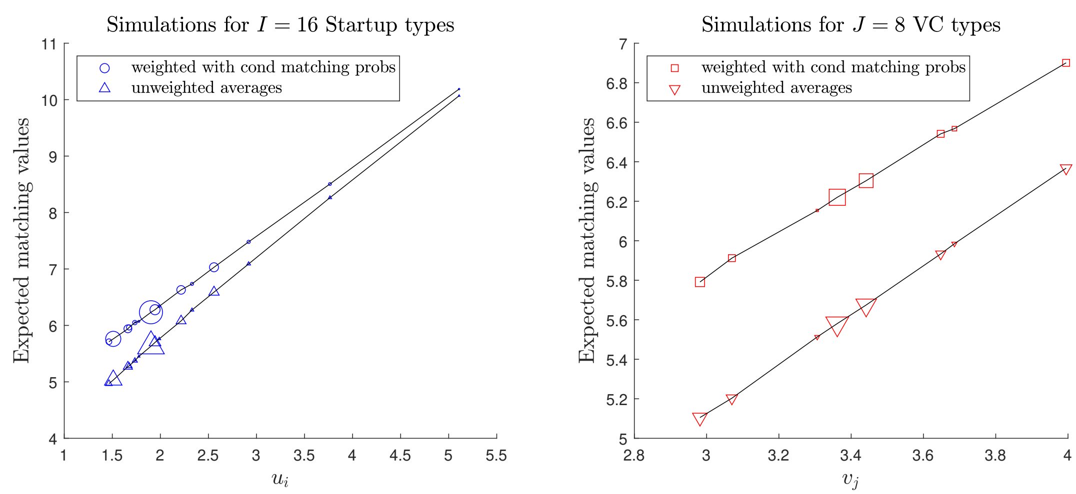
Notes. The left panel shows for each startup type the expected conditional value in matches with VCs $\sum_j n_j \cdot p_{ij} \cdot \mathbf{E}_\epsilon[z_{ij} + \epsilon \; |z_{ij} + \epsilon \geq u_i + v_j] / \sum_j n_j \cdot p_{ij}$ versus the expected number of funding offers received in a 5-year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

6.3 Endogenous Matching Formation and Realized Match Value

In this section, we discuss the role of endogenous matching between startups and VCs on conditional matching values in equilibrium. The realized matching value for a startup or VC type 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 the case that matching is random. Sørensen (2007) finds that the better outcome of startups that match with experienced VCs is in part due to the assortative match of *high-type* startups with experienced VCs.

We find the opposite result. Figure 5 shows that the gap in realized matching values and the matching value in a counterfactual setup with random matching *shrinks* for attractive types (those with higher continuation values), especially on the startup side. In equilibrium, startups and VCs of higher z_{ij}, are more likely to form a match in a given period (because of higher p_{ij}). Such types get a higher continuation value as a result. In contrast, types of lower z_{ij} search more to find a better draw of ϵ the shock to matching value. Hence, the *conditional* matching value for unattractive types is *more* than the average unconditional matching value. This result highlights the role of search friction and uncertainty on the link between endogenous matching formation and realized matching values. Sørensen (2007) do not have search friction and the value of matches among all participants is known ex ante.

Figure 5: Average matching values—unconditional and conditioned on endogenous matching likelihoods, versus continuation values of startup and VC types in equilibrium



Notes. Plots show the expected values of the match conditioned on matching with counterparties, $\sum_j n_j \cdot p_{ij} \cdot \mathbf{E}_\epsilon[z_{ij} + \epsilon \; |z_{ij} + \epsilon \geq u_i + v_j] / \sum_j n_j \cdot p_{ij}$ 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 startups and VCs, and unconditional averages of matching values, $\sum_j n_j z_{ij}$ and $\sum_i m_i z_{ij}$ for startups and VCs, versus continuation values, u_i and v_j for startups and VCs, in the left and the right panel, respectively. Marker sizes indicate the estimated underlying mass of types, $\{m_i\}$ and $\{n_j\}$ in the left and right panels.

7 Conclusion

This paper implements symmetric IRR experiments with both real US venture capitalists and real US startup founders to elicit investors' and founders' preferences about each other. To study investors' portfolio selection criteria, we invite real US venture capitalists to evaluate the quality, availability, and risk of multiple randomly generated startup profiles. Investors also need to indicate their intention to contact and invest in the startup in order to be matched with their ideal startups in our collaborating incubators. To understand startups' fund-seeking behaviors, we invite real US startup founders to evaluate the quality, availability, and informativeness of multiple randomly generated investor profiles. Founders also need to indicate their fundraising plans and likelihood of contacting each investor in order to receive an investor recommendation list generated by our developed machine learning matching algorithm.

Results from investor-side IRR experiment show that multiple startup team characteristics (i.e., human assets) and project characteristics (i.e., non-human assets) causally influence investors' contact decisions and investment decisions. Specifically, the impact of startups' traction is almost twice as important as startup founders' educational backgrounds, emphasizing the importance of projects in the early stage of raising capital from the US venture capital industry. Other discovered attractive startup characteristics include having a B2B business model, faster growth rates indicated by company ages, owning more comparative advantages, being founded by serial entrepreneurs, well-educated entrepreneurs, and US startup teams. These characteristics serve as signals of startups' quality, availability, and risk level. Among these mechanisms, investors' judgements on the startup's quality is the paramount factor influencing investors' decisions, almost five times as important as judgments on startups' availability. Moreover, taste-driven preferences in the initial contact stage are less likely to affect investment decisions, emphasizing the importance of identifying the nature of preferences. Lastly, the magnitude of investors' preferences varies with market conditions. However, the direction of these nonsensitive preferences is very stable in different investment settings. Our investor-side IRR experiment helps to decipher early-stage investors' investment preferences in the pre-selection stage of the entrepreneurial finance process.

Results from startup-side IRR experiment show that multiple individual-level investor characteristics (i.e., human capital) and fund-level organizational characteristics (i.e., organizational capital) casually affect startups' fund-raising plans and intentions to approach investors. Influential investor characteristics include investors' investment experiences and previous entrepreneurial experiences. Influential fund characteristics include the VC funds' previous financial performances and fund size. Specifically, startups highly prefer contacting larger funds with better historical performances. This provides explanations of persistent VC funds' performances through the sorting channel. Startups use these investor characteristics as indicators of the investor's quality, availability, and available informativeness. Different from investors' preferences, startups' judgements on the investors' willingness to invest in them (i.e., availability) is almost as important as their judgments on investors' quality. Lastly, the magnitude of founders' preferences also varies with market conditions and across the spectrum of investors' quality.

Based on the experimental results and matching equilibrium outcomes recorded in Pitchbook, we estimate dynamic search-and-matching model with bargaining between VCs and startups. This model demonstrates effects of different startup and investor characteristics on the equilibrium payoffs of VCs and startups. We find that an average VC gets 80% more value than an average startup due to more outside options. Moreover, a substantial heterogeneity in equilibrium payoffs exists across both startups and VCs. These hoterogeneity is mainly explained by both human and organizational characteristics. Overall, results from our experimental system and dynamic search-and-matching model provide thorough micro-level empirical foundations to understand the matching process between venture capitalists and startups in the US entrepreneurial finance process. Future research can replicate these experiments in different settings to test the external validity or study the impact of other startup and investor characteristics.

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Appendix—for Online Publication

A Startup-Side IRR Experiments

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.[22]

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.[23] 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., quality evaluation) or Q_4 (i.e., likelihood of contacting the investor), we also remove their responses in our formal data analysis. We create the following three measures for each subject i to detect such situations using their evaluation ratings Y_{ij}^k for the k^{th} question of j^{th} profile: i) sample variance of Q_1 (i.e., $Var_i(Q_1)$), $\frac{1}{20-1}\sum_{j=1}^{j=20}(Y_{ij}^k - \frac{1}{20}\sum_{k=1}^{k=20} Y_{ij}^k)^2$ where $k = 1$. ii) sample variance of Q_4 (i.e., $Var_i(Q_4)$), $\frac{1}{20-1}\sum_{j=1}^{j=20}(Y_{ij}^k - \frac{1}{20}\sum_{k=1}^{k=20} Y_{ij}^k)^2$ where $k = 4$. iii) sum of sample variance of Q_1 and sample variance of Q_4 (i.e., $Var_i(Q_1) + Var_i(Q_4)$). If any of the three measures for subject i falls below the $5th$ percentiles of the corresponding measures in the full sample, evaluation results of subject i will be removed. We do not apply this criteria to Q_2 (i.e., likelihood of being invested), Q_3 (i.e., funding to raise), or Q_5 (i.e., informativeness) because it is reasonable that participants give the same evaluation to these questions.[24]

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

[22]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.

[23]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.

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

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.[25]

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.

Distributional Effects across Startups' Internal Thresholds 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 A3 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, 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 A3 shows that the direction of startups' preferences is very stable in different

[25] 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.

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.

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. $*p < 0.10, **p < 0.05, ***p < 0.01$

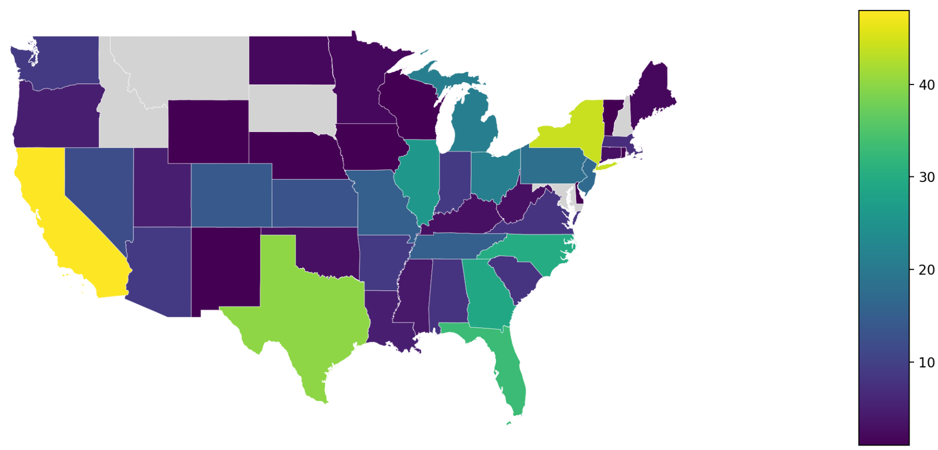
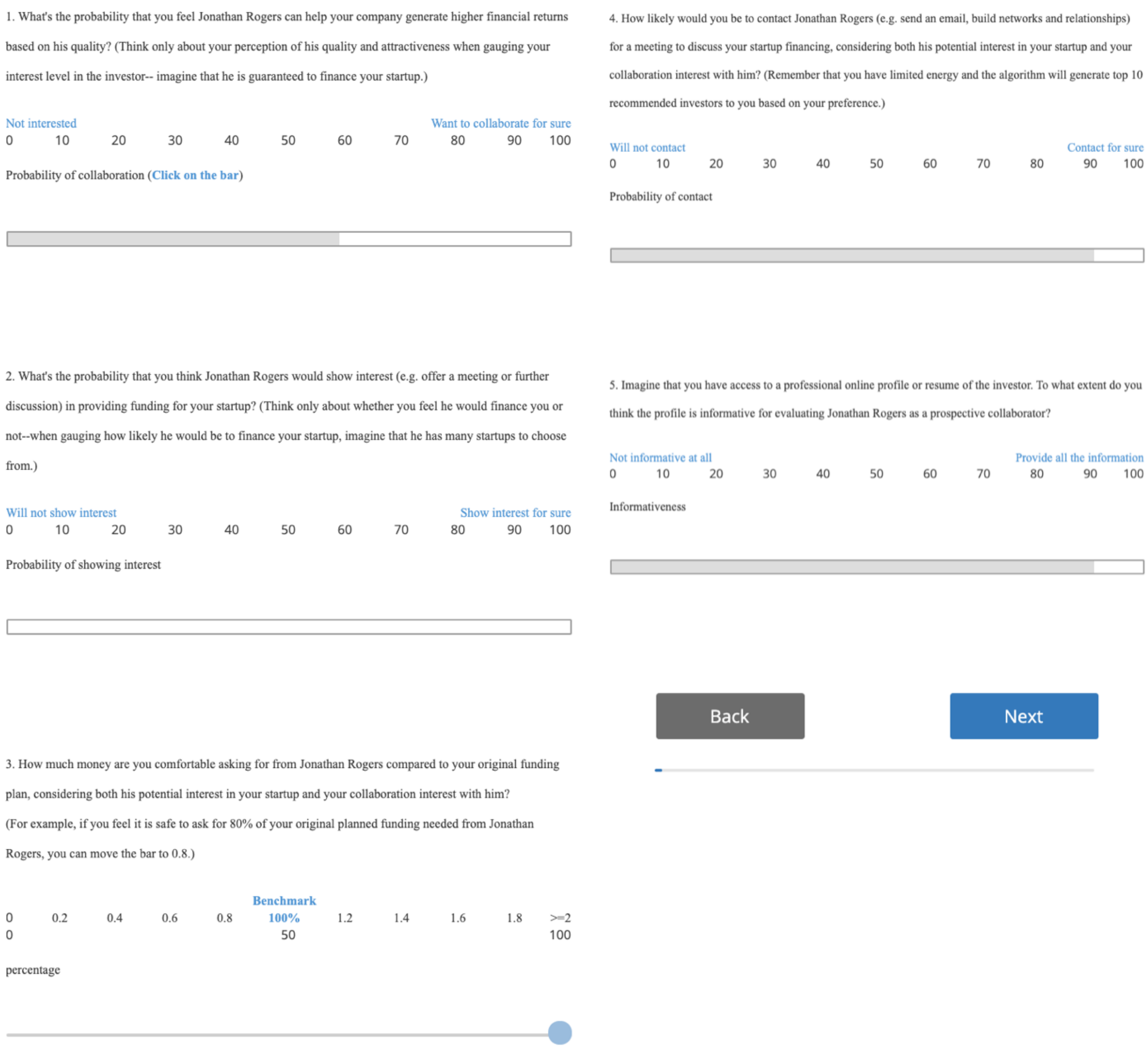


Figure A1: Geographical Distribution of Recruited US Startups



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

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Figure A2: Sample Evaluation Questions of Startup-side Experiments

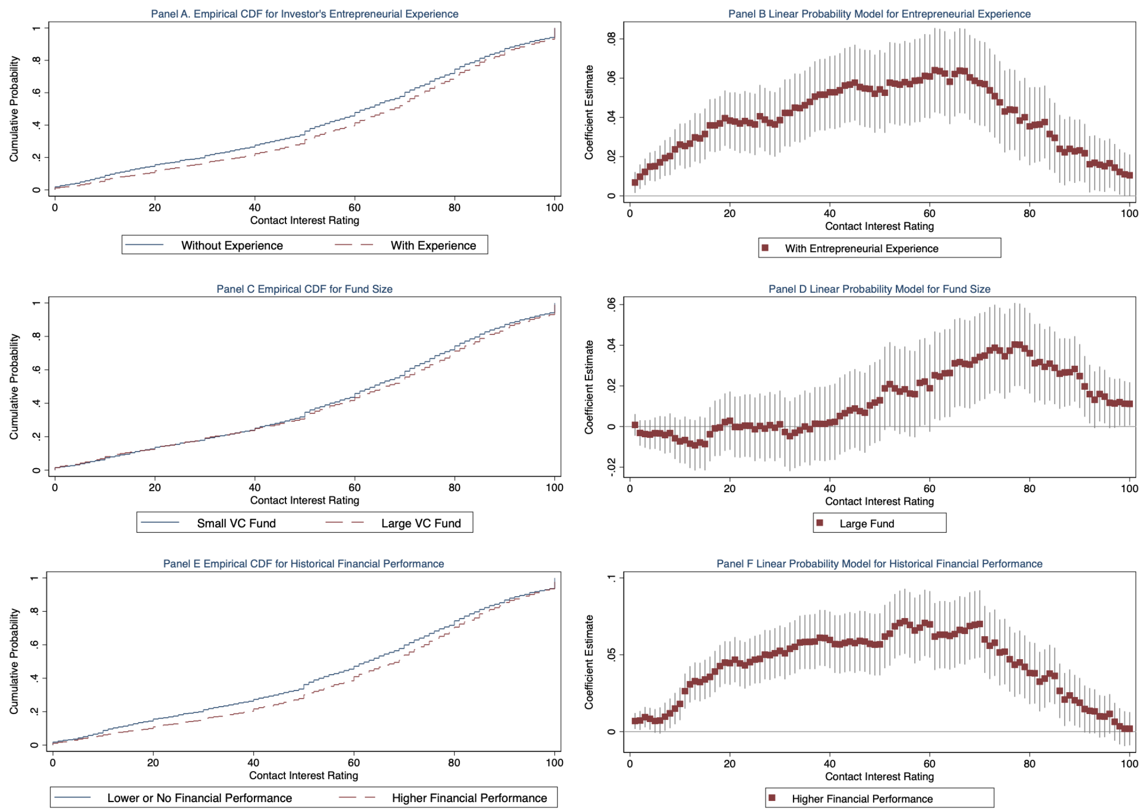
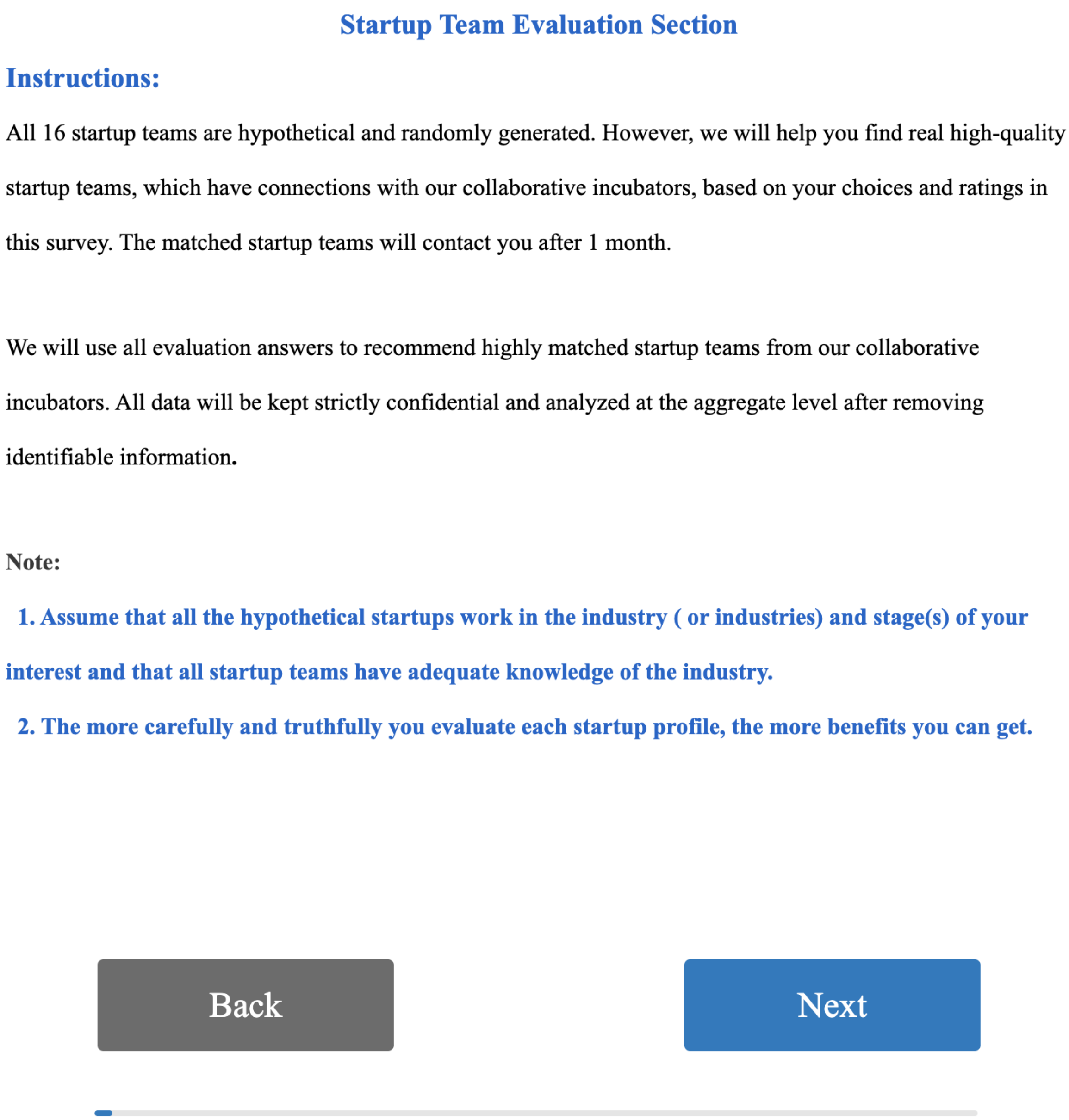


Figure A3: Distributional Effect across Startups' Contact Ratings

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



Startup Team Evaluation Section

Instructions:

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

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

Note:

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

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

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Figure B1: Instruction Page (Version 2)

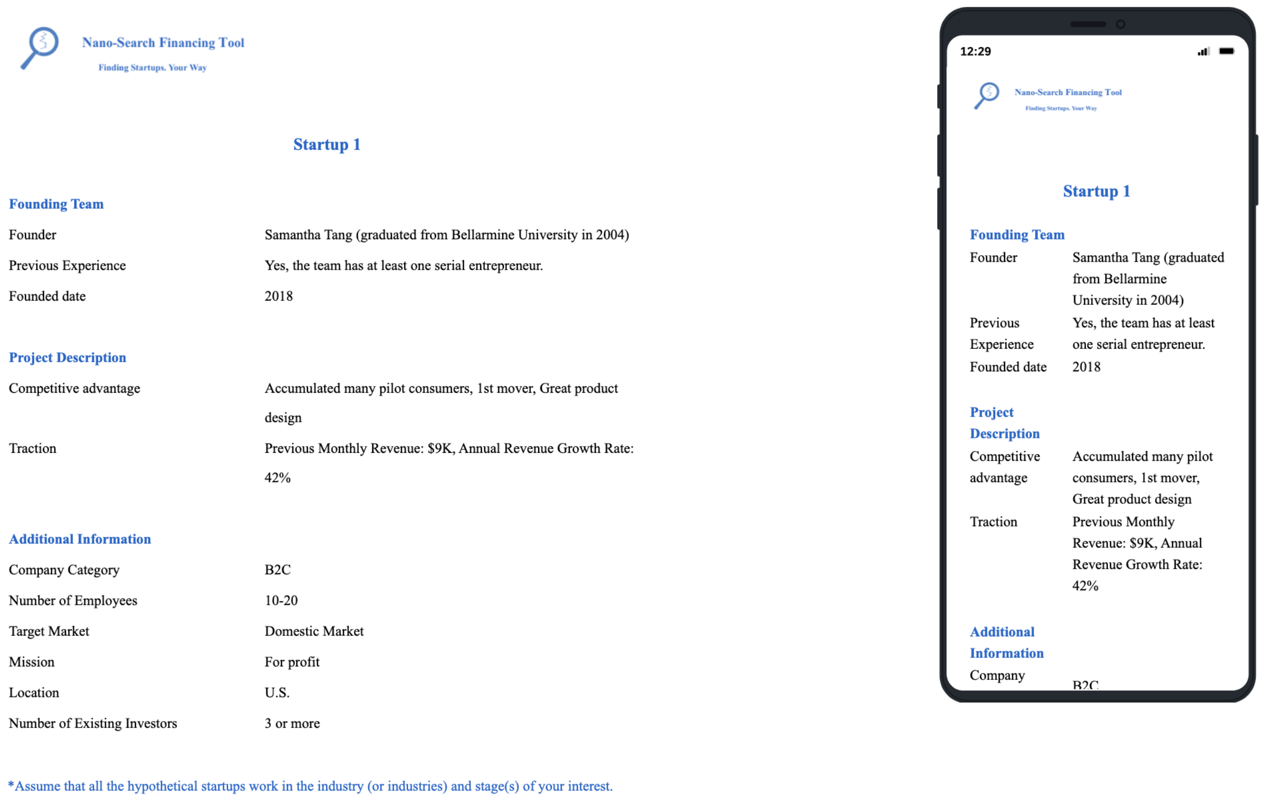


Figure B2: Randomly Generated Startup Profile

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

Extremely Low Quality — Extremely High Quality

0 10 20 30 40 50 60 70 80 90 100

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

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

Guaranteed Rejection — Guaranteed Acceptance

0 10 20 30 40 50 60 70 80 90 100

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

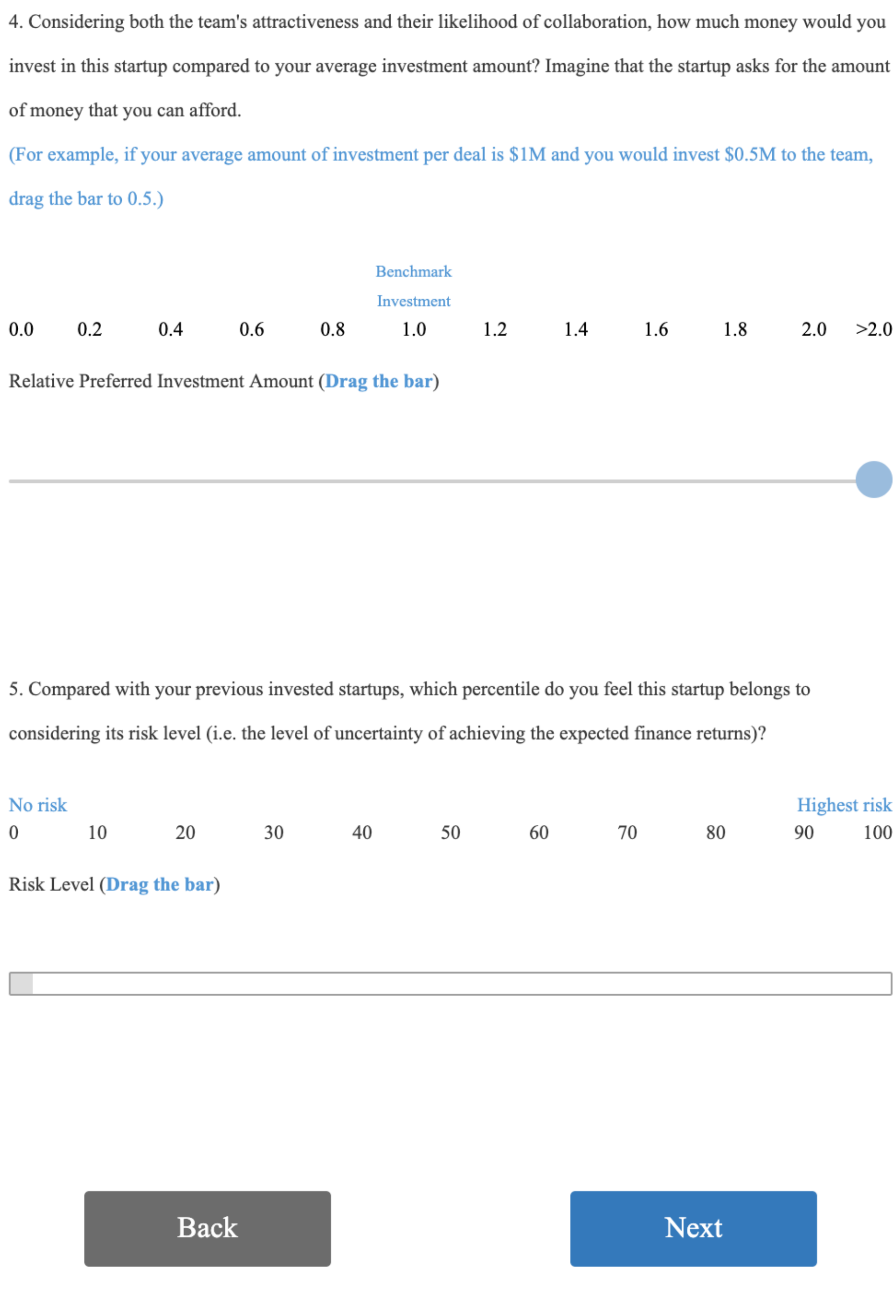
3. If you consider both the team's attractiveness and their likelihood of collaboration, how likely would you be to ask for their contact information or pitch deck?

Will Not Ask — Will Ask

0 10 20 30 40 50 60 70 80 90 100

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

Figure B3: Evaluation Questions (Part 1)



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

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

Benchmark
Investment

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

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

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

No risk
Highest risk

0 10 20 30 40 50 60 70 80 90 100

Risk Level (**Drag the bar**)

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Figure B4: Evaluation Questions (Part 2)

Dear [Investor Name],

Our research team learned about your startup investment experience from Pitchbook and would like to invite you to participate in a research project conducted by 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 B5: 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 B6: Recruitment Email (Version 2)

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

Figure B7: Recruitment Poster (Version 1)

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

Investors' Beliefs of Profitability Matter the Most Startup characteristics can affect investors' decisions through quality judgments, availability judgments, and risk evaluations. These mechanisms are hard to identify using traditional empirical methods but easy to study with IRR experiments. Columns (4) and (6) of Table 2 and Table B4 show that after controlling for the evaluations of Q_1 and Q_2, the influence of most startup characteristics decreases, especially the influence of previous entrepreneurial experiences and traction. Moreover, the coefficient of Q_1 is almost five times large as the coefficient of Q_2 when explaining investors' contact decisions. This indicates that investors' beliefs of startups' quality are the paramount factor influencing investors' decisions. Team characteristics and project characteristics mainly serve as quality indicators that our sample investors use for their startup selection decisions. Not surprisingly, the availability evaluation (i.e., Q_2) plays a marginal role in the contact stage but does not affect investors' investment decisions. This is consistent with our structural estimation results (see Section 5), showing that investors get more value than startups in the current US entrepreneurial finance market.

It is possible that future lab-in-the-field experiments find team characteristics are more important than project characteristics due to the following two reasons. First, investors have diverse investment strategies. Anecdotal evidence suggests that angel investors are more likely to bet on the "jockey" (i.e., team) rather than the "horse" (i.e., project) while institutional investors are likely to bet on the "horse" rather than the "jockey". Given that our experimental subjects are mainly institutional investors, our results are consistent with these anecdotal evidences. Second, if future researchers include certain extremely attractive team characteristics, such as being family members of celebrities and government leaders, these team characteristics can dominate other provided project characteristics. Therefore, the relative importance of team and project characteristics depends on both the provided startup characteristic pool and the recruited investors. However, no matter whether team matters more or project matters more, these startup characteristics fundamentally serve as signals influencing investors' expectations of the startup's quality and availability.

Also, investors' beliefs and judgements are not necessarily accurate or rational. Hu and Ma (2020) analyze the pitch video data and implement a lab experiment with students from Yale Business School. They find that investors do not seem to correctly form beliefs about startup quality based on founders' delivery features. These biases can be explained by a taste-based channel, accounting for 18% of results, and inaccurate beliefs, accounting for 82% of results. Hence, besides improving the startups' profitability and quality, it is crucial for founders to obtain good persuasion skills during their fundraising process.

Figure B8: Recruitment Poster (Version 2)

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

Taste-driven Preferences Columns (4) and (6) of Table 2 and Table B4 also provide suggestive evidence that our recruited investors have taste-driven preferences towards startups located in the U.S. and graduating from Ivy League Colleges. After controlling Q1 and Q2 in the regression, locating in the U.S. and graduating from Ivy League Colleges are still highly significant. These preferences towards US startups and well-educated founders cannot be explained by belief-driven mechanisms, such as quality evaluations or availability evaluations. Moreover, these two factors are not predictors of risk as shown in column (7). If we assume that preferences are either driven by beliefs or taste and investors' preferences follows linear functional form, these results suggest the existence of taste-driven preferences based on location and educational background. Given that experimental subjects are mainly US investors and participate in research supervised by Ivy League colleges, it is not surprising that they have these taste-driven preferences. Such results are also consistent with the finance literature documenting home bias.

Interestingly, "US Founders" and "Ivy League" factors are no longer significant in the regression examining investment interest after controlling Q_1 and Q_2. This provides suggestive evidence indicating that these taste-driven preferences in the initial contact stage do not enter investors' investment decisions. Different from contact decisions, investment decisions are more rational for professional investors. Hence, investigating the nature of investors' preferences is helpful to understand its implications in later-round decisions.

Distributional Effects Across Investors' Internal Thresholds 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 (2020a), 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.[26]

Figure B9 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). 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.

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' quality 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 char-

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

acteristics 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’ quality 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’ quality 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 quality 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. All the results are statistically significant at the 1% level, which support the suggestion of Kaplan et al. (2009) by confirming the crucial importance of startups’ project characteristics in the early stage of startup fundraising process.

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 (Team VS Project) q-value

Dependent Variable	Q1 Quality (1)	Q2 Collaboration (2)	Q3 Contact (3)	Q3 Contact (4)	Q4 Investment (5)	Q4 Investment (6)	Q5 Risk (7)
Serial Founder	5.23***	-0.81	5.64***	1.26	0.76***	0.13	-0.65
	(1.08)	(0.88)	(1.28)	(0.91)	(0.19)	(0.15)	(3.05)
Ivy	5.36***	-1.06	7.44***	3.01***	0.87***	0.2	-6.44
	(1.10)	(0.87)	(1.31)	(0.93)	(0.20)	(0.15)	(3.26)
Number of Founders	1.56	-1.21	1.17	-0.11	0.21	0.04	-5.32
	(1.07)	(0.88)	(1.29)	(0.91)	(0.20)	(0.15)	(3.06)
US Founder	0.95	0.02	4.23***	3.69***	0.08	0.03	-0.91
	(1.18)	(0.91)	(1.39)	(1.00)	(0.21)	(0.16)	(3.48)
# Comparative Adv	3.1***	-0.22	2.76***	0.34	0.55***	0.15	0.91
	(0.54)	(0.43)	(0.64)	(0.43)	(0.10)	(0.07)	(1.48)
Has Positive Traction	12.7***	1.75*	13.35***	1.91	1.81***	0.28	-9.51**
	(1.07)	(0.86)	(1.28)	(0.99)	(0.20)	(0.16)	(3.15)
Number of Employees [0-10]	0.67	2.37*	-1.73	-2.57*	-0.19	-0.29	-1.18
	(1.43)	(1.16)	(1.69)	(1.18)	(0.26)	(0.20)	(3.94)
Number of Employees [10-20]	-1.08	0.94	-3.26	-2.08	-0.46	-0.33	0
	(1.64)	(1.35)	(1.99)	(1.39)	(0.30)	(0.23)	(0.00)
Number of Employees [20-50]	-0.47	-0.02	-1.21	-0.72	-0.16	-0.12	-1.28
	(1.45)	(1.17)	(1.71)	(1.17)	(0.27)	(0.19)	(3.59)
Company Age	-4.59	-5.99**	-7.39**	-2.19	-1.26**	-0.54	-3.41
	(2.72)	(2.19)	(3.19)	(2.26)	(0.49)	(0.37)	(7.74)
Company Age^2	0.75	1.12**	1.27*	0.42	0.23**	0.1	0.77
	(0.54)	(0.44)	(0.64)	(0.45)	(0.10)	(0.07)	(1.52)
Is B2B	3.90***	3.73***	6.1***	1.47	0.81***	0.32	-4.91
	(1.07)	(0.86)	(1.28)	(0.89)	(0.20)	(0.15)	(3.01)
Domestic Market	-0.10	-0.60	0.09	0.57	0.08	0.13	-3.32
	(1.08)	(0.86)	(1.28)	(0.90)	(0.20)	(0.14)	(3.19)
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	67.01***
	(6.56)	(6.02)	(4.93)	(7.50)	(1.43)	(0.63)	(11.66)
Investor FE	Yes	Yes	Yes	Yes	Yes	Yes	
Observations	1,216	1,184	1,216	1,184	1,176	1,154	176
R-squared	0.44	0.55	0.56	0.80	0.44	0.70	0.34

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 (Team VS Project)

Dependent Variable	Q1 Quality (1)	Q2 Collaboration (2)	Q3 Contact (3)	Q3 Contact (4)	Q4 Investment (5)	Q4 Investment (6)	Q5 Risk (7)
Serial Founder	0.109***	-0.019	0.087***	0.019	0.089***	0.015	-0.014
	(0.022)	(0.021)	(0.020)	(0.014)	(0.023)	(0.017)	(0.067)
Ivy	0.111***	-0.025	0.114***	0.046***	0.101***	0.023	-0.142
	(0.023)	(0.021)	(0.020)	(0.014)	(0.023)	(0.017)	(0.069)
Number of Founders	0.033	-0.029	0.018	-0.002	0.024	0.005	-0.118
	(0.023)	(0.021)	(0.020)	(0.014)	(0.023)	(0.017)	(0.067)
Located in US	0.018	0.000	0.061***	0.053***	0.009	0.003	-0.019
	(0.022)	(0.020)	(0.020)	(0.014)	(0.023)	(0.017)	(0.068)
# Comparative Adv	0.131***	-0.010	0.087***	0.011	0.132***	0.036	0.041
	(0.022)	(0.020)	(0.020)	(0.014)	(0.023)	(0.017)	(0.067)
Has Positive Traction	0.265***	0.041*	0.207***	0.030	0.211***	0.033	-0.211**
	(0.022)	(0.021)	(0.020)	(0.015)	(0.023)	(0.018)	(0.068)
Number of Employees [0-10]	0.012	0.048*	-0.023	-0.034*	-0.020	-0.030	-0.023
	(0.026)	(0.024)	(0.023)	(0.016)	(0.027)	(0.020)	(0.071)
Number of Employees [10-20]	-0.018	0.018	-0.040	-0.026	-0.043	-0.031	0.000
	(0.027)	(0.025)	(0.024)	(0.017)	(0.027)	(0.020)	(0.000)
Number of Employees [20-50]	-0.009	0.000	-0.016	-0.010	-0.016	-0.012	-0.025
	(0.026)	(-0.317)	(0.023)	(0.016)	(0.027)	(0.020)	(0.072)
Company Age	-0.214	-0.317**	-0.256**	-0.076	-0.330**	-0.142	-0.170
	(0.127)	(0.116)	(0.112)	(0.078)	(0.129)	(0.097)	(0.387)
Company Age^2	0.177	0.301**	0.224*	0.074	0.300**	0.128	0.195
	(0.127)	(0.116)	(0.112)	(0.078)	(0.129)	(0.097)	(0.386)
Is B2B	0.081***	0.088***	0.095***	0.023	0.095***	0.037	-0.109
	(0.022)	(0.020)	(0.020)	(0.014)	(0.023)	(0.017)	(0.067)
Domestic Market	-0.002	-0.014	0.001	0.009	0.009	0.015	-0.074
	(0.022)	(0.020)	(0.020)	(0.014)	(0.023)	(0.017)	(0.068)
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	176
R-squared	0.44	0.55	0.56	0.80	0.44	0.70	0.34

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)-(7), the dependent variable is the evaluation results of Q1 (quality evaluation), Q2 (collaboration interest), Q3 (contact interest), Q4 (investment interest), and Q5 (risk evaluation). "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' quality 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. $*p < 0.10, **p < 0.05, ***p < 0.01$

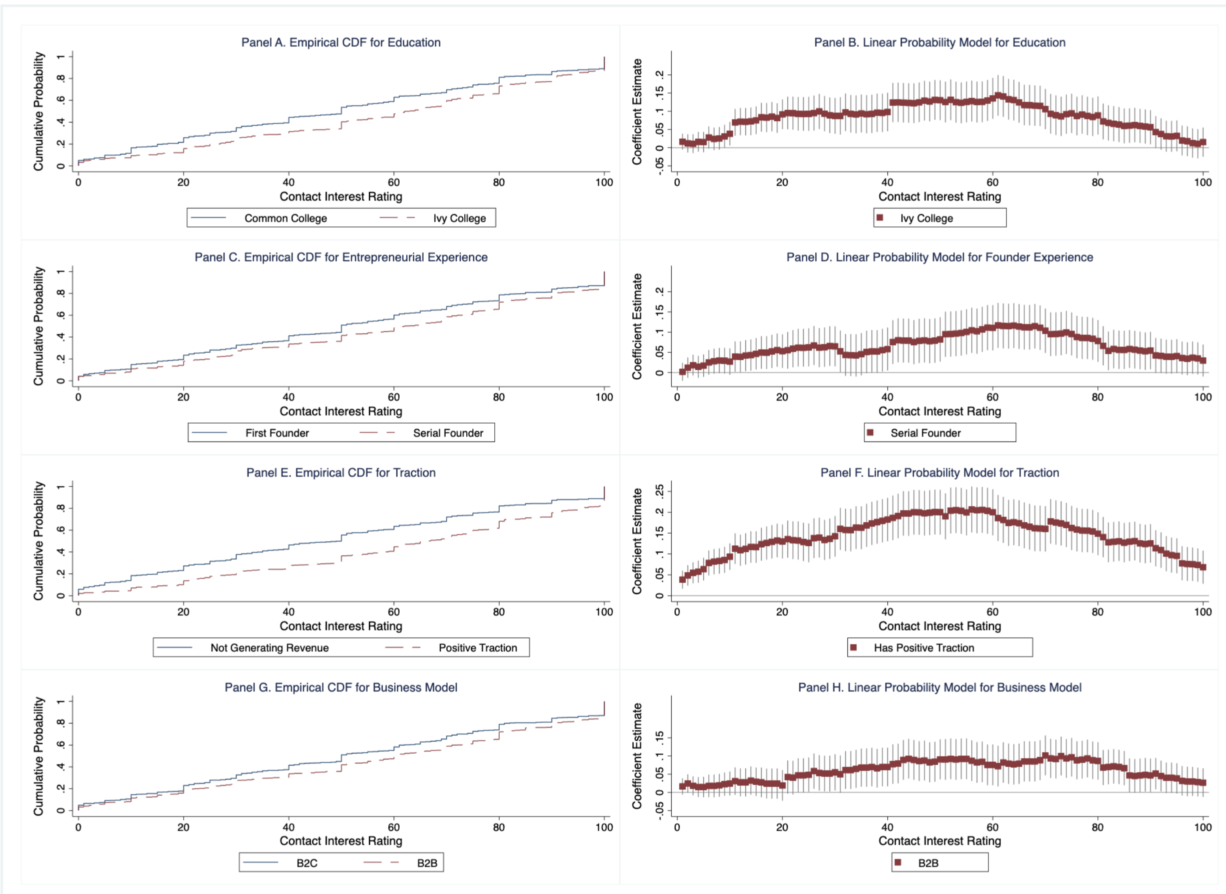


Figure B9: Distributional Effect across Investors' Contact Interest

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.

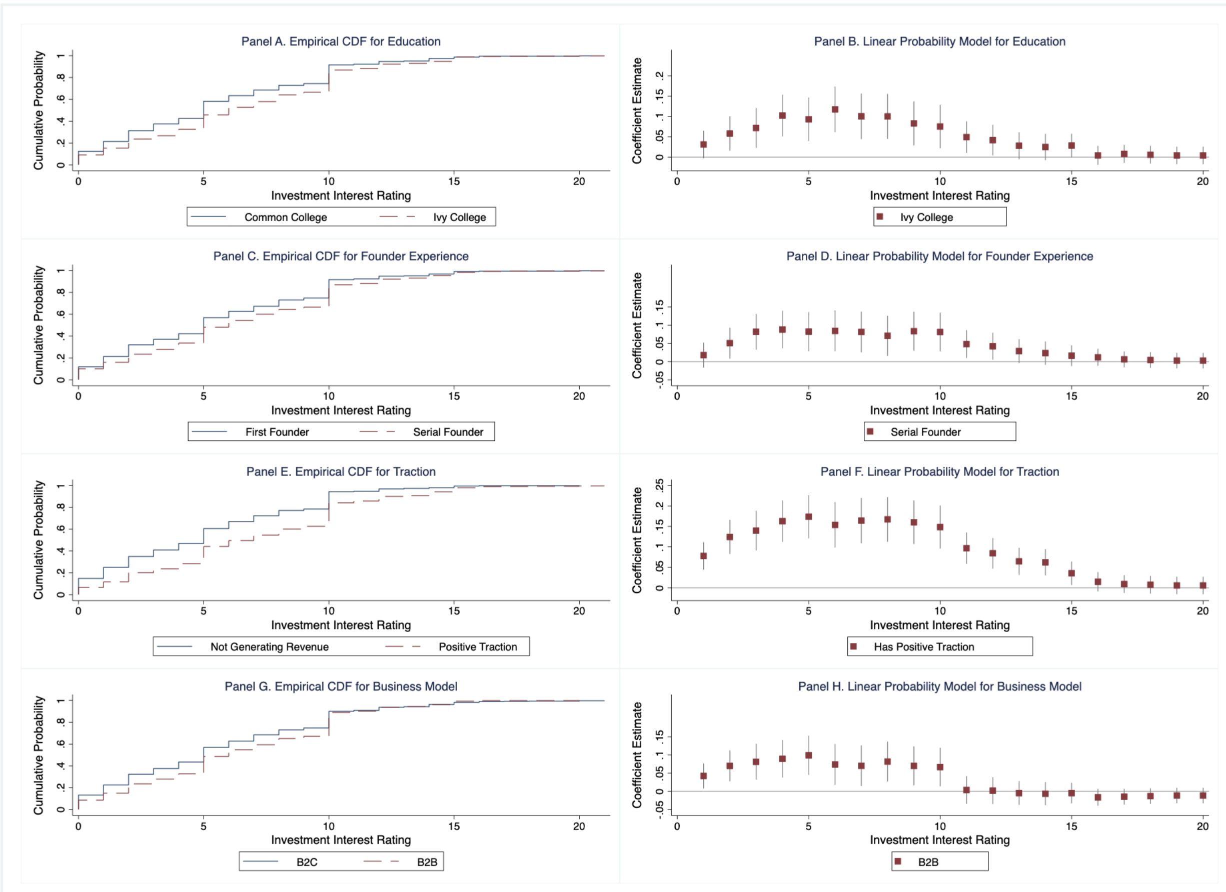
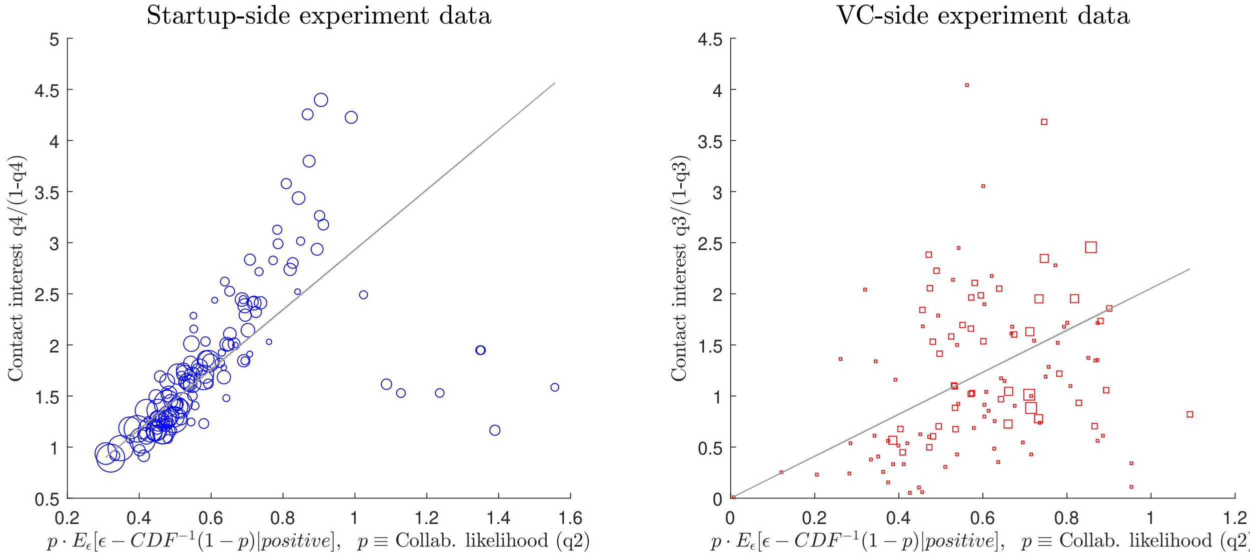


Figure B10: Distributional Effect across Investors' Investment Interest

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., $Pr(\text{Investment Interest} > x|$ Graduate from Ivy League College$)$ and $Pr(\text{Investment Interest} > x|$ Graduate from Common College$)$). Panel B provides the OLS coefficient estimates (i.e., $Pr(\text{Investment Interest} > x|$ Graduate from Ivy League College$) - Pr(\text{Investment Interest} > x|$ 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.

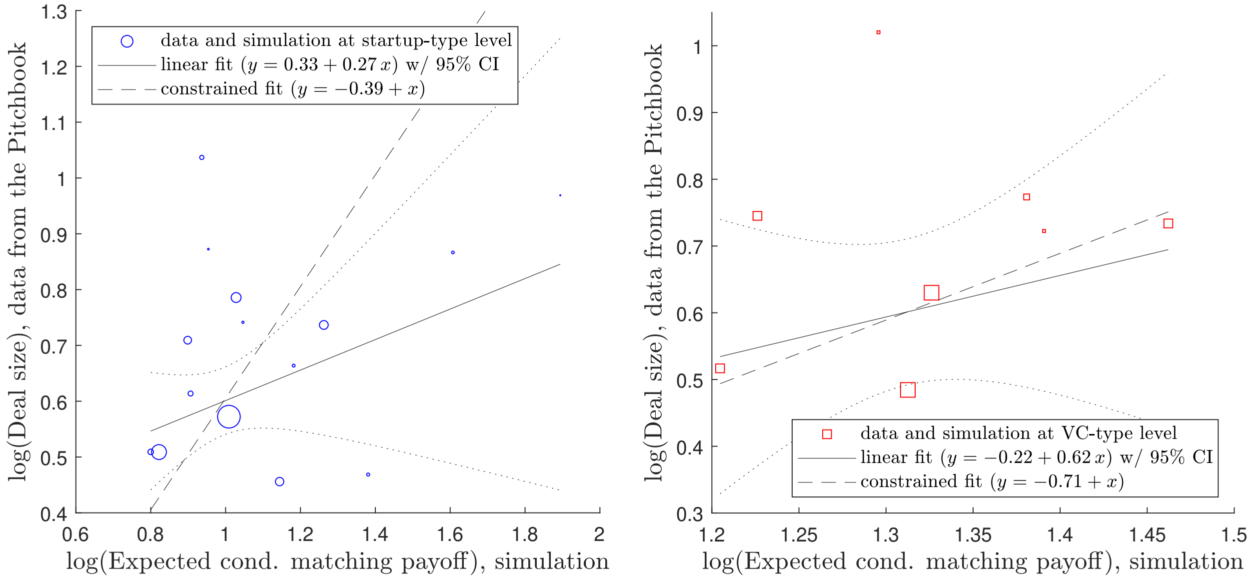
C Supplementary Simulation Results

Figure C11: Contact interest—direct reports vs. indirect derivation from collaboration likelihoods



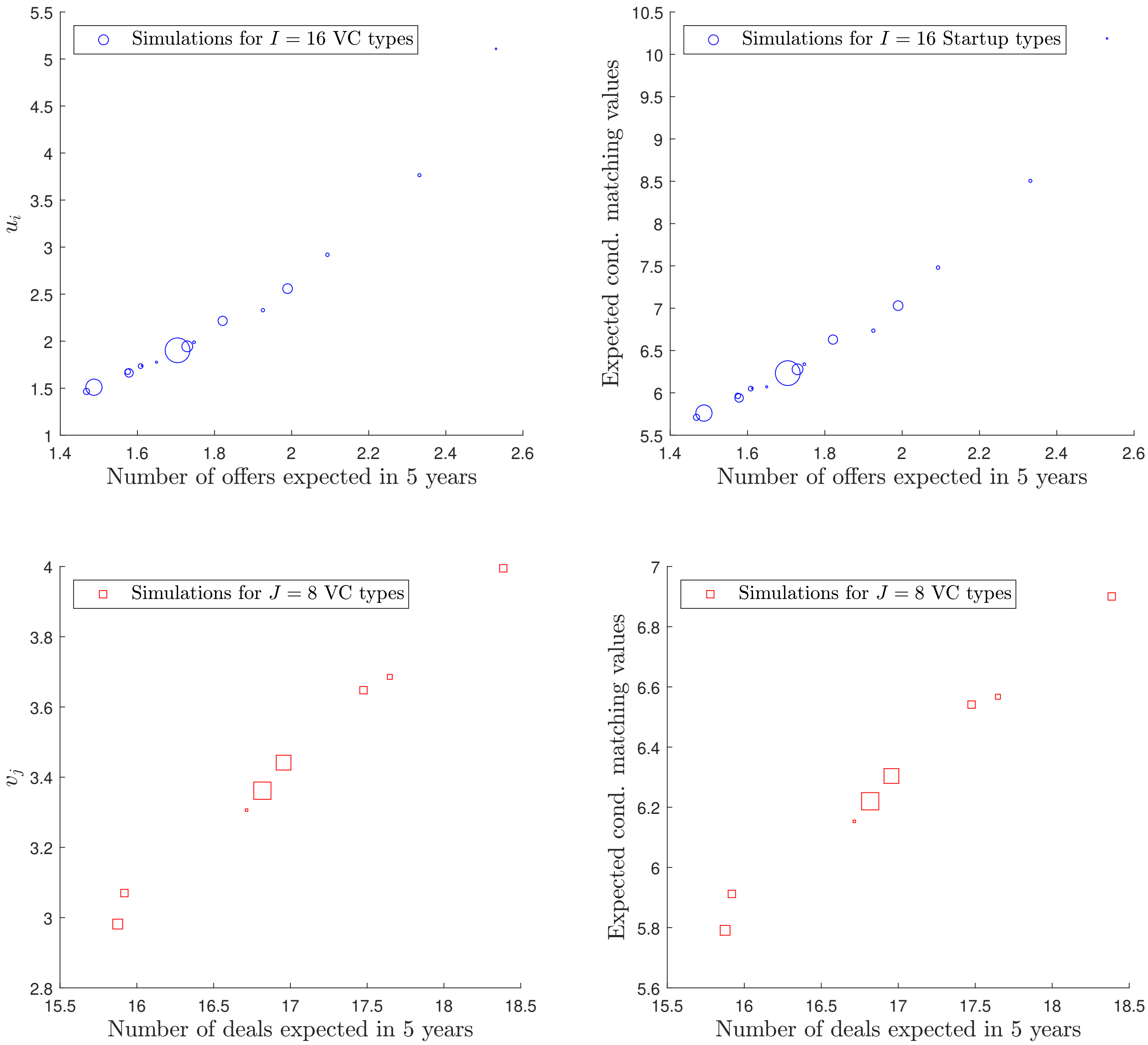
Notes. Y-axis shows revealed contact interests from experiment data, and X-axis shows the inferred contact interest using the model-implied equation for expected gains from matching: $p_{ij} \cdot \mathbf{E}_\epsilon[\epsilon - CDF^{-1}(1 - p_{ij}) \mid positive]$, with p_ij set from revealed collaboration 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.

Figure C12: Deal size vs. average expected conditional matching payoff for startups and VCs



Notes. Y-axis shows the average log deal size from the Pitchbook data, and X-axis shows the average log expected conditional matching payoffs from simulation. The left panel reports data collapsed at the startup-type level versus simulation results for the conditional payoff of startups $u_i + \pi \sum_j n_j \cdot p_{ij} \cdot \mathbf{E}_\epsilon[z_{ij} + \epsilon - u_i - v_j| \, positive]/\sum_j n_j \cdot p_{ij}$ both in log scales; The right panel reports data collapsed at the VC-type level versus simulation results for the conditional payoff of VCs $v_j + (1-\pi)\sum_i m_i \cdot p_{ij} \cdot \mathbf{E}_\epsilon[z_{ij} + \epsilon - u_i - v_j| \, positive]/\sum_i m_i \cdot p_{ij}$ both in log scales. Marker sizes indicate the estimated underlying mass of types, $\{m_i\}$ in the left panel and $\{n_j\}$ in the right panel.

Figure C13: Continuation values and expected conditional value of matches for startups and VCs



Notes. The top panels show simulation results for startup types on equilibrium continuation values u_i (top-left) and average expected conditional values in matches with VCs $\sum_j n_j \cdot p_{ij} \cdot \mathbf{E}_\epsilon[z_{ij} + \epsilon \mid z_{ij} + \epsilon \geq u_i + v_j]/\sum_j n_j \cdot p_{ij}$ (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 expected conditional values in matches with startups $\sum_i m_i \cdot p_{ij} \cdot \mathbf{E}_\epsilon[z_{ij} + \epsilon \mid z_{ij} + \epsilon \geq u_i + v_j]/\sum_i m_i \cdot p_{ij}$ (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.