How do Venture Capitalists (actually) make decisions? Internal evidence from a private startup accelerator

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ABSTRACT

Using a proprietary dataset detailing all startup applications, all internal judging scores and judges' written comments, all signed financing contracts, and even all audio recordings of interviews and contract negotiations involving one of the largest venture capital-backed startup accelerators in the United States, we open the 'black box' of venture capital (VC) decision-making. We first study the entire internal VC investment selection process by examining the key determinants of judging scores from initial screening through to final portfolio firm decisions. For example, by focusing on how individual VC partners/employees evaluate the same potential portfolio firm, we provide novel evidence on the existence of significant VC judge-founder 'homophily' biases and detail how different judging settings (e.g., solo vs. group evaluations; availability of quantitative vs. qualitative information) can amplify or mitigate such biases. Next, we are the first to empirically document the key features of a recent innovation in startup firm financial contracting instruments (namely Simple Agreement for Future Equity (SAFE) and Keep It Simple Security (KISS) contracts) and investigate their relationship with startup firm characteristics and internal VC evaluations. We offer novel insights into the role of a salient 'anchor' or 'reference point' in setting future equity pricing terms as well as the importance of startup financial constraints in VC term sheet negotiations.

Keywords: Venture capital, entrepreneurial finance, business accelerators, financial contracting, portfolio firm selection, homophily

JEL Classification: G24, G30, G41, K12, L26, M13

1. INTRODUCTION

Despite startup firms being a crucial driver of innovation in the economy and a key source of new job creation (e.g., Acemoglu, Akcigit, Alp, Bloom, and Kerr, 2018; Decker, Haltiwanger, Jarmin, and Miranda, 2014), it is a well-known fact that creating a new entrepreneurial venture is an extremely high-risk endeavor (e.g., Hall and Woodward, 2010; Kerr, Nanda, and Rhodes-Kropf, 2014). In particular, two of the key barriers to startup firm growth are the general lack of early-stage funding sources and the insufficient resources available to adequately train and mentor startup founders (Kerr and Nanda, 2011; Gonzalez-Uribe and Leatherbee, 2018). As a result, it is estimated that over 80% of "early-stage" startup firms will fail in the so-called "startup valley of death" which generally spans the seed and Series A funding round stages (Gompers and Lerner, 2001).[1]

To address these pervasive funding and educational impediments to startup firm development, there has been an explosion in the number of so-called "startup accelerator" programs across the world, from a handful of accelerators in 2005 to over 7,000 startup accelerator programs worldwide today (Yang, Kher, and Lyons, 2019). These fixed-term, cohort-based accelerator programs are designed to offer startups some upfront funding and provide startups with an intensive education and mentorship program to promote portfolio firm growth and prepare portfolio firms for raising future financing rounds. Importantly, as part of a broader push by venture capital (VC) funds into providing financing for earlier stage startup firms (Ewens, Nanda, and Rhodes-Kropf, 2018; Lerner and Nanda, 2020), VC-backed accelerator programs have become one of the most important sources of funding and business support for early-stage startup firms. For example, it is estimated that over 10% of the $11.5 billion invested in U.S. seed funding rounds in 2023 were made by VC-backed accelerators (see generally, Teare, 2024).

[1] This roughly approximates the time from the development of a prototype or minimum viable product (MVP) by the startup firm to when the business starts to generate meaningful revenues and cash flows.

However, despite the critical importance of VC investors (and the accelerators they sponsor) to the startup eco-system and broader economic growth, surprisingly little is known about how VCs select portfolio firms and make financial contracting decisions in practice. This is primarily because researchers are typically unable to observe any information on VCs' internal startup evaluation process and/or the financial contracts signed by startups with their VC investors (see generally, Kaplan and Strömberg, 2003, 2004; Gonzalez-Uribe, Klinger-Vidra, Wang, and Yin, 2023).[2]

As a result, researchers have typically been constrained to attempting to infer various aspects of the VC portfolio firm selection and financial contracting process using only very limited information on the completed investments made by VC funds into a small subset of startup firms (for a general review of this stream of literature, see e.g., Hall and Lerner, 2010; Da Rin, Hellmann, and Puri, 2013; Lerner and Nanda, 2020). Unfortunately, when attempting to explain the defining characteristics and ex-post outcomes of VC-backed startups based only on observed investments, there are a multitude of measurement and endogeneity issues that are virtually impossible to fully address using traditional research methods and datasets (Bernstein, Korteweg, and Laws, 2017).[3]

More recently, there have been efforts to rely on alternative research designs to try and understand the investment selection criteria of VC investors such as direct surveys of VCs (e.g., Gompers, Gornall, Kaplan, and Strebulaev, 2020) or to conduct field experiments with VCs using hypothetical firms/resumes (e.g., Bernstein et al., 2017; Gornall and Strebulaev, 2022; Zhang, 2023). However, these types of studies raise the obvious question as to whether VC investors really "do what they say" when there is actual money at stake in real-world scenarios.

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[2] For example, most traditional startup investment databases like VenturXpert, Pitchbook, and Crunchbase will only provide limited data on completed VC transactions such as basic information on the identity of the investor/s and the investee as well as the date and (total) amount of each VC investment round (Puri and Zarutski, 2012).

[3] For instance, it is extremely difficult to fully account for the possibility that the superior ex-post performance of VC-backed startups relative to non-VC backed startups is due to the fact that startup firms with higher (unobserved) intrinsic quality are both more likely to be initially selected by VC investors to receive funding and that entrepreneurial firms with higher intrinsic quality will generate better ex-post outcomes (Kerr, Lerner, and Schoar, 2016).

Alternatively stated, the overarching problem that has severely hampered empirical research on VC portfolio firm selection and VC-startup financial contracting is the lack of comprehensive data on the *entire* VC investment process, from (1) observing all startup firm applicants in VCs' initial investment opportunity set to (2) the internal evaluation of startup firm potential by VCs to (3) VCs' selection of portfolio firms to (4) the negotiation of signed funding contract terms between VCs and startups (including pricing). This means that much is still unknown about the internal functions of VC investors and the nature of the relationship between VCs, accelerators, and startups.

In contrast to the prior literature, our paper's unique solution is to use the confidential dataset of a large accelerator program run by a prominent U.S. VC firm to open the "black box" of VC portfolio firm selection and early-stage VC-startup financial contracting. This proprietary dataset contains comprehensive information on *all* startup applicants to our VC's accelerator program (totaling over 7,000 unique startups from 6 different continents and covering all major industry groups), *all* internal judging scores and written comments submitted by individual VC employees (comprising over 18,500 individual VC judge scores across 3 separate interview stages), *all* financial contracts signed by our VC firm with accepted accelerator applicants (encompassing 120 seed funding agreements across 10 cohorts), and even *all* available audio recordings of interviews and contract negotiations between our VC firm and accelerator applicants. As a result, our unique research setting allows us to "get inside the VC decision-making room" and observe how startup potential is judged and funding contracts are negotiated in practice.

There are many unique benefits of our proprietary VC-backed accelerator dataset and research setting relative to the existing literature. First, our setting is both *realistic* and relatively *high stakes*. Specifically, the VC partners and employees in our setting are deciding how to allocate millions of dollars of externally sourced investment capital amongst actual startup firms and are exclusively focused on maximizing financial returns. This contrasts with prior papers using other niche settings such as not-for-profit accelerators (e.g., Gonzalez-Uribe and Leatherbee, 2018) and new venture competitions (e.g., Howell, 2020; Howell, 2021) where startups often compete for small (non-equity) cash prizes and the startup evaluation criteria may not be 100% commercially focused (e.g. promote social goals, support the local economy etc.).[4] This also differs from experiments and simulations that rely upon the subject's evaluation of fake companies/people in hypothetical scenarios (see e.g., Bernstein et al., 2017). Second, our sample is *complete* and *comprehensive*. This is because our VC provides us with the entire record of all application materials, judging scores, and contracts across all accelerator cohorts in a 3-year period. As such, we do not face the sample selection issues[5] and omitted variable bias concerns[6] encountered by prior researchers. In addition, our rich startup firm applicant–VC judge–cohort linked dataset allows us to employ novel identification strategies that simultaneously combine startup firm, individual judge, and time fixed effects. Third, our setting involves *individual and group decision-making under high uncertainty*. Given our VC employees are assessing the long-term potential of early-stage startups, the scope for other (possibly extraneous) factors like personal biases to influence the evaluation process is significantly heightened (Ewens, 2023). Our setting also allows us to observe the same VC judge evaluate the same startup in alternative judging environments (e.g., individual vs. group interviews). Finally, as discussed in Section 5, our sample is broadly *representative* of the activities of sophisticated early-stage VC investors and the traits of startup firms seeking early-stage funding.

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[4] Furthermore, all judges in our VC accelerator setting are investment professionals where evaluating and working with startups is their full-time job, unlike not-for-profit/government-backed accelerators and new venture competitions that will often include judges that are not investment professionals such as academics and government representatives.

[5] For example, Kaplan and Strömberg (2004) surveyed VCs asking for example investment contracts and internal scoring memos of portfolio firms. Since these VCs only provided their own selected sample of signed financial contracts and memos to the researchers, this (non-random) sample selection process raises questions as to whether these provided documents truly represent the standard operating procedures of the focal VC firms.

[6] This is because empirical researchers typically do not have access to all the information available to the focal evaluator (whether a firm or an individual) at the time of their scoring assessment.

In this paper, we examine two main research questions. First, we explore how individual VC employees evaluate early-stage startup potential and select portfolio firms. Because our dataset contains multiple judges evaluating multiple firms on a repeated basis across time, we can better examine topical questions such as how judge's beliefs are formed and adjusted in individual vs. group decision-making environments as well as whether individual VC judge evaluations can be influenced by affinity biases with startup firm founding teams (i.e., judge-founder affinity biases). Second, we investigate what factors significantly influence the negotiation of financing contracts between VC investors and early-stage startup firms in the modern era. Specifically, we examine what financial contracting instruments are currently being used in early-stage funding rounds, what salient "anchors" are used to set key investment contract terms, and how important are startup financial constraints in affecting relative bargaining power and finalized contract terms.

Using our database of startup application data and individual VC employee judging scores, we first provide several unique insights into the investment selection process of (early-stage) VC investors. We initially show that, despite reviewing the exact same application materials, there is substantial heterogeneity in individual VC judging scores for the same startup applicant. To give a sense of the economic significance of these judging disagreements, if our VC firm had solely relied on the lowest pre-interview judging score for its initial applicant screening, then almost half of eventually selected portfolio firms may not have even progressed to the first-round interview stage!

Interestingly, while we do not observe any systematic evidence of outright discrimination against entrepreneurs from minority backgrounds, we do document that individual VC judges who share at least one affinity-based trait with a startup firm founder (based on having the same gender, ethnicity, or prior schooling) will consistently provide more favorable scores for those startups. The economic magnitude of these preferences is substantial, with 'affiliated' judges submitting 8–11% higher scores for the same startup applicant in the first evaluation stage than 'unaffiliated' judges.

Our additional analysis implies that this practice appears to be more consistent with the presence of significant judge-founder "homophily biases" rather than superior private information flows.

However, the magnitude of these judge-founder homophily biases appears to be context-specific. First, these judge-founder homophily biases appear to be more prevalent in cases where individual judges must rely more heavily on more qualitative 'soft' information, rather than more quantitative 'hard' data, when evaluating a startup's potential. Second, these biases appear to be exclusively concentrated in 'solo judge' settings where the VC judge does not have the opportunity to interact with a group of their VC firm colleagues prior to scoring applicants. Crucially, we find that establishing a panel of judges to jointly assess a startup's potential helps to improve the rigor of the VC selection process by eliminating the influence of personal judge-founder affinity biases.

Next, we analyze our sample of signed contracts between portfolio firms and our VC firm to document several new unknown trends in the VC-startup financial contracting process, especially in relation to early-stage startups. Initially, we provide some of the first empirical evidence that a new simplified financing instrument that we term "deferred equity agreements", comprised of Keep It Simple Security ('KISS') and Simple Agreement for Future Equity ('SAFE') contracts, seems to have replaced convertible debt as the contracting instrument of choice for initial financing rounds.

We then identify the key factors that influence the "real-world" negotiation of these deferred equity agreements. First, we find that the funded startup's current (pre-money) valuation at the time of application is a critical 'anchor' or 'reference point' in setting future equity pricing terms under these simplified financial contracting instruments. Specifically, we show that the 'valuation cap' in KISS/SAFE contracts (which determines the maximum price per share paid by the VC investor for startup shares received in a future financing round) is often set equal to the startup firm's current valuation. Second, unlike much of the prior 'financial constraints' literature, our unique setting allows us to directly (and separately) measure both an investor's perception of firm quality *and* the degree of financial constraints faced by the focal startup firm. This in turn allows us to generate credibly causal estimates of the extent to which startup financial constraints negatively impacts firm value. Our estimates suggest that startups suffer a 24% reduction in their negotiated valuation caps for each one year decrease in their remaining cash 'runway,' implying that financially constrained startup firms face an economically meaningful and costly reduction in their relative bargaining power when undertaking term sheet negotiations with sophisticated startup investors.

Our paper contributes to several strands of literature. First, since VCs often view portfolio firm selection as the primary driver of their investment success (Gompers et al., 2020), there has been much research into various aspects of how VCs select startup investments and their associated consequences. For example, a substantial body of work has used a variety of empirical methods to examine both the absolute and relative importance of the startup business ("the horse") versus the startup management team ("jockey") in driving VC selection decisions and ex post performance.[7] Other studies focus on the impact of angel investors, business accelerators, or government funding on startup firm outcomes using a regression discontinuity design based on variation in consensus judging scores across firms.[8] More recently, Jang and Kaplan (2023) use a dataset provided by an early-stage, U.S. Midwest-focused VC to assess how much skill VCs have in screening startups for investment (based on future startup outcomes) while Gonzalez-Uribe et al. (2023) use data provided by a UK seed-stage, software-focused VC fund to study how the VC due diligence process by itself can promote startup growth (even if those startups are not ultimately selected for VC investment).

Crucially, however, these prior studies take the investor's internal scoring process as given, whereby the development of startup applicant scores by individual judges is typically unobserved.

[7] See e.g., Kaplan and Strömberg (2004); Kaplan, Sensoy, and Strömberg (2009); Bernstein et al. (2018); Gompers et al. (2020); Jang and Kaplan (2023); Lyonnet and Stern (2024).
[8] See Kerr et al. (2014); Gonzalez-Uribe and Leatherbee (2018); and Howell, Rathje, Van Reenen, and Wong (2023).

In contrast, we are the first paper (to the best of our knowledge) to forensically examine how these individual VC employee scores are formulated in the first place (i.e., we put internal VC judging scores as the focal left-hand side dependent variable). As a result, our unique perspective and empirical strategy allows us to open the black box of VC portfolio firm selection by uncovering novel factors that significantly influence the VC selection process. For example, by only focusing on *within-firm* judge score variation, we show that shared affinity-based characteristics between individual judges and firm founders in terms of their inherited traits (i.e., gender and ethnicity) and prior experiences (i.e., shared education) can help to explain a significant part of the large disparity that we detect in the evaluations provided by different VC employees for the same startup applicant.

Second, our paper contributes to the ongoing debate about the prevalence of investor biases in startup funding markets and potential mechanisms for mitigating any such biases. To date, there is much disagreement in the prior literature about the existence and/or magnitude of biased startup evaluations by investors based on the inherited traits of startup founders (for example, 'minority' entrepreneurs that are female or non-White: see generally Ewens, 2023; Zhang, 2023; and Cassel, Lerner, and Yimfor, 2024). Depending on the empirical setting and data structure, some researchers find evidence of significant discrimination against minority entrepreneurs[9] while others find no persistent biases against minorities in investors' evaluations of startup firms and their founders.[10]

However, prior studies based on observational/archival data or laboratory experiments both suffer from crucial limitations. For example, with respect to observational-type studies, these regression-based methods likely suffer from omitted variable bias due to incomplete data and a lack of exogenous variations, especially since the researcher ordinarily does not have access to all the information available to the focal evaluator at the time of their scoring assessment. Also, these

[9] See e.g., Ewens and Townsend (2020), Fairle, Robb, and Robinson (2022), and Cook, Marx, and Yimfor (2023).
[10] See e.g., Bapna and Ganco (2021), and Gornall and Strebulaev (2022).

studies usually cannot observe cases where multiple judges from varying backgrounds are consciously evaluating the exact same subject. This in turn makes it difficult to ascertain whether it was differences in inherent applicant quality and/or judging information sets vs. a genuine bias against certain types of individuals that drove the variation in observed final scores (e.g., Ewens, 2023). Furthermore, beyond the usual questions regarding the external validity of experimental-type studies, experiments that involve the tracking of email responses by investors tend to suffer from low response rates, significant measurement error, unknown characteristics of the focal evaluator and/or unknown reasoning behind observed response behavior, and only capture initial expressions of interest rather than final decisions (Bertrand and Duflo, 2017; Zhang, 2023).

In contrast, our unique setting helps us to overcome many of these empirical challenges. First, all judges in our setting are asked to evaluate the *same startup* firm/founding team at the *same time* with the *same information set*. Second, because we can observe the same judge evaluating the same startup on repeated occasions in different situations (i.e., solo vs. group decision-making), we can assess whether group discussion prior to individual scores being submitted can help to mitigate the influence of a judge's personal preferences on the internal VC selection process. Third, by having access to all score assessments of each judge across several cohorts of applicants, we can overcome the statistical power and sample bias issues faced by prior studies. Fourth, we know the identity and background of each of our VC judges so that we can measure their (randomly generated) level of homophily with startup founders. These features thus make our empirical setting an attractive one to assess the magnitude of investor biases in startup funding markets, where we offer more nuanced findings on both the dimensions and the situations in which such biases are more prevalent.

Third, our paper contributes to the financial contracting literature that examines what factors influence the structure and pricing of funding contracts between startup firms and startup investors.

While most of these papers rely on theoretical models due to the inherent limitations in collecting a large sample of commercially sensitive financial contracting data,[11] there is a limited empirical literature that documents some of the key terms of traditional preferred stock agreements. However, each of these empirical studies can only investigate a subset of the entire contracting process. For example, Kaplan and Strömberg (2003 and 2004) and Bengtsson (2011) do not observe specific VC contract pricing terms while Hsu (2004) does not observe VCs' internal scoring assessments.

In contrast, we are first paper to the best of our knowledge to connect the internal VC selection process to finalized VC-startup financial contracting outcomes (including pricing), where we do so in the context of a new class of SAFE and KISS contracts that have not been empirically studied to date (Hodor, 2021). Using this unique dataset on the entire financial contracting process, we quantify the relative effect of internal VC scoring assessments, current firm valuation 'anchors', and startup financial constraints on startup firm valuation outcomes. The trends we document have important implications for both theoretical and empirical researchers as well as for practitioners. For example, our discovery of the standard industry practice of only having one negotiating item in deferred equity agreements (i.e., the valuation cap) to address several agency problems (i.e., 'double moral hazard', asymmetric information, hold-up problems etc.), as well as setting valuation caps quite close to a startup's current valuation, can have profound consequences for the relative incentives of entrepreneurs and VCs as well as the timing and amount of future financing rounds.[12]

Finally, our paper is related to the literature that examines the role of startup accelerators in promoting the growth of early-stage entrepreneurial ventures. Several papers have documented that

[11] For theory models examining the parameters of the 'optimal' financial contract between startups and VCs, see e.g., Casamatta (2003), Cornelli and Yosha (2003), Schmidt (2003), Hellmann (2006), and Yang and Zeng (2019).

[12] For example, if valuation caps are closely tied to a startup's current valuation, does this incentivise entrepreneurs to bring forward the timing of subsequent Series A financing rounds and/or accept lower funding amounts/valuations in future Series A rounds? Furthermore, does this practice undermine one of the most important claimed benefits of SAFE and KISS agreements that they are 'unpriced' securities that avoid establishing a firm's valuation upfront?

startup firms that participate in accelerator programs outperform their non-accelerator counterparts due to the benefits of specialized training and mentorship (e.g., Gonzalez-Uribe and Leatherbee, 2018; Robinson, 2022), external certification (e.g., Cohen, Fehder, Hochberg, and Murray, 2019), and entrepreneurs receiving timely and informative signals on whether to pivot or abandon their business idea (e.g., Yu, 2020). However, this prior literature tends to overlook the first order question of how firms are chosen for accelerator programs in the first place, a particularly pertinent selection issue given that typically only 1–2% of applicants are accepted in each accelerator cohort.

In contrast, we believe that we are the first paper to undertake a detailed investigation into how individuals at accelerator organizations evaluate and score startup applicants in practice, thus providing valuable new insights for entrepreneurs and investors into the accelerator selection process. Moreover, by focusing on a VC-backed accelerator program, we are the first paper to examine the determinants and consequences of financial contracting choices made by entrepreneurs and for-profit investors within the context of the rapidly expanding business accelerator landscape. For example, our contractual analysis highlights some of the potential costs, in terms of ownership dilution, faced by startup firm founders when they participate in a (for-profit) accelerator program.

2. INSTITUTIONAL SETTING AND DATA

2.1 Research setting

We focus our analysis on a large startup accelerator program run by a prominent U.S.-based venture capital firm. Our focal VC firm specializes in providing seed round funding to early-stage entrepreneurial firms through periodic fixed-term, cohort-based accelerator programs. Our VC firm operates these accelerator programs at several major startup hubs (e.g., New York and California) and it has raised multiple funds totalling more than $100 million. Our VC firm invests across all industries and geographies, although most portfolio companies are located in North America.

Analogous to other for-profit business accelerators worldwide, our VC firm provides program participants with both equity capital and educational/other resources to help promote rapid startup growth. To participate in the accelerator program, startups must complete a series of application forms and interviews with VC firm employees, with startups being evaluated on the relative quality of their product/service and management team. This is a highly competitive selection process whereby only 1–2% of applicants are accepted into any given accelerator cohort. Further details about our VC firm's investment selection process and criteria are given in Sections 2.2 and 3.1.

For selected portfolio companies, our VC firm typically makes initial investments of between \$150,000 to \$200,000 in exchange for a 3% to 7% equity ownership stake (see Sections 2.2. and 4.1 for further details on our VC firm's financial contracting process). In addition, portfolio firms are required to participate in an intensive 12-week education and mentorship program that is designed to assist portfolio firms with product development, operations, corporate strategy, human resource management, marketing, and fundraising. At the end of this 12-week program, accelerator participants will take part in a "Demo Day" event where startups are given the opportunity to formally pitch for additional funding and support by other VC investors and/or strategic partners.

In order to facilitate greater information sharing during the academic research process as well as to protect the confidentiality of the highly detailed and commercially sensitive information provided to us, we will not disclose the name of our VC investment firm, details of individual firm employees, or de-anonymized data on applicant firms to this VC investor's accelerator program.

2.2 Description of the accelerator selection and contracting process

For each cohort in our sample, our VC firm implemented the following process to select the subset of startup applicants who will be invited to participate in our VC's accelerator program. Please refer to Internet Appendix IA.1 for additional details on each evaluation stage.

2.2.1 Stage 1: Application and initial screening

All startups are required to submit an initial online application. One (junior) employee at our VC Fund is then asked to review each initial application to decide whether a further request for information (called a 'due diligence (DD) pack') is sent to the startup applicant to complete (a process we term the '*initial employee screen*'). This DD pack is a much more detailed questionnaire that asks for the startup's 'pitch deck' and answers to over 50 questions that cover a range of topics relating to the company's product or service, potential market size, business model, competitive landscape, milestones achieved to date (i.e., traction), financial information and other metrics, the background and skills of the management team, and the legal/ownership structure.

2.2.2 Stage 2: Pre-interview assessment

Next, it is expected that all VC firm employees will review and submit scores for each applicant based only on the submitted due diligence pack materials (otherwise referred to as '*pre-interview scores*'). This pre-interview score can range between 0 points (worst) to 100 points (best) and is based on sub-scores given for the market potential of the startup's product/service, the quality of the startup's management team, and the level of traction/customer engagement garnered to date.

Critically, our VC firm adopted a judging policy that emphasized the importance of each VC partner/employee submitting truly independent assessments of applicant quality, especially at the pre-interview stage. To enforce this policy, our VC firm implemented several procedures to ensure that individual VC employees would not communicate with each other and would not observe each other's scores and comments prior to submitting their final pre-interview judging assessments.

Our VC firm will then rank startups from best to worst based solely on their average pre-interview scores and invite the top 10% of all applicants to progress to the next evaluation round.

2.2.3 Stage 3: First round interview

Our VC firm will then invite selected applicants to a 30-minute meeting with all available VC firm partners and employees. At these meetings, the startup's management team will make a short presentation about the company and answer a series of questions from VC firm employees. At the conclusion of each first round interview, all attendees from the VC firm will have an open group discussion about the strengths and weaknesses of the applicant. However, analogous to the pre-interview scoring process, each interviewer is asked to provide a single overall score for each first round candidate based on that judge's holistic assessment of the startup's potential and fit for the accelerator program (otherwise referred to as '*first round interview scores*'). Our VC firm will then rank startups from best to worst based solely on their (weighted) average first round interview scores and invite the top 5% of all applicants to progress to the next evaluation stage.

2.2.4 Stage 4: Second round interview and final selection

For those applicants that pass the first round interview stage, these selected startups will hold a second (and final) 45-minute interview with all available VC firm employees where the startup's management team will make a longer presentation and answer additional questions from VC firm employees about the startup's business. After this interview, all VC firm interviewers have an open group discussion about the relative merits of the applicant and their suitability for investment. Each interviewer will then provide a single overall score for each firm candidate based on that VC judge's holistic assessment of the startup's potential and fit for the accelerator (otherwise referred to as '*second round interview scores*'). Our VC firm will then rank startups based solely on their (weighted) average second round interview scores and make funding offers to startup companies to join the accelerator cohort in order of rank until all available accelerator cohort slots are filled (where our VC firm will prespecify a capacity threshold of 12–16 startup firms for each cohort).

2.2.5 Stage 5: VC-startup financial contracting stage

For all accepted accelerator applicants, our VC firm will offer each startup firm a relatively 'standard form' financial investment contract. While the vast majority of contract terms will be identical across all members of the accelerator cohort (including the total amount of funding provided), some of the pricing-related terms will be specific to each accepted startup applicant. Startup companies will then have 1–2 weeks to negotiate these more sensitive pricing-related terms with our VC firm. Once agreement is reached, a finalized contract is signed, and the startup will formally begin its participation in the intensive 12-week accelerator program.

2.2.6 Additional observations on integrity of VC selection process

There are several features of our VC firm's internal process that helps to ensure the integrity of the portfolio firm selection process, including maintaining the independence of individual scoring assessments. For example, at every stage of the judging process, accelerator applicants *do not* know: (a) the number or identity of the judges evaluating their application, (b) their raw scores or relative ranking, and (c) the cut-offs for determining whether they progress to the next stage of the selection process. As such, it seems impossible for applicants to manipulate the ranking process.

Furthermore, we typically observe that each VC employee judge will either submit scores for all startup firms in the remaining application pool or for no applicants at all during each evaluation stage, consistent with our VC firm's stated judging philosophy that all VC employees are expected to judge every remaining applicant in the cohort pool wherever possible.[13] As a result, it seems unlikely that VC judges are strategically self-selecting which applicants to grade.[14]

[13] For example, at the pre-interview stage, we only found two instances across our entire sample where a judge provided scores for only part of the cohort applicant pool. In both cases it was due to the focal employee providing scores for all startups in one 'wave' of applications but not providing any scores for the other 'wave' of applications in the cohort.
[14] In additional unreported tests, we verify that, in the rare cases where a VC employee did not provide judging scores for the entire cohort, there is no systematic trend in the observable characteristics of scored vs. unscored startups.

Finally, it also appears unlikely that any judge could precisely manipulate the final ranking of applicants (for example to help a 'friend' to qualify for the accelerator program). This is because: (a) a relatively large number of VC employees evaluate each startup applicant[15] and each VC judge will often evaluate hundreds of applicants at each interview stage; (b) each judge does not know the scores of other judges prior to submitting their own scores;[16] and (c) no judge has any advance notice on the exact cut-off score needed for an applicant to progress to the next interview stage (since it depends on a relative ranking of (weighted) consensus applicant scores).

2.3 Sample outline

Our baseline sample consists of all application materials, judging scores, financial contracts, and other internal VC firm records pertaining to 10 accelerator cohorts between January 2017 and October 2019.[17] To link these records together, we utilize unique, permanent identifiers for each startup firm applicant (since it is possible for the same startup firm to submit an application for different accelerator cohort cycles) as well as unique identifiers for each VC firm employee judge.

Across our entire sample, we observe 7,004 initial applications, 1,562 due diligence packs, 13,518 pre-interview scores, 3,401 first-round interview scores, and 1,663 second-round interview scores provided by 23 distinct VC firm partners/employees. We also have access to all 120 funding contracts signed by accepted applicants and our VC firm during our sample period, including details of all offers and counteroffers, intermediate contract negotiations, and finalized agreements. See Figure 1 for a breakdown of the total number and progress of each application across our 10 cohort cycles and Figure 2 for the distribution of primary industry groups of startup firm applicants.

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[15] For example, the median number of individual judges for each startup applicant in the pre-interview process is 9.
[16] Each judge must separately submit an individual scoring spreadsheet for an administrative manager to compile.
[17] The start date of our sample corresponds to the first cohort where our VC firm started to systematically retain all materials and records generated throughout the entirety of the accelerator selection and contracting process.

2.4 Variable construction

In this section, we describe the dependent and independent variables used in our baseline analysis. Please see Appendix A for further details on the construction of each of these variables.

2.4.1 Outcome variables

With respect to our portfolio firm selection tests, we focus on the variation in individual VC judges' scores. We use the 'raw' overall pre-interview, first round interview, and second round interview scores submitted by each employee for each startup firm (referred to as the *Pre-interview overall score*, *First round interview score*, and *Second round interview score*, respectively).[18]

With respect to our empirical analysis concerning the VC-startup financial contracting process, our main dependent variable of interest is the amount of the funding agreement's 'valuation cap' (expressed in millions of US$ dollars), where the valuation cap effectively sets the maximum dollar price that our VC firm will pay for an equity ownership stake in the focal portfolio firm. As we discuss in more detail in Section 4.1, this valuation cap is the only relevant contractual term in practice that our VC and portfolio firms will negotiate over prior to entering the accelerator.

2.4.2 Judge-founder affinity-based traits and startup founding team inherited characteristics

To assess the possibility that shared affinity-based characteristics between individual judges and firm founders may significantly influence the internal VC scoring process, we construct several measures of judge-founder affinity-based traits. Specifically, we create four separate indicator variables that are equal to one if the focal VC firm judge and at least one of the startup's founders have the same gender (*Shared gender*), have the same ethnicity (*Shared ethnicity*), graduate from the same university (*Shared education*), or worked at the same employer (*Shared employer*), and

[18] In additional (unreported) robustness tests, we obtain similar results if we use 'scaled' score dependent variables by dividing a judge's raw score in the pre-, first round-, or second round-interview stage by that applicant's average score in the same evaluation round (computed across all 'raw' scores of VC firm judges in that cohort), respectively.

zero otherwise. To construct each affinity-based variable, we rely upon startup pitch decks (which include pictures and descriptions of each founder), detailed application materials with founder biographies and education/employment profiles like LinkedIn pages, and web searches to identify the gender and ethnicity of each firm founder as well as each founder's full list of prior employers and universities attended. We then use internal VC firm records and LinkedIn profiles to identify the corresponding traits for each VC employee judge.

To assess whether certain inherited traits of startup firm founding team members may have a general (negative) impact on their evaluation by VC firms, we include three additional indicator variables capturing the minority status of startup founding teams. First, we construct the dummy variable *All female founding team* that is equal to one when all co-founders are female, and zero otherwise. Second, we create the dummy variable *All Black founding team* that equals one when all co-founders are Black/African American, and zero otherwise. Third, we compute *All Hispanic founding team* that is equal to one when all co-founders are of Hispanic origin, and zero otherwise.

2.4.3 Controls for other judge-founder overlapping characteristics

To account for the possibility that other shared characteristics/experiences (that are separate from those based on affinity-based traits) may systematically influence individual judging scores, we include dummy variables for whether the focal VC firm judge and at least one of the startup's founders both have graduate degrees (*Shared graduate degree*) or both earnt a university degree from a top-tier university (*Shared top tier university*). We also control for each judge's years of experience working in the same industry sector as the focal startup (*Shared industry experience*).

2.4.4 Startup firm control variables

Through our access to a wealth of confidential and detailed information about each startup applicant, we can incorporate several firm characteristics in our regressions that capture the past progress, current status, and future potential of each startup to our VC's accelerator. Specifically, we include the following startup firm control variables: *Company stage of development*; *Company age*; *Company's lifetime revenue*; *Number of total users since launch*; *Number of paying users since launch*; *External funding raised to date*; *Company runway*; *Current firm valuation*; *Number of FTE company employees*; as well as *Estimated Serviceable Obtainable Market (SOM)*.

2.4.5 Startup founding team control variables

In addition to the inclusion of several confidential firm-level controls, our regressions also incorporate various measures of the educational attainment and professional experience of startup firm founders. Specifically, we include the following firm founding team control variables: *Number of company founders*; *Percentage of founding team with graduate degree*; *Percentage of founding team with degree from top tier university*; *Average top management team (TMT) experience of company founders*; and *Average prior startup experience of company founders*.

2.4.6 VC judge control variables

Our research setting also allows us to include several variables that control for the background and experience of individual VC firm employees. Specifically, we include indicators for whether the judge is a *Current Partner* of our VC firm, has a *Graduate degree*, or has attended a *Top tier university*, respectively; as well as the judge's *Years of Financial Investment experience*.

2.5 Summary statistics

Table 1 provides the mean, median, and standard deviation of the various characteristics of our baseline sample, alternatively computed across all startup applicants (comprising both accepted and rejected applicants) as well as across only the 120 accepted accelerator applicants.

In Panel A of Table 1, we present summary statistics for the number of individual judges and the range of 'raw' and 'scaled' judging scores for each startup applicant at each assessment phase.

Interestingly, we observe a high amount of disagreement amongst individual VC employees about an applicant's quality, even when all judges are evaluating the same startup firm. We explore the potential factors influencing the significant variation in individual judging scores in Section 3.

In Panel B of Table 1, we provide information on the characteristics of the startups that apply to participate in our VC firm's accelerator program. In Panel C of Table 1, we show the traits and experiences of individual VC employees who are responsible for judging potential candidates. We discuss the representativeness of our sample firms and our study's external validity in Section 5.1.

In Panel D of Table 1, we document the key characteristics of the financial contracts that are signed between accepted cohort firms and our VC firm investor. One important observation is that agreed valuation caps seem to be very closely tied to a startup's current valuation. We investigate this relationship and the impact of other factors on negotiated valuation caps in Section 4.

3. VC PORTFOLIO FIRM SELECTION

In this section, we investigate the potential drivers of disagreements among individual VC firm judges in the scoring evaluations of startup firm applicants and consider the circumstances in which any potential judging biases may be amplified or mitigated during the VC selection process.

3.1 Initial empirical observations on VC selection process

From Panel A of Table 1, we make two important initial observations about our VC-backed accelerator's internal portfolio firm selection process. First, there appears to be a large emphasis on consensus decision-making throughout our VC's various interview phases. For example, the median number of judges for each startup applicant in the pre-interview screening stage is 9 judges. This suggests that our VC firm places a high value on obtaining multiple independent perspectives about a startup's potential before formulating a consensus view on whether that applicant should proceed to the next phase of the internal evaluation process (see generally, Da and Huang, 2020).

Second, however, we also observe a very high amount of disagreement amongst individual VC employees about an applicant's quality and future potential, even when all judges are assessing the exact same startup firm. In statistical terms, when grading applicants in the pre-interview stage out of a total of 100 points, the standard deviation of internal judging scores for the same startup is 17% with an interquartile range of 29% (compared to a median pre-interview score of 53).

To express the real-world importance of this substantial individual judge score variability in more concrete economic terms, let us focus on the set of 120 eventually selected portfolio firms invested in by our VC firm. If our VC firm had relied on the bottom or lowest pre-interview judging score for its initial applicant screening rather than an average-based scoring system, then almost half of these eventually selected portfolio firms may not have even been invited to the first round interview stage and thus never participated in our VC firm's startup accelerator program at all!

3.2 Empirical methodology

Given these initial observations from our internal judging score data, we believe that a natural question to ask is what drives this substantial variation in individual VC employee judging scores? Despite the rapidly growing literature that relies upon the level or variation in *consensus* judging scores to examine the effect of various investor treatments on startup firm outcomes,[19] there has been no empirical research (to the best of our knowledge) that attempts to systematically understand and explain what shapes the *individual* judging scores that underlies any consensus assessments.

The first critical point to note in our research setting is that startup firm characteristics and/or differences between the information sets of individual VC judges *cannot* explain the high variation in within-startup firm individual VC judging scores. This is because all individual VC judges are

[19] See e.g., Kerr et al. (2014); Gonzalez-Uribe and Leatherbee (2018); Howell et al. (2023); Jang and Kaplan (2023). For example, Jung and Kaplan (2023) only use their VC firm's consensus scores for 'Team' quality, 'Market size & competition', 'Product & innovation', and likelihood of successful 'Exit' to examine how useful these sub-scores are in predicting the amount of future funding raised, probability of startup survival, and probability of an IPO/M&A exit.

tasked with using the exact *same information set* to evaluate the exact *same startup firm applicant*.[20] This means that alternative channels are required to explain the observed variation in within-startup firm judging scores, for example the unique traits and experiences of individual VC employees.

However, an intriguing hypothesis that we believe has not received sufficient attention in the prior literature is whether any shared affinity-based characteristics between an individual judge and a startup firm's founders (based on overlapping gender, ethnicity, educational background and/or employment experiences) may explain some of the large within-applicant judging score variation that we observe. While there is a long-standing literature indicating the presence of 'homophily' (namely the tendency of individuals to prefer to work with others who share similar personal or social characteristics) in other VC-related contexts,[21] there is no other empirical study that has undertaken a large-scale analysis of the relative importance of "judge-founder affinity-based preferences" in driving large differences in individual VC judge evaluations. We initially use the more neutral term "judge-founder affinity-based preferences" and then discuss in Section 5 whether these preferences are more consistent with rational information-based choices or personal biases.

To examine this variation in individual judging scores more formally, we run the following ordinary least squares (OLS) regression specification where our primary outcome variable is the overall score given to startup firm i applying to cohort c by individual VC employee judge j:

$$\begin{aligned} Judge\ score_{i-j,c} = \alpha &+ \beta_1 Shared\ gender_{i-j} + \beta_2 Shared\ ethnicity_{i-j} \\ &+ \beta_3 Shared\ education_{i-j} + \beta_4 Shared\ employer_{i-j} \\ &+ \beta_5 All\ Female\ founder\ team_{i,c} + \beta_6 All\ Black\ founder\ team_{i,c} \end{aligned} \tag{1}$$

[20] As discussed in Section 2 and Appendix IA.1, each VC employee is provided with an identical set of Q&A-based application materials, pitch decks, interview records, and other data for each different startup in each judging round.

[21] For example, see Gompers et al. (2016) in the context of the formation of venture capital syndicates as well as mixed evidence on the role of informationally relevant social networks and/or homophily in explaining the observed matching between startup firms and their VC investors (e.g., Hedge and Tumlinson, 2014; Huang, 2023; Garfinkel et al., 2024).

$$+ \beta_7 All\ Hispanic\ founder\ team_{i,c} + \delta Startup\ firm\ controls_{i,c}$$
$$+ \theta Startup\ founding\ team\ controls_{i,c} + \gamma Judge\ controls_{j,c}$$
$$+ \varphi Other\ judge - founder\ overlapping\ characteristics_{i-j}$$
$$+ Judge\ FEs_j + Startup\ firm\ FEs_i + Cohort\ FEs_c + \varepsilon_{ij,c}$$

The dependent variable $Judge\ score_{i-j,c}$ is equal to the total score given by judge j to startup firm i in cohort c (i.e., *Pre-interview overall score*, *First round interview score*, and *Second round interview score*, respectively). Our primary independent variables of interest are *Shared gender*, *Shared ethnicity*, *Shared education*, and *Shared employer*, respectively, which capture measures of potential affinity between individual judges and applicant firm founders. We also include *All Female founder team*, *All Black founder team*, and *All Hispanic founder team* to assess the possible prevalence of generalized discrimination against minority entrepreneurs in the VC selection process.[22] We also incorporate several additional controls for various observable startup firm, startup founding team, and VC judge characteristics as well as other judge–founder overlapping traits (see Section 2.4 and Appendix A for further details on variable construction).

There are several advantages afforded by the richness of our multiple judge, multiple startup firm dataset that allows us to cleanly parse out the relative importance of judge-founder affinity based preferences, individual VC judge characteristics, and startup firm attributes in explaining variation in individual VC judging scores. First, by including *Startup firm fixed effects* that keeps the evaluation subject (i.e., the startup firm applicant) and judges' associated information sets constant, we can specifically identify how the unique experiences and potential judge-founder

[22] For studies that study discrimination against minority applicants in other finance-related settings, see e.g., Gompers and Calder-Wang (2017) (venture capital firm partners), Frame, Huang, Mayer, and Sunderam (2023) (mortgage loan officers) and Huang, Mayer, and Miller (2024) (bank managers). For evidence of 'homophily' in other business-related contexts, see e.g., Ishii and Xuan (2014) (directors/executives), Gompers, Murkarlyamov, and Xuan (2016) (venture capitalists), Calder-Wang, Gompers, and Huang (2023) (firm founders), and Hedge & Tumlinson (2014) and Garfinkel, Mayer, Strebulaev & Yimfor (2024) (ethnic and university alumni ties between entrepreneurs and VCs, respectively).

affinity biases of individual VC employees may affect their personal evaluation of the *same startup firm applicant*. Second, by including *Judge fixed effects* that keeps the individual VC employee evaluator (with their leniency and personal taste preferences) constant, we can examine what startup characteristics and potential judge-founder affinity biases may influence the *same VC judge* in their evaluation of different startup firm applicants. Finally, by including *Cohort fixed effects* to focus on judge score variability within an accelerator cohort, we can account for any time-related trends at the micro- or macro-level that may impact individual judge scores.

Before continuing, we note that our VC firm did not have a formal randomization process for assigning individual judges to startup applications. However, as discussed in Section 2.2.6, the allocation of VC employees to judge each startup applicant is still somewhat of a random process because our VC firm's widely recognized (and followed) judging policy is that: (a) everyone who is available is expected to participate in judging the current interview round and (b) if an employee is involved in judging an interview round, they are expected to score all applicants in that cohort. By adhering to this policy, our VC selection sample is unlikely to suffer from any meaningful self-selection concerns since individual judges do not seem to have the ability (or even the incentive) to strategically select which accelerator applicants they will evaluate and grade.

3.3 Results with pre-interview scores in 'solo judge' setting

In this first empirical test, our dependent variable is judge j's pre-interview score between 0 and 100 points for a startup applicant i in cohort c. We reiterate that the key features of this judging setting are that: (a) each judge will evaluate and score accelerator applicants without consulting each other (a so-called '*solo judge*' setting), and (b) for each startup applicant, each judge will base their evaluations on the same set of application information (see Section 2.2 for further details).

In Table 2, we first find that judge-founder affinity-related traits strongly affect individual pre-interview judging scores for the same startup applicant despite our inclusion of a stringent set of fixed effects and control variables. Specifically, *Shared gender*, *Shared ethnicity*, and *Shared education*, all seem to exert a statistically significant influence on the scores that individual VC judges assign to the same startup applicant.[23] In terms of economic significance, if a judge shares the same gender, same ethnicity, or same university background as at least one of the startup founders, these 'affiliated' judges will on average give a 8–11% higher overall pre-interview score than 'non-affiliated' judges for the same applicant firm.[24] Given the closeness of applicant scores around the cut-off threshold for a first round interview invitation in our VC's highly competitive application process, these judge-founder affinity-based preferences can clearly affect a marginal startup's relative ranking and thus their chance of progression through the VC selection process.[25]

Second, however, we *do not* find any evidence of systematic bias in aggregate pre-interview judging scores either for or against all female, all Black, or all Hispanic entrepreneur founding teams. Thus, in contrast to much of the existing prior literature that documents the existence of pervasive discrimination against minorities in entrepreneurial finance settings (see e.g., Ewens, 2023), our results suggest that it is more subtle affinity-based personal preferences that are the more prevalent issue affecting individual VC judge evaluations during the VC selection process, rather than the existence of a more generalized bias against female, Black, and/or Hispanic entrepreneurs.

Finally, we identify several (observable) startup firm characteristics that VC judges appear to positively value when formulating their assessments of the relative merits of accelerator applicants.

[23] In additional robustness tests, we confirm that we obtain very similar results if we use an alternative variable bounded between 0 and 1 that captures the percentage of the startup firm founding team that has the same gender, same ethnicity, shared university experience, or shared prior employer as the focal individual judge, respectively.

[24] Somewhat unsurprisingly, we confirm in unreported tests that the effect of these shared affinity-based traits tends to be concentrated in individual judge's sub-scores for the quality/potential of the startup firm's founder team.

[25] When interpreting the magnitude of this result, it should be noted that if significant judge-founder homophily biases exist at even relatively high performing VC funds, then such biases may be even more prevalent at lower tier VC funds.

For example, we find that firm characteristics related to the "fundamentals" of the startup such as having a working prototype of the proposed product or service and demonstrating that the startup business has already attracted paying users appear to be critical data points used by VC firms to (at least initially) identify startup companies with the desired risk-return profile for VC investment. Furthermore, a startup firm having previously raised external capital (whether from angel investors, friends and family etc.) also appears to be viewed quite favorably by individual VC firm evaluators. Somewhat reassuringly, we find that these 'hard' data metrics appear to be at least four times more influential in affecting individual VC judge scores than judge-founder affinity-based preferences.

Nevertheless, it appears that individual VC firm employees combine both observable 'hard' data with more intangible 'soft' information about a startup firm and its founders in order to identify potential VC investment opportunities. For example, over 25% of startup applicants invited to the first round interview stage did not have a working prototype nor had a current source of revenue. This implies that VCs' portfolio selection process is a somewhat "part art, part science" process, especially when attempting to evaluate quite early-stage startup firm applicants to a business accelerator based only on submitted application materials and questionnaires.

3.4 Heterogenous treatment effects analysis using pre-interview judging scores

In the next stage of our analysis, we consider the circumstances under which the observed affinity-related preferences in pre-interview judging scores may become more prevalent during the initial stages of the VC selection process. Our hypothesis is that judge-founder affinity-based ties will be more influential in (positively) affecting individual VC judge evaluations when there is a lack of 'hard', quantitative information on which to base an early-stage startup assessment.[26]

[26] This is consistent with several theories of discrimination that postulate a greater role for biases when information asymmetries about types or intrinsic quality is heightened (for a general discussion of these theories, see Ewens, 2023).

Therefore, we split our sample of startup applicants into several sub-samples based on the level of opacity surrounding the startup firm's business and future prospects. Specifically, on the assumption that it is generally more difficult to evaluate a startup's potential when it does not have an established customer base and limited information exists on the sustainable level of pricing and margins, we first partition startup applicants participating in the pre-interview screening stage into whether or not they are 'pre-revenue' (i.e., a startup firm is 'pre-revenue' if it has not generated any revenue to date from product or service sales). As an alternative measure of firm opacity, we also partition our pre-interview startup firms into whether or not all the firm's founders are 'first-time entrepreneurs' (i.e., all members of the startup firm's founding team have not founded a prior entrepreneurial venture before the current focal startup). This is on the assumption that it is more difficult for a VC investor to evaluate a startup's potential if the applicant firm's founders do not have verifiable experience in creating and managing an entrepreneurial venture.

In Table 3, we find that the effect of judge-founder affinity-based preferences on individual VC judge pre-interview scores appears to be primarily concentrated in situations where there is relatively less "fundamental" information about the startup firm in terms of its existing revenue profile and/or the prior entrepreneurial experience of the firm founders. This suggests that when individual VC firm employees are given more scope to make subjective judgments about a startup's potential due to the lack of 'hard' quantitative data about the focal startup's business model and/or management team, there is a greater chance that individual judges will rely upon affinity-related personal characteristics to help shape their final evaluations of accelerator applicant firms.

3.5 Results with first round and second round interview scores in 'group judge' setting

Up until this point, our only dependent variable has been the pre-interview scores given to accelerator applicants by individual VC employee judges. Importantly, this judging setting involves each judge evaluating a "paper-based" application individually without consulting other judges (in other words, a somewhat siloed, 'solo judge' setting).

In contrast, in the first and second round interview stages of our VC firm's selection process, we often still have the *same* applicant firm being evaluated by the *same* individual VC judge as in the pre-interview round, but the judging setting now has two important differences from the preceding pre-interview round. First, all VC employee judges participate in a joint, in-person 'group interview' where each VC employee listens to an investment pitch from an accelerator applicant and can observe their VC colleagues' questions and interactions with the startup firm founders. Second, after each first and second round interview, VC employees will discuss the focal startup's interview performance and hear each other's perspectives on the startup's long-term potential before submitting their individual first or second round interview score.

Ex ante, it is not clear whether an interactive group interview and VC team discussion setting will mitigate or amplify the role of judge-founder affinity biases in the VC selection process for early-stage startup firms. On the one hand, the salience of shared personal characteristics and overgeneralized stereotypes may be heightened in judges' thought processes with more direct, in-person interactions with startup company founders.[27] Furthermore, the opinions of biased judges (especially more senior managers) may be more strongly transmitted to other firm colleagues in more intimate small group settings due to issues associated with 'social conformity' and 'group think' (see generally, Klocke, 2007; Ishii and Xuan, 2014; Calder-Wang and Gompers, 2021).

On the other hand, however, it is possible that a collaborative interview and team-based discussion of startup applicant firms may instead reduce the influence of idiosyncratic judge-

[27] For example, prior studies suggest that female entrepreneurs may be at a greater disadvantage to male entrepreneurs during in-person interviews compared to other VC judging environments due to the differing tone and substantive focus of interviewer questions (e.g., Kanze, Huang, Conley, and Higgins, 2018) as well as expected adherence to certain gender stereotypes (e.g., Bordalo, Coffman, Gennaioli, and Shleifer, 2019; Hu and Ma, 2022).

founder affinity biases by re-directing VC employees' attention towards more objective datapoints and issues that are directly relevant for the startup's business model. For example, a nascent stream of experimental research suggests that group decision-making is less likely to be influenced by behavioral biases, cognitive limitations, and social considerations than individual decision-making (see e.g., Charness and Sutter, 2012; and Maciejovsky, Sutter, Budescu, and Bernau, 2013).

3.5.1 Baseline specification and results

To test for the prevalence of judge-founder affinity-based preferences in our VC firm's first round and second round interview stages, we re-run the same specification as in Equation (1) but instead use either first-round interview scores (see Table 4) or second-round interview scores (see Table 5) as the dependent variable. Interestingly, all the coefficients on *Shared gender*, *Shared ethnicity*, *Shared education*, and *Shared employer*, are now statistically insignificant in both the first round and second round interview phases. This result holds even in the sub-sample of cases where the focal judge in the first or second round stage also evaluated the same startup in the pre-interview stage (see Column 3), meaning that changes in the composition of the VC judge pool is unlikely to explain the differential impact of judge-founder affinity traits across interview stages.[28]

This result implies that the group interview and post-interview discussion process among VC employees appears to have a positive impact on the integrity and "fairness" of the VC selection process, namely by helping to mitigate any undue influence of any judge-founder affinity-based preferences on individual judging scores. For example, consistent with our anecdotal discussions with our VC firm's employees, individual judges seem to appreciate hearing other perspectives on the strengths and weaknesses of each applicant firm and appear to understand the value of having

[28] Our results in Tables 4 and 5 are also unlikely to be explained by a reduction in test power compared to Table 3 given that we still utilize 3,401 first round and 1,663 second round judge score observations, respectively, and that the number of judges per applicant firm in later in-person interview stages remains similar to the pre-interview stage.

to articulate and justify their key conclusions to their colleagues in a dynamic feedback setting.[29] Our results also point more generally to the potential benefits of a collaborative, team-based evaluation process relative to a more 'siloed', individual decision-making process.

3.5.2 Alternative specification controlling for a judge's prior scores for the same applicant

When seeking to understand the drivers of an individual VC judge's first and second round interview scores for a given applicant, it is natural to assume that these later evaluations will be significantly influenced by the focal judge's earlier scores for the same startup applicant in the previous pre-interview phase.[30] However, it is an important and open empirical question as to how much VC firm employees are willing and able to update their assessments on startup firm potential based on additional (dynamic) interactions with startup firm founders and their VC firm colleagues. In other words, how much do "first impressions count" during the internal VC selection process?

As such, we run the following alternative OLS specification where we only include the first or second round interview scores of judges who also participated in the pre-interview evaluation process for the same startup firm applicant. For example,

$$\begin{aligned} First\ round\ interview\ score_{i-j,c} = \alpha + \beta_1 Preinterview\ overall\ score_{i-j,c} \\ + \beta_2 Shared\ gender_{i-j} + \beta_3 Shared\ ethnicity_{i-j} \\ + \beta_4 Shared\ education_{i-j} + \beta_5 Shared\ employer_{i-j} \\ + \beta_6 Preinterview\ overall\ score_{i-j,c} \times Shared\ gender_{i-j} \\ + \beta_7 Preinterview\ overall\ score_{i-j,c} \times Shared\ ethnicity_{i-j} \\ + \beta_8 Preinterview\ overall\ score_{i-j,c} \times Shared\ education_{i-j} \end{aligned} \tag{2}$$

[29] For example, individuals may be encouraged to focus on more "fundamental" business-relevant factors rather than (potentially extraneous) personal characteristics of startup founders, consistent with experimental evidence on the superior performance of teams in strategic laboratory games compared to individuals: see, for example, Laughlin, Bonner, and Miner (2002); Cooper and Kagel (2005); and Feri, Irlenbusch, and Sutter (2010).

[30] This is analogous to a Bayesian-like framework where the focal judge forms an initial view about the startup firm's potential (as expressed in their overall pre-interview scores) and then updates this prior as new information is procured during the VC firm's entire interview process (see generally, Bhuller and Sigstad, 2024).

$$
\begin{aligned}
&+ \beta_9 Preinterview\ overall\ score_{i-j,c} \times Shared\ employer_{i-j} \\
&+ \beta_5 All\ Female\ founder\ team_{i,c} + \beta_6 All\ Black\ founder\ team_{i,c} \\
&+ \beta_7 All\ Hispanic\ founder\ team_{i,c} + \delta Startup\ firm\ controls_{i,c} \\
&+ \theta Startup\ founding\ team\ controls_{i,c} + \gamma Judge\ controls_{j,c} \\
&+ \varphi Other\ judge - founder\ overlapping\ characteristics_{i-j} \\
&+ Judge\ FEs_j + Startup\ firm\ FEs_i + Cohort\ FEs_c + \varepsilon_{ij,c}
\end{aligned}
$$

The dependent variable is equal to the $First\ round\ interview\ score_{i-j,c}$ given by judge j to startup firm i in cohort c. $Preinterview\ overall\ score_{i-j,c}$ is equal to the overall score given by judge j to the *same* startup firm i during the preceding pre-interview evaluation phase in cohort c. As such, the coefficient β_1 captures the extent to which judge j updates their initial assessment of startup firm i after participating in the (group-based) first round interview process.

As before, we include the variables *Shared gender*, *Shared ethnicity*, *Shared education*, and *Shared employer*, respectively, which capture measures of potential affinity between individual judges and applicant firm founders. When these affinity-based traits are included in conjunction with the focal judge's prior pre-interview score for that particular startup, these coefficients will indicate whether the focal judge is more or less likely to grant a higher score after the first round interview and group discussion process if they share certain personal traits with that startup founder team (above and beyond any affinity-based biases captured in that judge's pre-interview score).

Furthermore, we also include the interaction of *Pre-interview overall score* and each of these four affinity-based variables. The coefficients on these interaction terms will indicate whether a judge is relatively more or less likely to revise their initial assessment of the focal startup firm after the first round interview process if they share certain personal traits with that startup founder team.

We also include *All Female founder team*, *All Black founder team*, and *All Hispanic founder team* as well as incorporate several additional controls for various observable startup firm, startup founding team, and VC judge characteristics in combination with other overlapping judge-founder characteristics as well as *Judge fixed effects*, *Startup firm fixed effects*, and *Cohort fixed effects*.

We present the results of this alternative specification in Table 6 where we provide several novel insights about the internal VC selection process. First, we show that, while a judge's initial per-interview assessment of a startup clearly has a persistent impact on that judge's first and second round scores for that same applicant, our VC firm's judges are surprisingly open to revising their personal assessment of a startup firm's potential after being given the opportunity to dynamically interact with both the startup firm's founders and their VC firm colleagues. In terms of economic significance, our estimates imply that VC judges will on average submit first round interview scores that are 15–25% different from their own pre-interview score for the same applicant. This suggests that dynamic interviews with startup founders and group discussions with VC firm colleagues play a critical role in shaping a VC employee's finalized assessment of a startup firm's quality/potential.

Second, we find that individual judges are relatively more likely to downwardly revise their assessment of a startup applicant's potential between the pre-interview and first round interview stages if that judge shares an affinity-based trait with the applicant's founder team. In other words, it appears that a judge's first round interview score for a startup firm applicant is more likely to revised downward if that judge had a relatively high pre-interview score for that same startup *and* they also shared a potential affinity-related trait with the startup's founder team. This implies that judges are relatively more likely to revise or update their priors about a startup applicant if that judge is relatively more likely to have formulated an (upwardly biased) initial assessment at the pre-interview stage for that startup firm applicant with whom the judge shares certain affinity-based traits. This result also suggests that interactive meetings with startup firm founders and group discussions with other VC colleagues about their respective startup assessments can help to somewhat "undo" the potentially distortive effect of shared judge-founder affinity-based characteristics on individual pre-interview scores in more isolated, 'solo judge' settings.

4. VC–STARTUP FINANCIAL CONTRACTING

In this section, we examine the key features of a new type of financial contracting instrument for early-stage venture investments (collectively referred to as "deferred equity agreements") and study the most important factors that determine how contract terms are set under these agreements.

4.1 Background and structure of deferred equity agreements

Up until about ten years ago, convertible (promissory) notes were the most common financial contracting instrument used for 'non-priced' startup financing rounds, where these 'non-priced' rounds most typically occur at the seed funding stage. Convertible notes have features of both debt (i.e., a contractually specified interest rate, a maturity date after which the investor can demand repayment etc.) and equity (i.e., the note investor has the right to convert their accrued investment into shares of the startup firm at a later point in time etc.). As justified by various theory models, these convertible notes were quite popular because they allowed investors the opportunity to retain equity upside in the startup while avoiding sensitive issues surrounding how to assign a specific valuation to very early-stage companies.

Crucially, however, there has been a recent innovation in startup funding markets where convertible notes have been increasingly replaced by a new type of financial contract known as "deferred equity agreements." The first such deferred equity instrument, known as a Simple Agreement for Future Equity (SAFE), was introduced by the VC-backed accelerator Y Combinator in 2013. This was followed one year later by the Keep It Simple Security (KISS) contract that was developed by the VC-backed accelerator 500 Startups. The key principle of these deferred equity agreements is that the investor immediately provides funds to the startup in return for the promise of receiving shares in the startup firm at some future point in time, with the price paid by the SAFE/ KISS investor dependent on the terms of a future priced financing round. This differs from a typical equity purchase where the investor provides funding today in return for shares today.

While we outline more extensively the similarities and differences in convertible notes versus deferred equity agreements in Internet Appendix IA.2, there are two very important features of SAFE/KISS contracts. First, unlike convertible notes, there are no debt obligations associated with SAFE or KISS contracts (i.e., no interest charges, no repayment deadlines etc.). Second, the number of shares received by the SAFE or KISS investor in the future is equal to the investment amount divided by the contract's 'conversion price'. This 'conversion price' is equal to the *lower* of two prices, namely: (1) the 'discount price' which equals the price paid by investors in a later priced round multiplied by (1 – discount rate), and (2) the 'capped price' which equals the maximum dollar price that the SAFE or KISS investor will effectively pay for shares in the startup firm, computed as the 'valuation cap' listed in the contract divided by fully diluted shares outstanding.[31]

According to practitioners, the primary reason for the rapid adoption of SAFE/KISS contracts for early-stage financing rounds is that they are much simpler, faster, and cheaper to negotiate compared to other contracting mechanisms, especially priced preferred stock financing instruments. This is because SAFE and KISS agreements are relatively short 'standard form contracts' that eliminate the loan-like structure underlying convertible notes, thus leaving a very limited set of contract terms requiring any negotiation prior to execution.

4.2 Empirical facts concerning deferred equity agreements

While it is estimated that the percentage of recent seed financing rounds that use SAFE/KISS contracts is over 80% and is growing rapidly, both practitioners and researchers appear to be

[31] In Internet Appendix IA.3, we provide a numerical illustration of how deferred equity agreements operate.

operating in an "empirical black hole" because of how little startup market participants seem to know about how these deferred equity agreements are used and negotiated in practice (Coyle and Green, 2018). This is simply because of the inability of prior researchers to access a sufficiently large set of signed SAFE/KISS contracts in their entirely. Therefore, as an initial starting point, we seek to provide a set of empirical facts about our unique sample of 120 SAFE/KISS contracts (comprising 104 KISS and 16 SAFE contracts) that we and other researchers can build upon (see Table 1 – Panel D for additional details).

First, we observe that, within each accelerator cohort, the only term that significantly differs across accepted portfolio firms is the valuation cap (which in turn dictates the maximum dollar price that the deferred equity investor will effectively pay for their shares in the startup firm).[32] This is consistent with the motivation and design of these standard form contracts to minimize the number of contract terms that require substantive negotiation by the parties. As such, under modern SAFE/KISS funding contracts, the only relevant term in practice that is actively negotiated between startup firms and their investors is the valuation cap.[33] Therefore, our subsequent analysis focuses exclusively on understanding how these valuation caps are determined.

Second, another interesting aspect of our confidential dataset is that every startup applicant that is invited to submit a due diligence package will be required to answer the question "what is the current valuation of your company?" Crucially, if one compares the current valuation provided by the startup firm with the final valuation cap in the signed KISS and SAFE contract for that firm, it becomes immediately apparent that a startup firm's current valuation at the time of application

[32] Note that even for the discount rate, the standard industry convention (which appears to be followed by our VC firm and its contractual counterparties) is that the discount rate in a SAFE or KISS contract is set at 20%.

[33] It should be noted that while the SAFE agreements signed by our VC firm between 2017 and 2019 set the conversion price equal to the lower of the 'capped price' and the 'discount price' (with an industry standard discount rate of 20%), more recent versions of SAFE contracts do not even include a discount price mechanism at all. As such, the conversion price under some more recent SAFE contract formulations is entirely dependent on the negotiated valuation cap (see Y Combinator's "Valuation Cap, No Discount" standard form template at: https://www.ycombinator.com/documents).

is a very important anchor or reference point for setting contractual valuation caps. In particular, the median cap-to-current valuation ratio of each portfolio firm in our sample is approximately one. We explore the implications of this very close relationship in our subsequent empirical analysis.

4.3 Empirical methodology and theoretical predictions

To further analyze the setting of valuation caps in deferred equity agreements (which is usually the only item for negotiation between portfolio firms and their VC investors), we use a simple OLS regression framework where our dependent variable is the natural logarithm of the agreed valuation cap in our sample of signed SAFE/KISS contracts:

$$\begin{aligned} Valuation\ cap_i = \alpha &+ \beta_1 Startup\ firm's\ current\ valuation_i \\ &+ \beta_2 Mean\ of\ firm's\ second\ round\ interview\ judging\ scores_i \\ &+ \beta_3 Startup\ firm's\ runway_{i,c} + \delta Startup\ firm\ controls_{i,c} \\ &+ \theta Startup\ founding\ team\ controls_{i,c} + Cohort\ FEs_c + \varepsilon_{i,c} \end{aligned} \tag{3}$$

Where *Startup firm controls* and *Startup founding team controls* includes the same control variables as those used in Equation (1) in Section 3.2,[34] along with *Cohort fixed effects* to ensure that all contract comparisons are occurring at the same point in time (as well as with the same VC investor counter-party).

As discussed previously, our first independent variable of interest is the natural logarithm of the startup firm's current valuation which appears to be a critical 'anchor' or 'reference point' in valuation cap negotiations between our VC firm investor and its portfolio companies.

Our second key independent variable of interest is the mean of the second round judging scores given to each eventually accepted accelerator applicant, where higher judging scores

[34] Although the consensus second round interview judging scores are supposed to incorporate all relevant information on startup firm characteristics and startup founding team traits, we nevertheless run a regression specification including these additional control variables for robustness purposes.

indicate a higher internal assessment of the startup's firm quality and potential by our VC firm.[35] Interestingly, in a double moral hazard setting where both the entrepreneur and accelerator must exert costly (unobservable) effort to influence project success, there are two competing effects on accelerator profits when setting valuation caps with reference to perceived startup firm quality (see Internet Appendix IA.4 for a theoretical model outlining the relevant setup and trade-offs involved).

On the one hand, the 'direct effect' is that a lower valuation cap leads to a lower conversion price which in turn leads to an increase in the amount of shares and profits earned by the accelerator. On the other hand, however, the countervailing 'indirect effect' is that a lower valuation cap leads to a decrease in the entrepreneur's incentives to exert effort. This reduced motivation for the firm's founders will thus likely decrease the probability of the firm raising a future priced financing round.

While it is ultimately an empirical question as to which effect dominates, if we assume that effort and startup firm quality type are complements in production, then higher type entrepreneurs will work relatively more, thus marginally boosting accelerator profits by a greater amount for these high type entrepreneurs. This in turn leads to the predication that the indirect effect on entrepreneur incentives outweighs the direct effect of higher valuation caps such that:

Prediction 1: A VC firm's higher internal assessment of startup firm quality (as reflected through higher average second round interview judging scores) leads to the negotiation and finalization of higher valuation caps.

Our third key independent variable of interest concerns whether accepted startup applicants that are facing a greater degree of financial constraints are more likely to receive less favorable financing terms (in the form of lower valuation caps). While it is quite intuitive to believe that startup firms facing greater financial constraints are likely to have lower bargaining power vis-à-

[35] As discussed in Section 2, internal judging score results are never revealed to any accepted or rejected applicants.

vis VC investors, attempts to directly measure the degree of financial constraints faced by a given firm is often extremely difficult, especially for private companies.

However, one important feature of our research setting and confidential dataset is that one of the due diligence questions explicitly asked to applicant firms is “how many months can the business continue to operate before your existing cash reserves are exhausted?” (otherwise known as the amount of “runway” that the startup has before it must raise a new funding round). As such, following Malmendier and Lerner (2010), we use a startup firm’s runway as a direct measure of how financially constrained is the focal startup firm and predict that:

Prediction 2: The greater the amount of runway that a startup firm possesses, the higher the negotiated valuation cap.

4.4 Advantages of our research setting when studying startup financial contracting outcomes

There are several unique advantages of our research setting that allow us to estimate more precisely the relative importance of various factors in driving VC-startup financial contracting outcomes. First, due to the standard form nature of SAFE and KISS contracts, there is only one item for negotiation between the entrepreneurial firm and the startup investor, namely the amount of the valuation cap. This is quite advantageous because it can be quite difficult in other more complicated financial contracting settings (for example, preferred stock issuances) to: (a) identify and collect data for all relevant contract terms and (b) understand the multi-dimensional trade-offs between different contract terms.

Second, all accepted applicants within each accelerator cohort in our sample will always negotiate with the same VC investor counter-party under the same prevailing market conditions. As such, we do not suffer from some of the confounding issues faced by other prior papers that are forced to compare contractual outcomes involving different VC investors who are engaging with different startup firms at different points in time.

Third, a critical issue faced by empirical researchers when studying the effect of firm financial constraints on various corporate outcomes is that it is usually very difficult to disentangle how much of the observed poor performance is due to financial constraints themselves and how much is due to other (endogenous) factors, such as the focal firm's lower unobservable quality causing both the poor operating performance and greater financial difficulties. In contrast, we can separately and directly measure an investor's perception of startup firm quality and suitability for our VC's accelerator program (through consensus second round interview judging scores) as distinct from the level of financial constraints faced by our VC's portfolio firms (as captured through each startup firm's cash runway measure).

4.4 Empirical results relating to VC-startup financial contracting

In Table 7, we first confirm that a startup firm's current valuation is a very important reference point in setting valuation caps in SAFE and KISS contracts. We discuss the important implications of this apparently widespread practice in entrepreneurial financial contracting in Section 5.3.

Second, consistent with the predictions of "double moral hazard" financial contracting models, we show that the level of the agreed valuation cap increases in entrepreneurial firm quality type. This implies that VC investors are willing to concede relatively more cash flow rights to high quality startup firms in order to appropriately incentivize firm founders to work with their VC investors in order to maximize startup firm value.

Finally, we show that startup firms that are less financially constrained (i.e., firms that have more cash 'runway') are, all else being equal, more likely to negotiate higher valuation caps relative to otherwise similar peers who are more financially constrained. To express this in economic terms, our estimates imply that startups suffer a 2% reduction in their negotiated valuation cap for each 1 month decrease in their available cash runway. This means that financially constrained firms face a meaningful and costly reduction in their relative bargaining power when it comes to valuation cap negotiations with sophisticated startup investors.

5. DISCUSSION OF RESULTS

In this section, we discuss three important points regarding the implications of our empirical analysis. First, we examine the external validity of our results. Second, we explore whether the observed influence of shared judge-founder affinity-based traits on the startup evaluation process stems from behavioral biases or rational information-based beliefs. Third, we consider the potential implications that may arise from the apparently common practice of setting valuation caps in SAFE and KISS contracts approximately equal to the startup firm's current (pre-money) valuation.

5.1 External validity

Despite the numerous advantages of our confidential dataset, it is reasonable to consider the extent to which our research setting, and its associated findings, can generalize to other investment-related settings, from accelerators more specifically to (early-stage) venture capital investors more generally. We examine this question of external validity from two perspectives.

First, in terms of the VC investment firm that forms the basis of our analysis, we claim that the internal practices and the observed outcomes of our focal VC firm are reasonably representative of other reputable VC investors in this investment space. With respect to the VC internal decision-making process, we first note that our VC firm's multi-step, group-focused evaluation of each investment opportunity is quite similar to the typical decision-making approach of other VC investors (e.g., Gompers et al., 2020).[36] Furthermore, our VC firm's key criteria for selecting portfolio firms for its accelerator (i.e., the quality of the startup's management team, the potential of the applicant's product/service, and the startup's level of traction/customer engagement garnered to date) aligns with existing survey and experimental evidence finding that other VC investors (including early-stage focused funds) also emphasize the critical importance of the startup's management team, business model, and core product/technology in selecting investments (Bernstein et al., 2017; Gompers et al., 2020).[37]

With respect to observed outcomes, our focal VC firm is widely recognized as one of the most prolific and accomplished seed investors in the United States. For example, a 2021 Beta Boom study of over 3,000 accelerators worldwide found that our sample VC firm ranked in the top 5% in terms of exit performance (Paluch, 2021), while the average fund internal rate of return (IRR) through to the end of 2024 is in excess of 25%. While our focal VC firm does appear to exhibit above-average return performance (particularly amongst earlier-stage investment funds), we argue that any bias that we have towards studying the selection and contracting outcomes of a relatively successful private accelerator program is helpful because we are more likely to identify the underlying methods and practices of relatively sophisticated, value-maximizing startup investors.

Second, in terms of the startup companies that participate in our VC-backed accelerator's selection and contracting process, we argue that the set of startup companies considered by our VC firm are broadly representative of the universe of entrepreneurial companies seeking early-stage investment funding. While obtaining comparable and comprehensive information on accelerator

[36] This is particularly true as it pertains to for-profit accelerator programs, where our VC firm's screening and selection process closely aligns with standard industry practice (see e.g., Yu, 2020).
[37] Interestingly, however, our VC firm does appear to place relatively less weight on the importance of the startup's management team when selecting portfolio investments compared to other early-stage VC investors (see e.g., Jang and Kaplan, 2023). This may help to explain why our VC firm exhibits relatively strong ex post return performance.

applicants is extremely challenging (especially for VC-backed accelerator programs), the Global Accelerator Learning Initiative's (GALI) Entrepreneurship Database Program provides some useful summary statistics about the types of startup companies that typically apply to business accelerators.[38] Importantly, the average age (2.6 years), the average number of full-time equivalent (FTE) employees (3.1), the average revenue ($78,230), and the average amount of equity financing raised ($45,698) by applicants to our VC-backed accelerator program is comparable to the mean figures reported in the full sample of applicants in the GALI Entrepreneurship Database (2.7 years, 3.3 FTE employees, revenues of $70,109, and equity financing of $43,906, respectively).[39] In addition, our VC firm considers all early-stage startup companies irrespective of location and industry because our VC firm is not geographically or industry restricted in its investment mandate.

Therefore, based on the observable characteristics of our VC firm and the profile of applicants to our VC-backed accelerator program, we argue that our empirical analysis is highly relevant for understanding the portfolio selection and contracting decisions of early-stage VC investment funds (especially within a private seed accelerator context).[40]

5.2 Explanation for role of affinity-based traits in judging process

Given our combined results, a reasonable question to ask is whether the systematically higher pre-interview scores awarded to startup applicants whose founders share the same gender, ethnicity, or university background as the focal judge is due to a rational 'information-based' explanation or

[38] Through a joint collaboration between Emory University and the Aspen Network of Development Entrepreneurs (ANDE), this database is based on information from over 23,000 startups applying to over 300 accelerator programs worldwide that operated between 2013 and 2019.

[39] Although our sample of startups may display slightly more advanced development in terms of revenue and equity funding raised, it should be noted that the GALI Database includes data from not-for-profit accelerator organizations that generally consider even earlier-stage applicants than those typically considered by for-profit accelerators.

[40] Nevertheless, regardless of the similarities between our VC-backed accelerator program and other early-stage investment vehicles, we acknowledge that each early-stage startup investor will have their own unique characteristics (for example with respect to internal processes, geographic/industry focus, and portfolio firm outcomes) that may somewhat affect the generalizability of our findings to other related investment contexts.

a ‘homophily-based’ preferential bias. On the one hand, it is possible that judge-founder affinity-based ties provide ‘affiliated’ VC judges with informative signals about the startup founders’ underlying quality and facilitate greater information flow between VCs and entrepreneurs during the VC portfolio firm selection process (see generally, Garfinkel et al., 2024). On the other hand, it is plausible that judges have a preference (consciously or unconsciously) to work with others who share similar personal traits or that judges hold an innate belief/prior that startup founders with similar backgrounds to the focal judge have higher intrinsic quality or potential, thus (positively) biasing that judge’s evaluation of the startup applicant firm (see Ewens, 2023).

While it is difficult to conclusively distinguish between these two theories in our research setting (for example, because our VC firm aggregates individual assessments to make collective final investment decisions), we argue that our evidence is more consistent with the latter ‘homophily-based’ explanation. First, in our VC firm’s pre-interview stage judging process, there is no dynamic interaction or communication between individual judges and startup firm founders, meaning that it is impossible for confidential new information to flow between a ‘connected’ judge and a startup founder to assist with the focal judge’s pre-interview assessment. As such, private information flows are unlikely to explain the large and persistent differences in pre-interview scoring between ‘affiliated’ and ‘unaffiliated’ judges.

Second, all our regression estimates with respect to judge-founder affinity-based preferences are conditional on a wide variety of ‘fundamental’ firm and founder characteristics (including educational experience at a top-tier university) as well as startup firm, VC judge, and time fixed effects. Furthermore, we also explicitly control for other judge–founder overlapping characteristics that arguably capture elements of a judge having more information about the underlying quality of the startup firm and its founders (for example, both the startup founder and the VC judge having a graduate degree and/or both graduating from a top university) and yet we still see a significant incremental effect of affinity-based traits on individual judging scores. As such, any additional information revealed by shared gender, ethnicity, or university education between a VC judge and a founder must be orthogonal to these observable characteristics.

Finally, if a judge did have meaningful "inside" information on a startup firm applicant due to their overlapping personal characteristics with the startup's founders, then an 'affiliated' judge's more positive startup evaluation relative to their peers should continue to persist beyond the pre-interview stage into the first and second round interview phases. However, we find in Table 6 that 'affiliated' judges are instead more likely to *downwardly* revise their first round interview scores relative to their pre-interview scores as compared to 'unaffiliated' judging colleagues. This pattern is again inconsistent with a pure rational and enduring information-based explanation.

5.3 Implications of anchoring on current startup valuation in deferred equity agreements

As suggested from our univariate analysis in Table 1 and subsequently confirmed by our OLS regressions reported in Table 7, we show that a startup firm's current (pre-money) valuation is a very important reference point in setting valuation caps in SAFE and KISS contracts. In fact, we find that over half of the SAFE/KISS contracts in our sample set the valuation cap exactly equal to the portfolio firm's stated current valuation at the time of initial application.

This is a critical empirical observation for both theoretical researchers and practitioners because one of the key justifications given for these deferred equity agreements is that they are supposed to delay any problematic pricing questions until later financing rounds when the startup firm is more mature. However, if valuation caps are regularly set at or below a firm's current valuation, this implies that a firm's valuation does not need to increase by too much (approximately

25%) after contract signing before the valuation cap 'binds' and thus sets the SAFE/KISS conversion price in the next financing round.

As a result, this observed practice seems to somewhat undermine the argument that seed funding rounds involving deferred equity agreements are not "priced" rounds and raises interesting strategic questions as to when and how much an entrepreneur should seek in a subsequent (priced) Series A funding round. For example, it may be optimal, all else being equal, for an entrepreneur to undertake a new financing round as soon as the startup firm's equity value per share is equal to the maximum capped price under the seed round SAFE/KISS contract. This is because a disproportionate share of the benefits of any incremental effort on the part of the entrepreneur will accrue to the SAFE/KISS investor rather than the entrepreneur.[41]

$$\begin{aligned} Series\ A\ outcome_i = {} & \alpha + \beta_1 Startup\ firm's\ valuation\ cap_i \\ & + \beta_2 Mean\ of\ firm's\ second\ round\ interview\ judging\ scores_i \\ & + \beta_3 Startup\ firm's\ runway_{i,c} + \ \delta Startup\ firm\ controls_{i,c} \\ & + \theta Startup\ founding\ team\ controls_{i,c} + Cohort\ FEs_c + \varepsilon_{i,c} \end{aligned} \tag{4}$$

Where the $Series\ A\ outcome_i$ variables of interest are either *Length of time until Series A round*, defined as the number of months between the signing of the KISS/SAFE contract with our VC firm and the closing of a subsequent Series A financing round by the focal portfolio firm, and *Size of the subsequent Series A round* (expressed as the natural logarithm of the Series A investment amount in absolute dollars). *Startup firm controls* and *Startup founding team controls* includes the same control variables as those used in Equation (1) in Section 3.2 along with *Cohort fixed effects*

[41] Alternatively, however, it is also possible that VC financiers will be more incentivized under such SAFE/KISS contracting terms to exert effort and to share their valuable knowledge and resources with portfolio firms in order to promote long-term startup firm growth and development for the benefit of both contracting parties.

to ensure that all contract comparisons are occurring at the same point in time (as well as with the same VC investor counter-party).

Consistent with this theory, we show in Column (1) of Table 8 that the *Length of time until Series A round*, defined as the number of months between the signing of the KISS/SAFE contract with our VC firm and the closing of a subsequent Series A financing round by the focal portfolio firm, is significantly shorter for portfolio firms that have lower valuation caps (in absolute terms). Furthermore, in Column (2) of Table 8, we find that the *Size of the subsequent Series A round* (in absolute dollar terms) is significantly lower for portfolio firms that have lower valuation caps. This observed phenomenon is consistent with the notion that entrepreneurs financed by SAFE/KISS contracts with relatively low valuation caps may choose to delay raising large amounts of capital until later financing rounds, thus (hopefully) reducing the founders' ownership stake dilution.

Nevertheless, we leave these and other interesting questions regarding these new financial contracting instruments to future research to assess from a theoretical and an empirical perspective.

6. CONCLUSION

Given that venture capital firms are one of the most important sources of funding for aspiring entrepreneurs in the modern knowledge economy, understanding the inner workings of the VC decision-making process remains a critical question for academics, practitioners, and policymakers. However, research on this essential topic remains scarce due to fundamental issues associated with data availability, measurement error, and omitted variable bias. To overcome these pervasive problems, we use a confidential accelerator dataset provided by a prominent U.S. based VC firm to open the black box of VC portfolio firm selection and VC-startup financial contracting.

We first offer novel evidence that at least part of the substantial heterogeneity that we observe in individual judging scores submitted by our VC firm's employees for the same startup applicant can be explained by significant judge-founder affinity biases, which are especially prevalent in solo judge settings where there is a high amount of ambiguity about the startup's potential. However, our empirical results suggest that encouraging judges to interact with each other can at least mitigate such individual biases, thus providing support for the common use of judging panels and other dynamic group judging arrangements in competitive award settings.

We then present novel evidence on the key dynamics governing the negotiation of a new type of financial contracting instrument known as deferred equity agreements. Specifically, we highlight the profound influence of 'reference points' like a portfolio firm's pre-money valuation, an investor's perception of underlying portfolio firm quality, and the degree of financial constraints faced by the portfolio firm in competitive bargaining situations. As a result, our results offer unprecedented insight into the complex mix of private information (both fundamental and behavioural) utilized in "behind the scenes" negotiations between VCs and startups that act as critical determinants of observed financial contracting outcomes.

REFERENCES

Acemoglu, D., Akcigit, U., Alp, H., Bloom, N., and W. Kerr. 2018. Innovation, reallocation, and growth. *American Economic Review* 108(11): 3450–3491.

Bapna, S., and M. Ganco. 2021. Gender gaps in equity crowdfunding: Evidence from a randomized field experiment. *Management Science* 67(5): 2679–2710.

Bengtsson, O. 2011. Covenants in venture capital contracts. *Management Science* 57: 1926–1943.

Bernstein, S., Giroud, X., and R. Townsend. 2016. The impact of venture capital monitoring. *Journal of Finance* 71(4): 1591–1622.

Bernstein, S., Korteweg, A., and K. Laws. 2017. Attracting early-stage investors: evidence from a randomized field experiment. *Journal of Finance* 72(2): 509–538.

Bertrand, M., and E. Duflo. 2017. Field experiments on discrimination. In *Handbook of Economic Field Experiments*. Vol 1, ed. Banerjee, A., and E. Duflo, pp. 309–393. Elsevier: Amsterdam.

Bhuller, M., and H. Sigstad. 2024. Feedback and Learning: The Causal Effects of Reversals on Judicial Decision-Making. *Review of Economic Studies*, forthcoming.

Bordalo, P., Coffman, K., Gennaioli, N., and A. Shleifer. 2019. Beliefs about gender. *American Economic Review* 109: 739–773.

Calder-Wang, S., and P. Gompers. 2021. And the Children Shall Lead: Gender Diversity and Performance in Venture Capital. *Journal of Financial Economics* 142: 1–22.

Calder-Wang, S., Gompers, P., and K. Huang. 2023. Diversity and Performance in Entrepreneurial Teams. Working Paper, Harvard Business School.

Casamatta, C. 2003. Financing and advising: Optimal financial contracts with venture capitalists. *Journal of Finance* 58(5): 2059–2085.

Cassel, J., Lerner, J., and E. Yimfor. 2024. Racial diversity in private capital fundraising. Working Paper, National Bureau of Economic Research.

Charness, G., and M. Sutter. 2012. Groups Make Better Self-Interested Decisions. *Journal of Economic Perspectives* 26(3): 157–176.

Cohen, S., Fehder, D., Hochberg, Y., and F. Murray. 2019. The design of startup accelerators. *Research Policy* 48(7): 1781–1797.

Cook, L., Marx, M., and E. Yimfor. 2023. Funding black high-growth startups. Working Paper, Columbia University.

Cooper, D., and J. Kagel. 2005. Are Two Heads Better than One? Team versus Individual Play in Signalling Games. *American Economic Review* 95(3): 477–509.

Cornelli, F., and O. Yosha. 2003. Stage financing and the role of convertible securities. *Review of Economic Studies* 70: 1–32.

Da, Z., and X. Huang. 2020. Harnessing the Wisdom of Crowds. *Management Science* 66(5): 1847–1867.

Da Rin, M., Hellmann, T., and M. Puri. 2013. A survey of venture capital research. In *Handbook of the Economics of Finance*. Vol 2A: Corporate Finance, ed. Constantinides, G. Harris. M., and R. Stulz, pp. 537–638. Elsevier: Amsterdam.

Decker, R., Haltiwanger, J., Jarmin, R., and J. Miranda. 2014. The role of entrepreneurship in US job creation and economic dynamism. *Journal of Economic Perspectives* 28(3): 3–24.

Ewens, M., and R. Townsend. 2020. Are early stage investors biased against women? *Journal of Financial Economics* 135(3): 653–677.

Fairle, R., Robb, A., and D. Robinson. 2022. Black and white: Access to capital among minority-owned start-ups. *Management Science* 68(4): 2377–2400.

Feri, F., Irlenbusch, B., and M. Sutter. 2010. Efficiency Gains from Team-Based Coordination – Large-scale Experimental Evidence. *American Economic Review* 100(4): 1892–1912.

Frame, S., Huang, R., Mayer, E., and A. Sunderam. 2023. The impact of minority representation at mortgage lenders. *Journal of Finance*, forthcoming.

Garfinkel, J., Mayer, E., Strebulaev, I., and E. Yimfor. 2024. Alumni networks in venture capital financing. Working Paper, University of Wisconsin-Madison.

Gompers, P., Gornall, W., Kaplan, S., and I. Strebulaev. 2020. How do venture capitalists make decisions? *Journal of Financial Economics* 135: 169–190.

Gompers, P., and J. Lerner. 2001. *The money of invention: how venture capital creates new wealth*. Cambridge, MA: Harvard Business School Press.

Gompers, P., Murharlyamov, V., and Y. Xuan. 2016. The Cost of Friendship. *Journal of Financial Economics* 119(3): 626–644.

Gonzalez-Uribe, J., and M. Leatherbee. 2018. The effects of business accelerators on venture performance: Evidence from Start-Up Chile. *Review of Financial Studies* 31(4): 1566–1603.

Gonzalez-Uribe, J., Klinger-Vidra, R., Wang, S., and X. Yin. 2023. Reducing entrepreneurial capability constraints: The broader role of venture capital due diligence. Working Paper, London School of Economics.

Gornall, W., and I. Strebulaev. 2022. Gender, race, and entrepreneurship: A randomized field experiment on venture capitalists and angels. *Management Science*, forthcoming.

Hall, B., and J. Lerner. 2010. The financing of R&D and innovation. In *Handbook of the Economics of Innovation*, ed. Hall, B., and N. Rosenberg, pp. 609–639. Amsterdam: Elsevier.

Hall, R., and S. Woodward. 2010. The burden of the non-diversifiable risk of entrepreneurship. *American Economic Review* 100(3): 1163–1194.

Hedge, D., and J. Tumlinson. 2014. Does social proximity enhance business partnerships? Theory and evidence from ethnicity's role in U.S. venture capital. *Management Science* 60(9): 2355–2380.

Hellmann, T. 2006. IPOs, acquisitions, and the use of convertible securities in venture capital. *Journal of Financial Economics* 81: 649–679.

Hodor, I. 2021. Financing innovation with future equity. Working Paper, Monash University.

Howell, S. 2020. Reducing information frictions in venture capital: The role of new venture competitions. *Journal of Financial Economics* 136(3): 676–694.

Howell, S. 2021. Learning from feedback: Evidence from new ventures. *Review of Finance* 25(3): 595–627.

Howell, S., Rathje, J., Van Reenen, J., and J. Wong. 2023. Opening up military innovation: Causal effects of 'bottom-up' reforms to U.S. defense research. Working Paper, New York University.

Hsu, D. 2004. What do entrepreneurs pay for venture capital affiliation? *Journal of Finance* 59(4): 1805–1844.

Hu, A., and S. Ma. 2022. Persuading investors: A video-based study. Working Paper, Yale University.

Huang, C. 2023. Networks in venture capital markets. Working Paper, University of Illinois.

Huang, R., Mayer, E., and D. Miller. 2024. Gender bias in promotions: Evidence from financial institutions. *Review of Financial Studies* 37: 1685–1728.

Ishii, J., and Y. Xuan. 2014. Acquirer-Target Social Ties and Merger Outcomes. *Journal of Financial Economics* 112: 344–363.

Jang, Y.S., and S. Kaplan. 2023. Venture capital start-up selection. Working Paper, University of Chicago.

Kanze, D., Huang, L., Conley, M., and T. Higgins. 2018. We Ask Men to Win & Women Not to Lose: Closing the Gender Gap in Startup Funding. *Academy of Management Journal* 61(2): 586–614.

Kaplan, S., and P. Strömberg. 2003. Financial contracting theory meets the real world: An empirical analysis of venture capital contracts. *Review of Economic Studies* 70: 281–315.

Kaplan, S., and P. Strömberg. 2004. Characteristics, contracts, and actions: Evidence from venture capitalist analyses. *Journal of Finance* 59(5): 2177–2210.

Kerr, W., and R. Nanda. 2011. Financing constraints and entrepreneurship. Handbook of Research on Innovation and Entrepreneurship, 88.

Kerr, W., Nanda, R., and M. Rhodes-Kropf. 2014. Entrepreneurship as experimentation. *Journal of Economic Perspectives* 28(3): 25–48.

Kerr, W., Lerner, J., and A. Schoar. 2014. The consequences of entrepreneurial finance: Evidence from angel financings. *Review of Financial Studies* 27(1): 20–55.

Klocke, U., 2007. How to Improve Decision-Making in Small Groups: Effects of Dissent and Training Interventions. *Small Group Research* 38(3): 437–468.

Laughlin, P., Bonner, B., and A. Miner. 2002. Groups Perform Better than the Best Individuals on Letters-to-Numbers Problems. *Organizational Behavior and Human Decision Processes* 88(2): 605–620.

Lerner, J., and R. Nanda. 2020. Venture capital's role in financing innovation: What we know and how much we still need to learn. *Journal of Economic Perspectives* 34(3): 237–261.

Lyonett, V., and L. Stern. 2024. Machine Learning about Venture Capital Choices. Working Paper, University of Michigan.

Maciejovsky, B., Sutter, M., Budescu, D., and P. Bernau. 2013. Teams Make You Smarter: How Exposure to Teams Improves Individual Decisions in Probability and Reasoning Tasks. *Management Science* 59(6): 1255–1270.

Malmendier, U., and J. Lerner. 2010. Contractibility and the design of research agreements. *American Economic Review* 100: 214–246.

Paluch, S. 2021. The best startup accelerators in 2021. *Beta Boom*. Published 20 January 2021. URL: https://betaboom.com/beta-boom-insights/the-best-startup-accelerators-in-2021-beta-boom-ae2b3629748.

Puri, M., and R. Zarutskie. 2012. On the life cycle dynamics of venture capital and non-venture capital financed firms. *Journal of Finance* 67: 2247–2293.

Robinson, M. 2022. Factors impacting entrepreneurial success in accelerators: Revealed preferences of sophisticated mentors. *Review of Corporate Finance* 2(3): 617–661.

Schmidt, K. 2003. Convertible securities and venture capital finance. *Journal of Finance* 58(3): 1139–1166.

Teare, G. 2024. "U.S. seed investment actually held up pretty well for the past 2 years. Here's what it means for 2024" URL: https://news.crunchbase.com/seed/us-investment-held-up-forecast-2024/#:~:text=Seed%20trends%20over%20the%20decade&text=At%20the%20market%20peak%20in,years%20of%202019%20and%202020

Ulan, J., and V. Harrison. 2023. Quantifying the success of YC and the Largest Accelerators: Takeaways for VCs, LPs, and Startups. *Pitchbook*: Seattle, United States.

Yang, S., R. Kher, and T. Lyons. 2019. Where do accelerators fit in the venture creation pipeline? Different values brought by different types of accelerators. *Entrepreneurship Research Journal* 8(4): 13.

Yang, M., and Y. Zeng. 2019. Financing entrepreneurial production: Security design with flexible information acquisition. *Review of Financial Studies* 32(3): 819–863.

Yu, S. 2020. How do accelerators impact the performance of high-technology ventures. *Management Science* 66(2): 530–552.

Zhang, Y. 2023. Discrimination in the venture capital industry: Evidence from field experiments. Working Paper, Stockholm School of Economics.

Figure 1: Overview of our VC firm's accelerator deal flow by cohort

This figure shows the total number of applications received by our VC firm's startup accelerator by cohort, and the percentage of applicants that were eliminated from further consideration by our VC firm at the initial screening stage, the pre-interview stage, the first round interview stage, and the second round interview stage, as well as the percentage of applicants that were ultimately accepted into our VC firm's accelerator program.

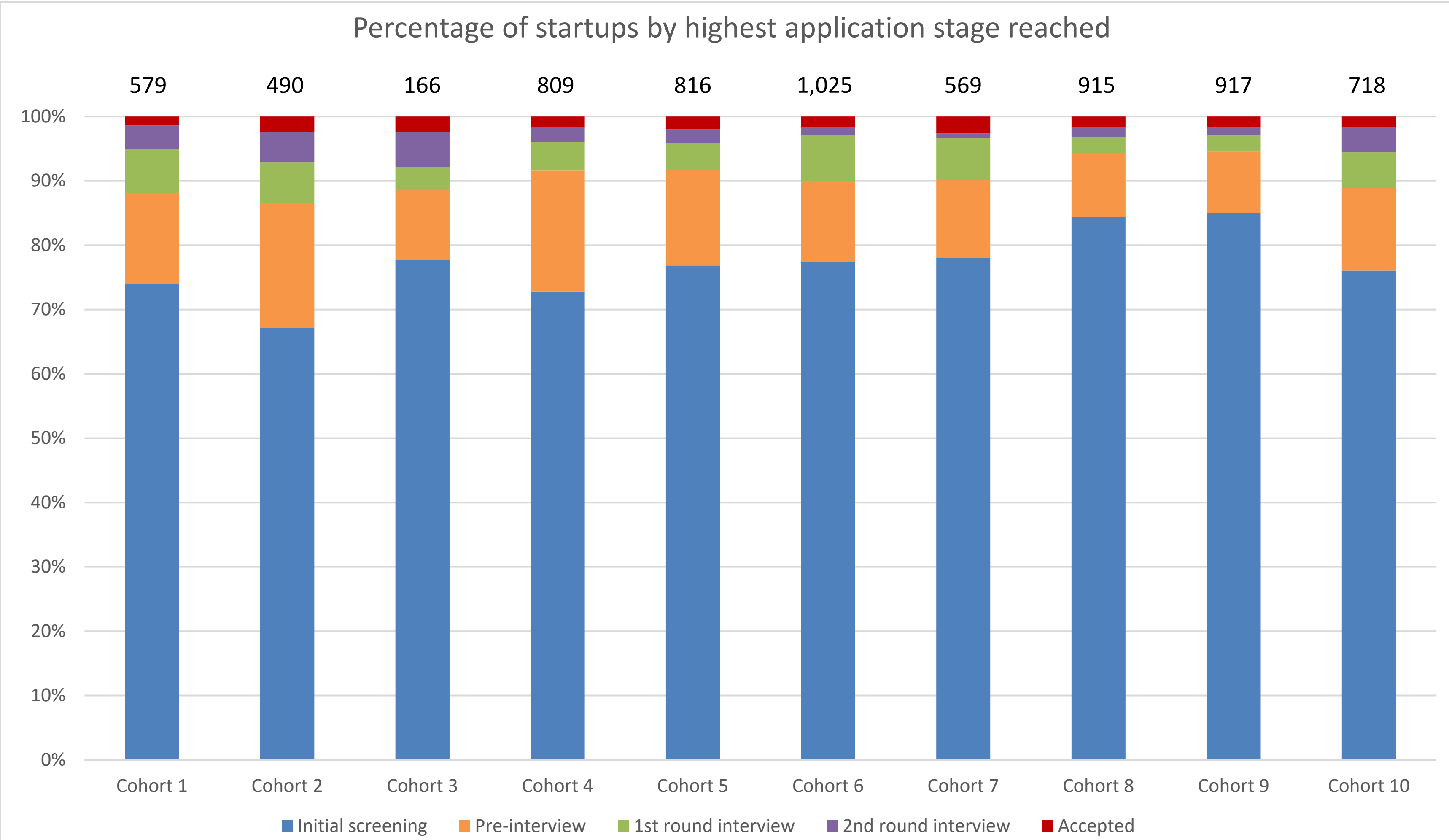

Figure 2: Applicants by industry across all accelerator cohorts

This figure shows the percentage of startup applicants by industry sector across all 10 of our VC firm's accelerator cohorts. The startup firm applicant's industry sector was obtained from answers provided by the startup applicant to the application question, "What is your industry?" Applicants were offered the following choice of industry sectors: (1) Fintech/Financial Services, (2) Biotechnology/Medical Devices/Healthcare, (3) Foodtech/Consumer Food Products, (4) Adtech/Digital Marketing/Media, (5) Internet/Web Service/"Apps"/Software/eCommerce, (6) Hardware/Electronic, (7) Agtech/Energy, (8) Education Technologies/Human Resources, and (9) Other.

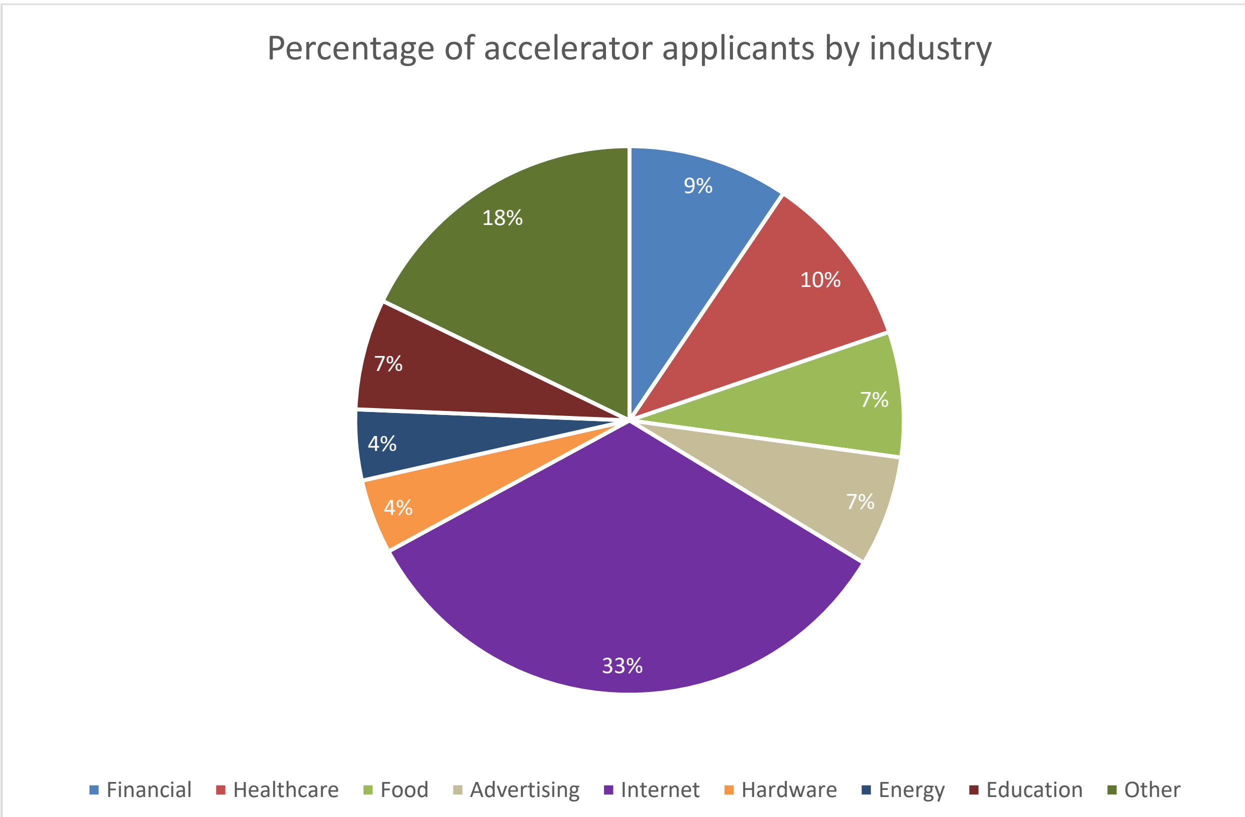

Table 1: Summary statistics

This table reports the summary statistics for the entire sample of startups applying to our VC firm's accelerator program as well as for the sub-sample of startups that are ultimately accepted into the accelerator. Panel A outlines the characteristics of internal VC judging scores for accelerator applicants throughout the VC selection process. Panel B lists the characteristics of startup firms at their time of application. Panel C presents the characteristics of our VC firm's employee judges. Panel D provides details of the financial contracts signed between our VC firm and accepted portfolio firms. Refer to Appendix A for the definition of all variables listed.

Panel A: Internal VC judge score characteristics

	All applicants			*Accepted applicants only*		
	Mean	Median	Std dev.	Mean	Median	Std. dev.
Scores per applicant in pre-interview stage	8.60	9.00	4.13	8.40	9.00	4.48
Scores per applicant in 1st round interview	6.34	7.00	3.45	6.16	7.00	3.18
Scores per applicant in 2nd round interview	6.41	7.00	3.73	6.09	7.00	3.49
Overall pre-interview judge score	0.53	0.53	0.17	0.67	0.66	0.13
First round interview judge score	0.49	0.46	0.23	0.70	0.71	0.14
Second round interview judge score	0.48	0.48	0.30	0.71	0.72	0.20

Panel B: Startup firm applicant characteristics

	All applicants			*Accepted applicants only*		
	Mean	Median	Std dev.	Mean	Median	Std. dev.
Company age (years)	2.55	1.91	1.62	3.29	2.75	1.94
Company lifetime revenue to date (US$)	78,230	10,012	995,875	401,940	69,434	960,017
External funding raised to date ($US)	45,698	0	201,589	49,772	0	155,587
Company runway (months)	6.54	6.00	7.45	6.90	6.00	4.63
No. of company founders	2.25	2.00	0.88	2.29	2.00	0.87
No. of FTE employees	3.15	3.75	3.74	4.95	4.00	4.33

Panel C: VC employee judge characteristics

	Entire judge sample		
	Mean	Median	Std. dev.
Judge has a Graduate degree	0.46	0.00	0.51
Judge attended a Top tier university	0.50	0.50	0.51
Years of financial investment experience	6.59	3.00	5.88

Panel D: Financial contracting characteristics

	Accepted applicants only		
	Mean	Median	Std. dev.
Gross investment amount ($US)	165,000	150,000	26,135
Accelerator fees (US$)	32,920	30,000	5,205
Discount rate (%)	19.7%	20.0%	1.4%
Valuation cap (US$ million)	3.47	3.50	1.25
Startup firm's current valuation (US$ million)	3.91	3.50	1.69
Cap-to-valuation ratio (x)	0.94	1.00	0.27

Table 2: VC selection analysis – Baseline tests using Pre-interview scores

This table presents the results of ordinary least squares (OLS) regression specification outlined in Equation (1) where the dependent variable is the overall score given by an individual judge for a specific startup firm applicant during the pre-interview judging stage. The judge-founder affinity-based traits are *Shared gender*, *Shared ethnicity*, *Shared education*, and *Shared employer*. The independent variables measuring possible discrimination against minority entrepreneurs are *All Female founder team*, *All Black founder team*, and *All Hispanic founder team*. The list of variables included in the *Startup firm controls*, *Startup founding team controls*, *Judge controls*, and *Controls for other judge–founder overlapping characteristics* vectors, respectively, are described in Sections 2.4 and Appendix A. All regressions include Judge fixed effects, Startup firm fixed effects, and Cohort fixed effects. Robust standard errors (clustered at the startup applicant level) are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Scoring outcome variable	Overall pre-interview score (1)	Overall pre-interview score (2)
Shared gender	0.04** (0.02)	0.04** (0.02)
Shared ethnicity	0.06*** (0.02)	0.05** (0.02)
Shared education	0.06** (0.03)	0.05* (0.03)
Shared employer	0.00 (0.03)	0.00 (0.03)
All Female founder team		-0.02 (0.03)
All Black founder team		-0.01 (0.04)
All Hispanic founder team		0.01 (0.05)
Startup firm controls	Yes	Yes
Startup founding team controls	Yes	Yes
Judge controls	Yes	Yes
Controls for other judge–founder overlapping characteristics	Yes	Yes
Judge FEs	Yes	Yes
Startup firm FEs	Yes	Yes
Cohort FEs	Yes	Yes
Number of observations	13,518	13,518
Adjusted R^2	0.57	0.59

Table 3: VC selection analysis – Heterogenous treatment effects tests using Pre-interview scores

This table presents the results of ordinary least squares (OLS) regression specification outlined in Equation (1) for various sub-samples of applications where the dependent variable is the overall score given by an individual judge for a specific startup applicant during the pre-interview judging stage. In Columns (1) and (2), our sample is split into startup applicant firms that are pre-revenue versus those that are not pre-revenue. In Columns (3) and (4), our sample is split into firms where all the startup's founders are founding their first ever entrepreneurial venture versus those firms who have founders that are serial entrepreneurs. The judge-founder affinity-based traits are *Shared gender*, *Shared ethnicity*, *Shared education*, and *Shared employer*. The independent variables measuring possible discrimination against minority entrepreneurs are *All Female founder team*, *All Black founder team*, and *All Hispanic founder team*. The list of variables included in the *Startup firm controls*, *Startup founding team controls*, *Judge controls*, and *Controls for other judge–founder overlapping characteristics* vectors, respectively, are described in Sections 2.4 and Appendix A. All regressions include Judge fixed effects, Startup firm fixed effects, and Cohort fixed effects. Robust standard errors (clustered at the startup applicant level) are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Scoring outcome variable	Overall pre-interview score	Overall pre-interview score	Overall pre-interview score	Overall pre-interview score
Application subsample	Pre-revenue firms	Not pre-revenue firms	No prior founding experience	Does have prior founding experience
	(1)	(2)	(3)	(4)
Shared gender	0.07**	0.00	0.06*	-0.01
	(0.03)	(0.02)	(0.03)	(0.02)
Shared ethnicity	0.08***	0.01	0.09***	0.00
	(0.02)	(0.02)	(0.03)	(0.03)
Shared education	0.06**	-0.01	0.07**	-0.01
	(0.03)	(0.03)	(0.03)	(0.04)
Shared employer	0.01	-0.01	0.00	-0.01
	(0.03)	(0.02)	(0.04)	(0.04)
All Female founder team	-0.02	-0.01	-0.01	0.00
	(0.04)	(0.03)	(0.05)	(0.03)
All Black founder team	-0.00	-0.01	-0.01	0.00
	(0.05)	(0.04)	(0.04)	(0.04)
All Hispanic founder team	-0.00	-0.01	-0.01	0.00
	(0.05)	(0.04)	(0.04)	(0.04)
Startup firm controls	Yes	Yes	Yes	Yes
Startup founding team controls	Yes	Yes	Yes	Yes
Judge controls	Yes	Yes	Yes	Yes
Controls for other judge–founder overlapping characteristics	Yes	Yes	Yes	Yes
Judge FEs	Yes	Yes	Yes	Yes
Startup firm FEs	Yes	Yes	Yes	Yes
Cohort FEs	Yes	Yes	Yes	Yes
Number of observations	5,399	8,119	9,147	4,471
Adjusted R^2	0.51	0.52	0.46	0.48

Table 4: VC selection analysis – Baseline tests using First and Second round interview scores

This table presents the results of ordinary least squares (OLS) regression specification outlined in Equation (1) where the dependent variable is the overall score given by an individual judge for a specific startup firm applicant during the first round interview judging stage (Columns (1) and (2)) and the second round interview judging stage (Columns (3) and (4)), respectively. The judge-founder affinity-based traits are *Shared gender*, *Shared ethnicity*, *Shared education*, and *Shared employer*. The independent variables measuring possible discrimination against minority entrepreneurs are *All Female founder team*, *All Black founder team*, and *All Hispanic founder team*. In Columns (1) and (3), all first round and second round interview scores are included in the test sample, irrespective of whether or not an individual employee also judged and scored an accelerator candidate in the pre-interview stage, respectively. In contrast, Columns (2) and (4) only includes the first round and second round interview scores of judges who also submitted an interview score for the same startup applicant in a previous interview round. The list of variables included in the *Startup firm controls*, *Startup founding team controls*, *Judge controls*, and *Controls for other judge–founder overlapping characteristics* vectors, respectively, are described in Sections 2.4 and Appendix A. All regressions include Judge fixed effects, Startup firm fixed effects, and Cohort fixed effects. Robust standard errors (clustered at the startup applicant level) are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Scoring outcome variable	First round interview score (1)	First round interview score (2)	Second round interview score (3)	Second round interview score (4)
Shared gender	0.01	0.01	0.02	0.01
	(0.03)	(0.03)	(0.04)	(0.06)
Shared ethnicity	0.02	0.02	0.02	0.01
	(0.04)	(0.04)	(0.05)	(0.04)
Shared education	0.00	0.00	0.00	0.01
	(0.05)	(0.05)	(0.04)	(0.05)
Shared employer	-0.01	-0.01	-0.01	-0.02
	(0.04)	(0.04)	(0.04)	(0.05)
All Female founder team	-0.01	-0.01	-0.01	-0.01
	(0.04)	(0.04)	(0.04)	(0.05)
All Black founder team	0.01	0.01	0.01	0.00
	(0.05)	(0.05)	(0.05)	(0.04)
All Hispanic founder team	0.01	0.01	0.01	0.00
	(0.05)	(0.05)	(0.05)	(0.04)
Require employee to have judged startup in a previous interview round?	*No*	*Yes*	*No*	*Yes*
Startup firm controls	Yes	Yes	Yes	Yes
Startup founding team controls	Yes	Yes	Yes	Yes
Judge controls	Yes	Yes	Yes	Yes
Controls for other judge–founder overlapping characteristics	Yes	Yes	Yes	Yes
Judge FEs	Yes	Yes	Yes	Yes
Startup firm FEs	Yes	Yes	Yes	Yes
Cohort FEs	Yes	Yes	Yes	Yes
Number of observations	3,401	2,203	1,663	1,152
Adjusted R^2	0.51	0.47	0.49	0.46

Table 5: VC selection – Heterogenous treatment effects tests using First round interview scores

This table presents the results of ordinary least squares (OLS) regression specification outlined in Equation (1) for various sub-samples of applications where the dependent variable is the overall score given by an individual judge for a specific startup applicant during the first round interview judging stage. In Columns (1) and (2), our sample is split into startup firms that are pre-revenue versus those that are not pre-revenue. In Columns (3) and (4), our sample is split into firms where all the startup's founders are founding their first ever entrepreneurial venture versus those firms who have founders that are serial entrepreneurs. The judge-founder affinity-based traits are *Shared gender*, *Shared ethnicity*, *Shared education*, and *Shared employer*. The independent variables measuring possible discrimination against minority entrepreneurs are *All Female founder team*, *All Black founder team*, and *All Hispanic founder team*. The list of variables included in the *Startup firm controls*, *Startup founding team controls*, *Judge controls*, and *Controls for other judge–founder overlapping characteristics* vectors, respectively, are described in Sections 2.4 and Appendix A. All regressions include Judge fixed effects, Startup firm fixed effects, and Cohort fixed effects. Robust standard errors (clustered at the startup applicant level) are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Scoring outcome variable	First round interview score	First round interview score	First round interview score	First round interview score
Application subsample	Pre-revenue firms	Not pre-revenue firms	No prior founding experience	Does have prior founding experience
	(1)	(2)	(3)	(4)
Shared gender	0.01	0.00	-0.02	-0.04
	(0.04)	(0.04)	(0.03)	(0.02)
Shared ethnicity	0.02	0.01	0.01	0.02
	(0.03)	(0.03)	(0.03)	(0.03)
Shared education	0.04	-0.01	-0.01	-0.03
	(0.06)	(0.04)	(0.03)	(0.04)
Shared employer	0.01	-0.01	0.00	-0.02
	(0.03)	(0.06)	(0.04)	(0.04)
All Female founder team	-0.02	-0.01	-0.01	0.01
	(0.03)	(0.03)	(0.03)	(0.03)
All Black founder team	-0.00	-0.01	-0.03	0.00
	(0.06)	(0.04)	(0.05)	(0.06)
All Hispanic founder team	-0.00	-0.01	-0.02	0.02
	(0.07)	(0.04)	(0.04)	(0.04)
Startup firm controls	Yes	Yes	Yes	Yes
Startup founding team controls	Yes	Yes	Yes	Yes
Judge controls	Yes	Yes	Yes	Yes
Controls for other judge–founder overlapping characteristics	Yes	Yes	Yes	Yes
Judge FEs	Yes	Yes	Yes	Yes
Startup firm FEs	Yes	Yes	Yes	Yes
Cohort FEs	Yes	Yes	Yes	Yes
Number of observations	1,105	2,296	2,607	794
Adjusted R^2	0.45	0.47	0.43	0.45

Table 6: VC selection analysis – Alternative tests controlling for judge's prior score for focal startup

This table presents the results of ordinary least squares (OLS) regression specification outlined in Equation (2) where the dependent variable is the overall score given by an individual judge for a specific startup firm applicant during the first round interview judging stage. *Pre-interview overall score* is equal to the score that the individual judge gave for the focal startup applicant during their pre-interview evaluations. The judge-founder affinity-based traits are *Shared gender*, *Shared ethnicity*, *Shared education*, and *Shared employer*. The independent variables measuring possible discrimination against minority entrepreneurs (i.e., *Controls for startup founding team's minority status*) are *All Female founder team*, *All Black founder team*, and *All Hispanic founder team*. The list of variables included in the *Startup firm controls*, *Startup founding team controls*, *Judge controls*, and *Controls for other judge–founder overlapping characteristics* vectors, respectively, are described in Sections 2.4 and Appendix A. All regressions include Judge fixed effects, Startup firm fixed effects, and Cohort fixed effects. Robust standard errors (clustered at the startup applicant level) are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Scoring outcome variable	First round interview score	First round interview score	Second round interview score	Second round interview score
	(1)	(2)	(2)	(3)
Pre-interview overall score	0.26***	0.22***	0.15***	0.16***
	(0.05)	(0.06)	(0.04)	(0.05)
Shared gender		0.02		0.01
		(0.04)		(0.06)
Shared ethnicity		0.02		0.01
		(0.05)		(0.04)
Shared education		0.00		0.01
		(0.04)		(0.05)
Shared employer		-0.01		-0.02
		(0.04)		(0.05)
Pre-interview overall score × Shared gender		-0.06**		-0.05*
		(0.03)		(0.03)
Pre-interview overall score × Shared ethnicity		-0.07**		-0.05**
		(0.03)		(0.02)
Pre-interview overall score × Shared education		-0.06**		-0.06*
		(0.03)		(0.04)
Pre-interview overall score × Shared employer		0.01		-0.04
		(0.04)		(0.05)
Controls for startup founding team's minority status	Yes	Yes	Yes	Yes
Startup firm controls	Yes	Yes	Yes	Yes
Startup founding team controls	Yes	Yes	Yes	Yes
Judge controls	Yes	Yes	Yes	Yes
Controls for other judge–founder overlapping characteristics	Yes	Yes	Yes	Yes
Judge FEs	Yes	Yes	Yes	Yes
Startup firm FEs	Yes	Yes	Yes	Yes
Cohort FEs	Yes	Yes	Yes	Yes
Number of observations	2,203	2,203	1,152	1,152
Adjusted R^2	0.43	0.44	0.42	0.40

Table 7: VC-startup financing contracting analysis – Baseline tests

This table presents the results of ordinary least squares (OLS) regression specification outlined in Equation (3) where the dependent variable is the natural logarithm of the agreed valuation cap in the signed SAFE or KISS funding contract (expressed in millions of $US dollars). *Startup firm's current valuation* is equal to the natural logarithm of the startup applicant's response on the due diligence question "What is the current valuation of your company?" (expressed in millions of $US dollars). *Mean of firm's second round interview judging scores* is equal to the (weighted) average of second round interview scores submitted by individual VC firm employees for the applicant firm. *Startup firm's runway* is the number of months that the startup can continue its ordinary operations before it exhausts its existing cash reserves. The list of variables included in the *Startup firm controls* and *Startup founding team controls* vectors are described in Sections 2.4 and Appendix A. All regressions include Cohort fixed effects. Robust standard errors (clustered at the cohort level) are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Financial contracting outcome variable	Startup firm valuation cap (1)	Startup firm valuation cap (2)
Startup firm's current valuation	0.60***	0.59***
	(0.05)	(0.05)
Mean of firm's second round interview judging scores	0.25**	0.26**
	(0.10)	(0.10)
Startup firm's runway	0.02**	0.02**
	(0.01)	(0.01)
Startup firm controls	No	Yes
Startup founding team controls	No	Yes
Cohort FEs	Yes	Yes
Number of observations	120	120
Adjusted R^2	0.70	0.70

Table 8: VC-startup financing contracting analysis – Impact on Series A financing outcomes

This table presents the results of ordinary least squares (OLS) regression specification outlined in Equation (4). The dependent variable in Column (1) is *Length of time until Series A round*, defined as the natural logarithm of the number of months that elapses between the signing of the KISS/SAFE contract with our VC firm and the closing of a subsequent Series A financing round by the focal portfolio firm. The dependent variable in Column (2) is *Size of the subsequent Series A round*, defined as the natural logarithm of the amount of money raised by the portfolio company in its subsequent (Series A) financing round (expressed in US$ millions). *Startup firm's valuation cap* is the natural logarithm of the agreed valuation cap in the signed SAFE or KISS funding contract (expressed in millions of $US dollars). *Mean of firm's second round interview judging scores* is equal to the (weighted) average of second round interview scores submitted by individual VC firm employees for the applicant firm. *Startup firm's runway* is the number of months that the startup can continue its ordinary operations before it exhausts its existing cash reserves. The list of variables included in the *Startup firm controls* and *Startup founding team controls* vectors are described in Sections 2.4 and Appendix A. All regressions include Cohort fixed effects. Robust standard errors (clustered at the cohort level) are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Series A round outcome variable	Length of time until Series A round (1)	Size of the subsequent Series A round (2)
Startup firm's valuation cap	0.35*** (0.08)	0.21*** (0.07)
Mean of firm's second round interview judging scores	0.20* (0.12)	0.24** (0.09)
Startup firm's runway	0.03** (0.01)	-0.01 (0.04)
Startup firm controls	No	Yes
Startup founding team controls	No	Yes
Cohort FEs	Yes	Yes
Number of observations	120	120
Adjusted R^2	0.53	0.48

Appendix A: Variable definitions

Variable	Description
Panel A: Outcome variables	
Pre-interview overall score	The total score awarded for an individual startup applicant by each judge during our VC firm's pre-interview evaluation process. Scores are standardized across cohorts to be bounded between 0 and 1.
First round interview score	The total score awarded for an individual startup company by each judge after our VC firm conducts a first round interview with the accelerator applicant. Scores are standardized across cohorts to be bounded between 0 and 1.
Second round interview score	The total score awarded for an individual startup company by each judge after our VC firm conducts a second round interview with the accelerator applicant. Scores are standardized across cohorts to be bounded between 0 and 1.
Valuation cap	The natural logarithm of the startup firm valuation amount (expressed in US$ millions) that effectively sets the maximum price per share to be paid by the SAFE/KISS investor for their equity ownership stake in the focal startup firm. This figure is specified in the portfolio company's SAFE/KISS financing contract.
Length of time until Series A round	The natural logarithm of the number of months that elapses between the signing of the KISS/SAFE contract with our VC firm and the closing of a subsequent Series A financing round by the focal portfolio firm.
Size of the subsequent Series A round	The natural logarithm of the amount of money raised by the portfolio company in its subsequent (Series A) financing round (expressed in US$ millions).
Panel B: Judge-founder affinity-based traits and startup founding team inherited characteristics	
Shared gender	An indicator variable equal to one if the individual judge and at least one of the startup firm's founders have the same gender (male or female), and zero otherwise. To identify a person's gender, we start with a startup firm's application materials (including pitch decks and LinkedIn profiles) which almost always includes pictures of each firm founder along with biographies and other work-related descriptions. Typically, the gender of each firm founder is clearly identified from these materials through word use (e.g., written references to 'she', 'he', 'her', 'him', etc.) and/or visual inspection of pictures. For the few remaining ambiguous cases, we use both genderize.io and forebears.io that predict gender based on first names, supplemented with manual web searches using publicly available online sources.
Shared ethnicity	An indicator variable equal to one if the individual judge and at least one of the startup firm's founders have the same ethnicity (White, East Asian, Indian, Middle Eastern, Black/African American, Hispanic/Latino, and Other), and zero otherwise. To identify a person's ethnicity, we use ChatGPT's *Ethnicity Identifier* tool. For each founder, we upload their profile picture and ask this specialized ChatGPT program the following prompt: "based on the attached picture, the person's full name of [insert name], the person's current location of [insert city name, country name], and [if available] the location of the person's undergraduate academic institution (namely [insert university name]), what is the ethnicity and country of origin of this person? Provide a confidence score between 0 and 10 for your predictions, with 0 being the least confident and 10 being the most confident." If the tool identifies the individual as having a mixed ethnic background or the assigned confidence score is less than 9, we set the relevant founder's Ethnicity = "Other". For robustness, we provide the same inputs into ChatGPT's *Ethnicity Guesser* tool and set Ethnicity = "Other" if the two programs disagree on their ethnicity prediction.

Shared education	A dummy variable equal to one if the individual judge and at least one of the startup's founders graduated with a degree from the same university, and zero otherwise. To identify the full list of universities attended (and the associated degrees earned) by each firm founder, we use both application questions asking for the educational background of each member of the firm's current management team as well as education-related information listed in LinkedIn and other similar profiles.
Shared employer	An indicator variable equal to one if the individual judge and at least one of the startup firm's founders worked at the same employer, and zero otherwise. To identify each firm founder's complete list of previous employers prior to founding the focal startup firm, we use both application questions asking for the employment background of each member of the firm's current management team as well as employment-related information listed in LinkedIn and other similar profiles.
All Female founding team	An indicator variable that is equal to one when all startup firm co-founders are female, and zero otherwise.
All Black founding team	An indicator variable that is equal to one when all startup firm co-founders are Black/African American, and zero otherwise.
All Hispanic founding team	An indicator variable that is equal to one when all startup firm co-founders are of Hispanic origin, and zero otherwise.
Panel C: Other judge-founder overlapping characteristics	
Shared graduate degree	A dummy variable equal to one if both the VC firm judge and at least one of the startup's founders have earned an academic degree after their initial bachelor's degree (namely a Master's degree or a PhD), and zero otherwise.
Shared top tier university	A dummy variable equal to one if both the VC firm judge and at least one of the startup's founders have been granted a degree from a university that is ranked as one of the world's Top 50 best bachelor's degree-granting institutions (according to that year's *Times Higher Education World University Rankings*), and zero otherwise.
Shared industry experience	The natural logarithm of one plus the number of years of experience that the focal VC firm judge has working in the same industry sector as the focal startup company.
Panel D: Startup firm characteristic control variables	
Company stage of development	A dummy variable equal to one if the firm has already publicly launched its product or service, and zero otherwise. For example, a startup firm that is still in the concept or prototype phase will have a value of zero for this indicator variable.
Company age	The natural logarithm of the number of months between the firm's founding date and the date of the startup's application to our VC firm's accelerator program.
Company's lifetime revenue	The natural logarithm of one plus the dollar amount of sales revenue generated by the startup firm's products/services to date.
Number of total users since launch	The natural logarithm of one plus the total number of people that have used the startup's product or service since its launch (if applicable). This variable is set to equal zero if the startup's product or service has not yet been launched.
Number of paying users since launch	The natural logarithm of one plus the total number of people who have paid to use the startup's product or service since its launch (if applicable). This variable is set to equal zero if the startup's product or service has not yet been launched.
External funding raised to date	The natural logarithm of one plus the total amount of capital raised from investors who are not part of the startup's management/founding team (e.g., angel investors, family & friends, governmental entities etc.).
Company runway	The natural logarithm of one plus the number of months left before the startup company exhausts its existing cash reserves (in the absence of any new investment).
Current firm valuation	The natural logarithm of the startup company's (self-reported) current valuation.

Number of FTE company employees	The natural logarithm of one plus the total number of full-time equivalent (FTE) employees working at the startup applicant.
Estimated Serviceable Obtainable Market (SOM)	The natural logarithm of one plus the startup's estimate of the serviceable obtainable market (SOM) for its product or service, defined as the portion of the estimated serviceable addressable market (SAM) that the startup can realistically capture given its business model. We set SOM equal to zero if the startup firm declines to provide an estimate of its SOM due to uncertainty about its preferred target market. Note: SAM is defined as the segment of estimated total addressable market (TAM) realistically targeted by the startup's products and services, where TAM is defined as the total (maximum) revenue opportunity available for a product or service.
Panel E: Startup founding team control variables	
Number of company founders	The natural logarithm of the number of individuals listed as a founder/co-founder of the startup company applicant.
Percentage of founding team with graduate degree	The percentage of startup co-founders that have earned an academic degree after their initial bachelor's degree (namely a Master's degree or a PhD).
Percentage of founding team with degree from top tier university	The percentage of startup firm co-founders that have been granted a degree from a university that is ranked as one of the world's Top 50 best bachelor's degree-granting institutions (according to that year's *Times World University Rankings*).
Average TMT experience of company founders	The natural logarithm of one plus the average number of years that each startup co-founder acted in a top management team (TMT)/corporate executive role prior to starting the current applicant company.
Average prior startup experience of company founders	The natural logarithm of one plus the average number of unique startup companies created by the applicant's co-founders prior to establishing the focal startup applicant firm.
Panel F: VC judge control variables	
Current Partner	An indicator variable that is equal to one if the focal VC judge is a current partner of our VC firm, and zero otherwise.
Graduate degree	A dummy variable that is equal to one if the focal VC judge has earned an academic degree after their initial bachelor's degree (namely a Master's degree or a PhD), and zero otherwise.
Top tier university	An indicator variable that is equal to one if the focal VC judge has been granted a degree from a university that is ranked as one of the world's Top 50 best bachelor's degree-granting institutions (according to that year's *Times Higher Education World University Rankings*).
Years of financial investment experience	The natural logarithm of one plus the number of years that the focal VC firm judge has worked in the financial investment sector (including experience gained in venture capital/private equity-focused roles as well as positions in the asset management, investment banking, and management consulting industries.
Panel G: Additional independent variables for financial contracting analysis	
Mean of second round interview scores	The average of our VC firm employees' second round interview scores for startup firm applicants that are ultimately accepted into the accelerator program.
Std deviation of second round interview scores	The standard deviation of our VC firm employees' second round interview scores for startup firm applicants that are ultimately accepted into the accelerator program.

The Internet Appendix of

"How do Venture Capitalists (actually) make decisions? Internal evidence from a private startup accelerator"

Appendix IA.1: Additional details on our VC firm's selection and contracting process

In this Appendix, we provide additional information about the entire process that our VC firm employs to select the subset of startup firm applicants who will be invited to participate in our VC's accelerator program as well as how investment contracts are negotiated with accepted applicants.

Stage 1: Application and initial screening

The first step in our VC firm's selection process requires that startups submit an initial online application by the relevant cohort application deadline. This online form asks a series of more basic questions about the company, the firm's founders, the startup's business model, and the company's progress to date. One junior employee at our VC Fund will then review each initial application to make a binary 'Yes' or 'No' determination as to whether a further request for information (called a 'due diligence pack' or 'DD pack') is sent to the startup applicant to complete (a process that we term the '*initial employee screen*'). This DD pack is a much more detailed questionnaire that asks 50+ questions and covers a broad range of subjects relating to the company's product or service, potential market size, business model, competitive landscape, milestones achieved to date (i.e., traction), financial information and other related business metrics, the background and skills of the management team, and the legal/ownership structure. In addition, applicants are also expected to submit 'pitch decks' that provide a more visual representation of the startup's business plan and offer applicants a more open-ended outlet to describe the founding team, the market opportunity, the proposed solution, potential challenges, funding needs etc.

As an aside, the only part of our VC firm's entire investment selection process for which we *do not* have complete information concerns the initial employee screening process. While we observe whether a startup applicant was invited to submit a due diligence pack or not, our VC firm never required their sole junior screener to provide any written justification for their decision nor kept any formal records relating to these decisions. However, during discussions with employees tasked with undertaking this initial screening, it became apparent that the primary purpose of these 'initial screens' was only to filter out obviously poor applications that were clearly not worthy of any further consideration rather than serve as a meaningful part of the VC firm's overall investment selection process. Examples of startups that were rejected at this initial phase were those that did not take the time to fill out many of the basic questions on the initial application form, companies that did not have a functioning website, and/or businesses that were clearly unsuitable for a high-growth orientated accelerator program (e.g., small local businesses with no plans for meaningful expansion). These anecdotal observations are supported empirically in Appendix Table IA.1 where we find that answering every one of our VC's initial online application questions is overwhelming the most important predictor of whether an applicant is asked to submit a DD pack for further evaluation by the entirety of the VC firm's personnel.[42] As such, it appears unlikely that these initial screening decisions will have a material impact on our subsequent analysis and conclusions.

Stage 2: Pre-interview assessment

Once all requested DD packs and pitch decks are received, the widely recognized expectation at our VC firm is that all VC employees who are available to read and evaluate these due diligence materials will submit individual scores for each applicant (otherwise referred to as '*pre-interview scores*'). This pre-interview score can range between 0 points (worst) to 100 points (best) and is based on sub-scores given for the market potential of the startup's product/service, the quality of the startup's management team, and the level of traction/customer engagement garnered to date (with each category assigned roughly equal weights).[43] Given the high volume and wide diversity

[42] Also, our VC firm progressed over 23% of applicants to its pre-interview assessment stage, much higher than the 4% of applicants that the VC firm studied in Jang and Kaplan (2023) chose to "intensively analyze" and formally score.
[43] To protect our VC firm's identity, we cannot disclose the precise weights that they put on each of these three criteria. Thus, our later empirical analysis of pre-interview judging scores will only focus on the total 0-to-100-point scores.

of applicants that each VC employee 'judge' must evaluate within a compressed time period, these pre-interview scores are only meant to be based on the submitted DD packs and pitch decks.[44]

Critically, our VC firm adopted a judging policy that prioritized each VC partner/employee submitting truly independent assessments of applicant quality, especially at the pre-interview stage. Specifically, our VC firm went to great lengths to proactively ensure the independence and integrity of the internal judging process. For example, during the entirety of the pre-interview judging period, employees were physically separated and instructed not to communicate with one another about their personal assessments of startup applicants (e.g., all employees were not allowed to review applications in the office but instead had to work from home during this time period). VC employees would then be required to separately submit an individual scoring spreadsheet to an administrative manager to compile and summarize, thus helping to ensure that no VC judge had access to other employees' scores prior to submitting their own scores and comments.

Next, once all individual pre-interview judging scores are received, a weight is then applied to each individual score. For most cohorts, each pre-interview score (whether from a partner or a full-time employee) is assigned the same weight.[45] Our VC firm then takes an average of the (weighted) judges' scores and ranks startups from best to worst based solely on these weighted average scores. At the beginning of each cohort cycle, our VC firm will prespecify a capacity threshold for how many startups they can include as portfolio firms in the accelerator program (typically 10–12 startups) and how many interview slots they can feasibly accommodate at each

[44] For example, within a two-day period at the start of each cohort cycle, the average number of applications that each VC judge will score in this pre-interview stage is approximately 200 firms. As such, our conversations with VC firm employees suggest that there is simply insufficient time to conduct significant additional research outside of relying on the (extensive) submitted application materials during this pre-interview evaluation process.

[45] In some later cohorts, however, the scores of VC partners received up to double the weight of other VC employees.

stage of the selection process (typically 80–100 startups in the pre-interview stage). Our VC firm then makes first round interview offers in order of rank until all interview slots have been filled.

Stage 3: First round interview

The third step in our VC firm's selection process is that these selected startup applicants would be invited to a 30-minute meeting with all available VC firm partners and employees. These meetings were usually conducted in-person although there were some instances where a video-conferencing call was instead scheduled. At these meetings, key members of the startup's management team will be invited to make a short presentation about the company and answer a series of (impromptu) questions from VC firm employees. At the conclusion of each first round interview, all attendees from the VC firm would have an open group discussion about the strengths and weaknesses of the applicant. However, analogous to the pre-interview scoring process, each interviewer would be required to separately submit an individual scoring spreadsheet after all first round interviews are conducted. For each first round candidate, each interviewer is asked to provide a single overall score based on that VC judge's holistic assessment of the startup's potential and fit for the accelerator program (otherwise referred to as '*first round interview scores*').

Next, once all individual first round interview judging scores are received, a weight is then applied to each individual score based on level of seniority. In this round, all individual scores receive the same weight, with the exception that each VC firm partner's first round interview score was typically given 1.5 times the weight of scores submitted by other full-time VC employees. Our VC firm then takes an average of the (weighted) judges' scores and ranks startups from best to worst based solely on these weighted average first round interview scores. Our VC firm then makes second round interview offers in order of rank until all available interview slots have been filled.

Stage 4: Second round interview and final selection

For applicants that successfully pass the first round interview stage, these shortlisted startup companies will then have a second (and final) 45-minute, in-person interview with all available VC partners and employees. At this second interview, key members of the startup's management team will be invited to make a longer presentation pitch for VC funding and answer a series of additional questions from VC firm employees about the startup's business. At the end of each second round interview, all VC firm interviewers have an open group discussion about the relative strengths and weaknesses of the applicant and their suitability for VC investment. For each second round interview candidate, each interviewer will then be asked to provide a single overall score based on that VC judge's holistic assessment of the startup's potential and fit for the accelerator program (otherwise referred to as '*second round interview scores*'). Analogous to the first round interview process, however, each VC firm interviewer is required to separately submit an individual scoring spreadsheet with associated comments after all second round interviews are conducted.

Next, once all individual second round interview judging scores are received, a weight is then applied to each individual score based on level of seniority. In this round, each VC firm partner's second round interview score was typically given 1.5 times the weight of scores submitted by other full-time VC employees, but all individuals within the same level of seniority received the same scoring weight. Our VC firm then takes an average of the (weighted) judges' scores and ranks startups from best to worst based solely on these weighted average second round interview scores.[46] Our VC firm will then make offers to startup companies to join the accelerator cohort and receive VC firm funding in order of rank until all available accelerator cohort slots are filled.

[46] It should be noted that our VC firm only uses the second-round interview scores to decide whether a startup company is ultimately accepted into the VC's accelerator program (i.e., an applicant's second round interview scores effectively supersede that applicant's pre-interview and first round interview scores).

Stage 5: VC-startup financial contracting stage

The final stage of our VC firm's investment process involves our VC firm initially offering all accepted applicants to the relevant accelerator cohort a relatively 'standard form' financial investment contract. While the vast majority of contract terms will be identical across all members of the accelerator cohort (including the total amount of funding provided), some of the pricing-related terms will be specific to each accepted startup applicant. Startup companies will then have a short amount of time (approximately 1–2 weeks) to negotiate these more commercially sensitive pricing-related terms with our VC firm. Once agreement is reached between the parties, a finalized investment contract is signed, and the startup company will formally begin its participation in the VC firm's intensive 12-week accelerator program. We discuss further details on the structure and negotiation of these financial contracts in Section 4.1.

Appendix IA.4: Theoretical model

1. The Model

There are three players in this game: an entrepreneur, an accelerator, and a venture capitalist (VC). The entrepreneur is a founder who forms a startup company (hereafter, a "firm") and exerts effort. The accelerator is an organization that recruits cohorts of entrepreneurs into a structured program over time, and advises and provides seed financing for the entrepreneur. The VC is an external investor that takes equity in the venture for a substantial investment in the company. All parties are risk neutral.

Let $\theta \in [0,1]$ be the type of the entrepreneur and $\gamma \in [0,1]$ be the type of firm. Assume information on the firm and entrepreneur's type is symmetric and, for simplicity, known to all parties.[47] This will focus analysis on the contract structure and the moral hazard aspects. Observability of θ means that a message game between the entrepreneur and the firm is unnecessary, as are any screening contracts; truth-telling constraints are relevant only if the entrepreneur can fool the firm by claiming he is a different type than he is. Our experience with the data provider is that this is not a tenable assumption as the firm has long histories of selecting thousands of applicants for a few select spots, giving, if anything, the accelerator an information advantage over the entrepreneur.

In the first stage of the game, the entrepreneur forms the firm and Nature reveals θ to all parties. The company has issued q_0 outstanding shares at inception, each at a price of $p_0 > 0$,

[47] In our data set, the entrepreneur has no better assessment of his type than the accelerator. In fact, the accelerator forms an estimate of the entrepreneur's type, which may be more accurate than the entrepreneur's own assessment. As we discuss in the data description section, the accelerator conducts an exhaustive analysis to determine the entrepreneur's type, measured by an aggregate score. In this process, the accelerator requests hard information from the entrepreneur that is difficult to manipulate, like bank statements.

giving a pre-seed valuation of $v_0 = p_0 q_0$. The entrepreneur has a claim to $\beta < 1$ of this valuation. We will observe measures of β from disclosures of the cap table.

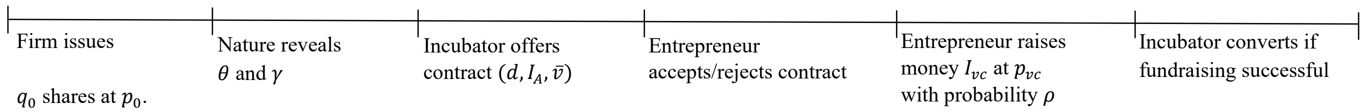

Figure A: Timeline of the Game

In the second stage, the accelerator offers a contract $(d, I_A, \bar{v})$ to the entrepreneur, where $d \in (0,1)$ is the discount rate, $\bar{v}$ is the valuation cap, and I_A is the investment that the accelerator makes into the business. Valuation of the business increases to $v_A = v_0 + I_A$, the pre-seed valuation plus the accelerator's investment. The entrepreneur either accepts or rejects this contract. If he rejects the contract, he can claim the outside option $\bar{u}_e$, and the incubator claims its outside option $\bar{u}_A$. If the entrepreneur accepts the contract, the game proceeds to the next stage. Payoffs from other parameters of the contract will be realized in the later stages of the game.

In stage three, the entrepreneur exerts unobservable effort e at cost $C(e) = \frac{c_e}{2} e^2$, and the firm exerts unobservable effort a at cost $C(a) = \frac{c_a}{2} a^2$. Call e entrepreneurial effort, and a advisory effort from the accelerator. This collectively generates the probability of success given by $\rho = \gamma\theta e + a$.

In the last stage, the payoffs depend on whether the entrepreneur can raise money from the VC. If he fails to raise money (with probability $1 - \rho$), the VC makes no investment in the firm, receives no shares, and the valuation of the firm remains at v_A. The entrepreneur remains the primary owner of the business with β of the equity, and total outstanding shares of the firm are still q_o.

The entrepreneur is successful in acquiring an investment from the VC with probability ρ. Call this event an "equity financing," or "priced round," since the VC establishes a post-money valuation that provides a value to the nascent firm.

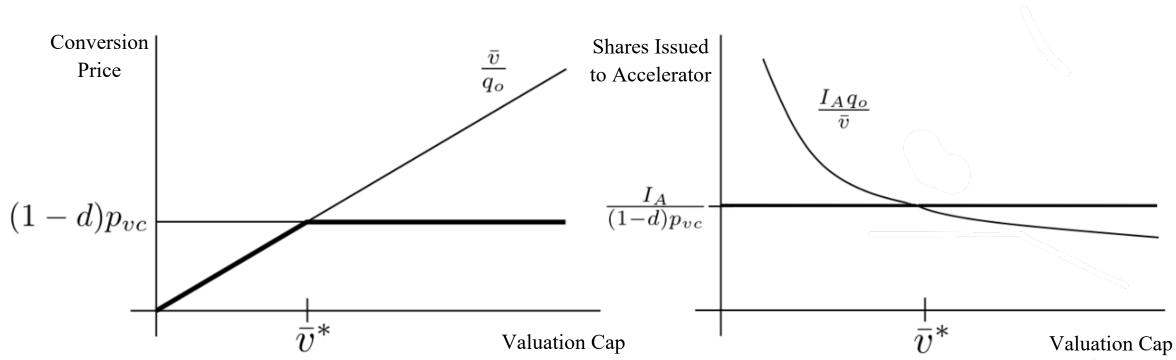

Figure B

At this stage, the incubator can convert its investment into shares in the firm based off the equity financing (e.g., a Series-A investment). In this case, the VC invests I_{vc} into the firm, giving a post-money valuation of $v = v_A + I_{vc}$. Let p_{vc} be the price that the VC pays for each of the q_{vc} new shares that the firm issues. Take $p_{vc} > p_0$ to be exogenous.

If the accelerator converts, then it receives a number of shares given by

$$q_A = \frac{I_A}{\min\left((1-d)p_{vc}, \frac{\bar{v}}{q_0}\right)}, \tag{1}$$

where the denominator is the conversion price p_A at which the accelerator converts its shares into an ownership stake in the priced round.

The conversion price is by definition the smaller of a "discount price," a discount to the VC's price per share, and a "capped price" based off of a valuation cap $\bar{v}$ divided by the number of shares outstanding. The valuation cap relies on a comparison to the pre-money valuation. By construction, $p_A \leq (1-d)p_{vc} < p_{vc}$, so the accelerator purchases on better terms than the VC. The reason for the discount is that the accelerator makes an early investment into the firm at its seed stage, which entails higher risk than the Series-A stage when the VC enters. To compensate for this risk, it receives shares at a discount. The benefit of this Deferred Equity Agreement is that it postpones the valuation decision to the external investor, rather than placing the burden on the accelerator in picking a valuation.[48] Figuring the valuation itself places a large obligation on the accelerator, whereas it is more efficient for later round investors specialized in valuation to make that assessment.

Figure A shows the timeline of the game. The key feature of the game is the conversion of the accelerator's investment into equity. Figure B plots the conversion price as a function of the valuation cap. The threshold valuation $\bar{v}^*$is the cap that satisfies $(1-d)p_{vc} = \frac{\bar{v}^*}{q_0}$. For all valuations $\bar{v} > \bar{v}^*$, the accelerator purchases at a price that does not vary with respect to valuation. The conversion price ensures that the incubator buys into the firm at the lower envelope of the two functions plotted in Figure B1. This conversion price then generates an ownership stake of the accelerator graphed in Figure B2 as a function of the valuation cap, which is the upper envelope of the two functions in Figure B3. For high valuation caps, the conversion price remains at the discount price $(1-d)p_{vc}$ and the accelerator receives $\frac{I_A}{(1-d)p_{vc}}$ shares. For low valuation caps, the accelerator receives $\frac{I_A q_0}{\bar{v}}$ shares, which increase in number as the valuation cap decreases. The accelerator prefers lower valuation caps, because it reduces the price of the shares that it pays (relative to what the VC pays).

[48] For example, for years the startup accelerator Y-combinator made a standard investment of a $150,000 for 6% of each new venture, valuing every new start up at a fixed $2.5 million. While this was a simple contract for all entrepreneurs to understand, it forced all startups onto the same valuation and ignored differences between the companies in the cohort.

2. Analysis

The accelerator's full contract $(d, I_A, \bar{v})$ is multi-dimensional. However, our data shows that most of the variation in the contract rests in the valuation cap. Within each cohort of the accelerator, nearly all contracts have the same discount rate and investment amount. As such, we take d and I_A to be exogenous, as we are examining the contract choice of $\bar{v}$ within a cohort. Future research can solve for the optimal discount rates and investment amounts of the accelerator across multiple cohorts.

Because the incubator can contract on the entrepreneur's type, we seek to derive the optimal contract $\bar{v}(\theta)$ and generate implications that can be tested against data. To solve the game, work backwards. Take the contract as given, and solve for the optimal effort choices of the entrepreneur and accelerator, then solve for the optimal contract. Because the accelerator and entrepreneur must both exert unobservable effort to influence project success, this is a double moral hazard problem. See papers X1 and X2 for similar analysis of this class of games.

Rolling the game backward, the key uncertainty is whether the entrepreneur can raise money or not. If he can, then he increases the value of his firm to v. The entrepreneur collects his share of the valuation, which is his ownership stake of β, less his cost of effort, yielding payoff $\frac{\beta q_0}{Q} v - C(e)$, where $Q = q_0 + q_{vc} + q_A$ is the total shares issued and outstanding. If he is successful in raising the money and attracting the VC, then the valuation of his firm increases to $v = v_A + I_{vc}$, but his own share of that valuation dilutes. If he is unsuccessful, he retains all the ownership of the firm but at a lower valuation of $v_A = v_0 + I_A$. Therefore, the entrepreneur's expected utility is

$$EU = \rho\beta\frac{q_0}{Q} + (1-\rho)\beta v_A - C(e). \qquad (2)$$

Differentiating with respect to effort generates the incentive constraint for the entrepreneur:

$$\hat{e} = \frac{\beta\gamma\theta}{c_e}\left[\frac{q_0}{Q}v - v_A\right]. \qquad (IC_e)$$

Recall that the cap threshold $\bar{v}^*$ is exactly the threshold below which the cap binds, i.e. the cap determines the conversion price. For valuations $\bar{v} > \bar{v}^*$, $p_A = (1-d)p_{vc}$, and for valuations $\bar{v} < \bar{v}^*$, $p_A = \frac{\bar{v}}{q_0}$. The cap binds over $(0, \bar{v}^*)$, but not over $[\bar{v}^*, \infty)$. When the cap binds, the conversion price is a function of the valuation cap, and therefore, so are the shares issued to the accelerator q_A. In this case, when the valuation cap increases, the issued shares q_A decrease, and so too do the total shares outstanding and issued (Q), leading to a strict increase in entrepreneur's effort. He retains relatively more of the equity in the firm, since the accelerator converts at less favorable prices, yielding it fewer shares. But if the discount rate determines the conversion price, the conversion price is invariant to the valuation cap, as is q_A and Q. In this case, the effort of the entrepreneur does not change with the valuation cap. The effect of the valuation cap on entrepreneurial effort is therefore weakly increasing.

Now, consider the accelerator's problem. If the entrepreneur fails to raise money, then valuation stays at v_A. The accelerator pays its cost of investment and cost of effort. So, the profit for the accelerator is $\pi_A = -I_A - C(a)$. If the entrepreneur succeeds in raising money, then the valuation rises to v and the accelerator receives an ownership stake of $\frac{q_A}{Q}$ of this higher valuation. After paying the cost of investment and effort for advising the entrepreneur, the accelerator's expected profits are

$$E\pi_A = \rho\left[\frac{q_A}{Q}v\right] - I_A - C(a). \qquad (3)$$

Maximizing these expected profits with respect to advising effort yields the incentive constraint for the accelerator:

$$\hat{a} = \frac{1}{c_a}\left[\frac{q_A}{Q}v\right]. \tag{IC_a}$$

Just as with entrepreneurial effort, the effect of the valuation cap on advisory effort depends on whether the cap binds or not. If it does not bind, then the conversion price and ownership stake of the accelerator $\frac{q_A}{Q}$ are both invariant to the valuation cap, so this has no effect on the accelerator's payoffs, nor on advisory effort a. But if the cap binds, increasing the valuation cap increases the conversion price, decreasing the shares issued to the accelerator q_A and decreasing the accelerator's ownership stake $\frac{q_A}{Q}$, leading to a decrease in advisory effort.

Let $\hat{a} = \hat{a}(\hat{\bar{v}})$, $\hat{e} = e(\hat{\bar{v}})$ be equilibrium effort and $\hat{\rho} = \gamma\theta\hat{e} + \hat{a}$ the equilibrium probability of raising money. The entrepreneur's participation constraint is given by

$$\widehat{EU} = \frac{\hat{\rho}\beta v q_0}{Q} + (1-\hat{\rho})\beta v_A - C(\hat{e}) \geq \bar{u}_e \tag{PC_e}$$

Assume the entrepreneur is protected by limited liability. The accelerator's participation constraint is:

$$\widehat{E\pi}_A = \hat{\rho}\left[\frac{q_A}{Q}v\right] - I_A - C(a) \geq \bar{u}_A, \tag{PC_A}$$

Assume the parameters $I_{VC}, I_A, c_a, \bar{u}_A, \bar{u}_E$ and v_0 are such that (PC_A) and (PC_e) hold. The accelerator chooses a contract $\bar{v}$ to maximize expected profits. The contract terms will directly affect the expected profits by determining the accelerator's ownership stake in the final valuation, but it will also indirectly affect profits through effort choices of both the entrepreneur and the accelerator. Therefore, the expected profit function can be written in terms of the contract as $E\pi_A\big(\bar{v}, \hat{e}(\bar{v}), \hat{a}(\bar{v})\big)$, where $\hat{e}$ and $\hat{a}$ are given by (IC_e) and (IC_A). Maximizing this expected profit function with respect to the contract generates the optimal contract.

PROPOSITION 1: If VC's investment is sufficiently large relative to the accelerator's investment $\left(I_{vc} > \frac{(v_0+I_A)q_{vc}}{q_0}\right)$, then the optimal valuation cap is:

$$\hat{\bar{v}} = \frac{\frac{vc_e q_0}{c_e(q_0+q_{vc})} - \frac{vc_e}{c_a\beta\gamma^2\theta^2} + v_A}{\frac{I_{vc}}{I_A} - \frac{v_A q_{vc}}{I_A q_0}} \tag{4}$$

Proof: Write the expected profit function of the accelerator as

$$E\pi_A\big(\bar{v}, e(\bar{v}), a(\bar{v})\big) = v\rho\left[\frac{q_A}{Q}\right] - I_A - C(a). \tag{5}$$

Differentiating expected profits $E\pi_A$ with respect to $\bar{v}$ gives

$$\frac{dE\pi_A}{d\bar{v}} = \frac{\partial E\pi_A}{\partial \hat{e}}\frac{\partial \hat{e}}{\partial \bar{v}} + \frac{\partial E\pi_A}{\partial \bar{v}} + \frac{\partial E\pi_A}{\partial \hat{a}}\frac{\partial \hat{a}}{\partial \bar{v}} = 0. \tag{6}$$

The third term is zero because (IC_a) requires $\frac{\partial E\pi_A}{\partial \hat{a}} = 0$. For valuation caps $\bar{v} > \bar{v}^*$, the conversion price and q_A do not change with respect to the cap. Therefore, in this region the total derivative is $\frac{dE\pi_A}{d\bar{v}} = 0$, so the choice of the cap is arbitrary. For $\bar{v} < \bar{v}^*$, write the shares given to the accelerator and total shares as:

$$q_A = \frac{I_A q_0}{\bar{v}} \text{ and } Q = q_0 + q_{vc} + q_A. \tag{7}$$

Differentiating with respect to the valuation cap gives

$$\frac{\partial Q}{\partial \bar{v}} = \frac{\partial q_A}{\partial \bar{v}} = -\frac{I_A q_0}{\bar{v}^2} < 0. \tag{8}$$

These are the only terms that vary with $\bar{v}$. Thus,

$$\frac{\partial\left(\frac{q_A}{Q}\right)}{\partial\bar{v}} = \frac{\left(Q\frac{\partial q_A}{\partial\bar{v}} - q_A\frac{\partial Q}{\partial\bar{v}}\right)}{Q^2} = \frac{\frac{\partial q_A}{\partial\bar{v}}(q_0 + q_{vc})}{Q^2} = -\frac{I_A q_0(q_0 + q_{vc})}{(\bar{v}Q)^2} < 0 \tag{9}$$

Finally, evaluating the partial derivatives gives

$$\frac{\partial\hat{e}}{\partial\bar{v}} = -\frac{\beta\gamma\theta}{c_e}\frac{vq_0}{Q^2}\frac{\partial Q}{\partial\bar{v}} = \frac{\beta\gamma\theta v I_A q_0^2}{c_e Q^2\bar{v}^2} > 0. \tag{10}$$

Now, since $\rho = \gamma\theta e + a$,

$$\frac{\partial E\pi_A}{\partial e} = \frac{\gamma\theta q_A v}{Q} \tag{11}$$

And,

$$\frac{\partial E\pi_A}{\partial\bar{v}} = \rho\left[\frac{\partial\frac{q_A}{Q}}{\partial\bar{v}}\right]v = -\frac{v\rho I_A q_0(q_0 + q_{vc})}{(\bar{v}Q)^2} < 0. \tag{12}$$

Combining,

$$\frac{dE\pi_A}{d\bar{v}} = \frac{\partial E\pi_A}{\partial\hat{e}}\frac{\partial\hat{e}}{\partial\bar{v}} + \frac{\partial E\pi_A}{\partial\bar{v}} = \left(\frac{\gamma\theta q_A v}{Q}\right)\left(\frac{\beta\gamma\theta v I_A q_0^2}{c_e Q^2\bar{v}^2}\right) - v\rho\left(\frac{I_A q_0(q_0 + q_{vc})}{(\bar{v}Q)^2}\right)$$

The optimal $\bar{v}$ satisfies $\frac{dE\pi_A}{d\bar{v}} = 0$, or

$$\left(\frac{\gamma\theta q_A v}{Q}\right)\frac{\beta\gamma\theta v I_A q_0^2}{c_e Q^2\bar{v}^2} = \frac{v\rho I_A q_0(q_0 + q_{vc})}{(\bar{v}\bar{Q})^2} \tag{13}$$

Simplifying,

$$\frac{q_A\beta\gamma^2\theta^2 v q_0}{Qc_e} = (\gamma\theta\hat{e} + \hat{a})(q_0 + q_{vc})$$

Write (IC_e) and (IC_a) as

$$\hat{e} = \frac{\beta\gamma\theta}{c_e}\left[\frac{vq_0 - v_A Q}{Q}\right] \text{ and } \hat{a} = \frac{1}{c_a}\left(\frac{q_A}{Q}v\right) \tag{14}$$

So the prior equation becomes

$$\frac{q_A \beta\gamma^2\theta^2 v q_0}{c_e} = \left[\frac{\beta\gamma^2\theta^2}{c_e}(vq_0 - v_A Q) + \frac{1}{c_a} v q_A\right](q_0 + q_{vc}) \tag{15}$$

Now,

$$vq_0 - v_A Q = (v_A + I_{vc})q_0 - v_A(q_0 + q_A + q_{vc}) = I_{vc}q_0 - v_A(q_A + q_{vc}). \tag{16}$$

Dividing by q_A, the prior equation becomes:

$$\frac{\beta\gamma^2\theta^2 v q_0}{c_e} = \left[\frac{\beta\gamma^2\theta^2}{c_e}\left(\frac{I_{vc}q_0}{q_A} - v_A\left(1 + \frac{q_{vc}}{q_A}\right)\right) + \frac{v}{c_a}\right](q_0 + q_{vc}) \tag{17}$$

Substituting $q_A = (I_A q_0)/\bar{v}$, we have:

$$\frac{\beta\gamma^2\theta^2 v q_0}{c_e(q_0 + q_{vc})} = \frac{\beta\gamma^2\theta^2}{c_e}\left[\frac{I_{vc}q_0\bar{v}}{I_A q_0} - v_A\left(1 + \frac{q_{vc}\bar{v}}{I_A q_0}\right)\right] + \frac{v}{c_a} \tag{18}$$

Rearranging,

$$\frac{\beta\gamma^2\theta^2 v q_0}{c_e(q_0 + q_{vc})} - \frac{v}{c_a} = \frac{\beta\gamma^2\theta^2}{c_e}\left[\bar{v}\left(\frac{I_{vc}}{I_A} - \frac{v_A q_{vc}}{I_A q_0}\right) - v_A\right] \tag{19}$$

Thus, the optimal cap is

$$\hat{\bar{v}} = \frac{\left(\frac{\beta\gamma^2\theta^2 v q_0}{c_e(q_0 + q_{vc})} - \frac{v}{c_a}\right)\frac{c_e}{\beta\gamma^2\theta^2} + v_A}{\frac{I_{vc}}{I_A} - \frac{v_A q_{vc}}{I_A q_0}} \tag{20}$$

Assume the parameters of the model are such that this optimal cap lies below $\bar{v}^*$, which is the cap that satisfies $(1-d)p_{vc} = \frac{\bar{v}^*}{q_0}$. (If this were not the case, accelerator's profit function would be invariant with respect to the cap, and so the accelerator would be indifferent to any cap).

Now, write equation (19) as $\frac{dE\pi_A}{d\bar{v}} = 0$, so

$$\frac{dE\pi_A}{d\bar{v}} = \frac{\beta\gamma^2\theta^2 v q_0}{c_e(q_0 + q_{vc})} - \frac{v}{c_a} - \frac{\beta\gamma^2\theta^2}{c_e}\left[\bar{v}\left(\frac{I_{vc}}{I_A} - \frac{v_A q_{vc}}{I_A q_0}\right) - v_A\right] = 0 \tag{21}$$

The second order condition $\frac{d^2E\pi_A}{d^2\bar{v}} < 0$ becomes

$$-\frac{\beta\gamma^2\theta^2}{c_e}\left(\frac{I_{vc}}{I_A} - \frac{v_A q_{vc}}{I_A q_0}\right) < 0 \qquad (SOSC)$$

which holds if $I_{vc} > \frac{v_A q_{vc}}{q_0} = \frac{(v_0 + I_A) q_{vc}}{q_0}$.

QED.

Proposition 1 derives the optimal contract. In this game, we take the accelerator's investment amount and the discount rate as exogenous and optimize only over the single variable, the valuation cap. Therefore, the accelerator has one instrument to satisfy two constraints: the incentive and participation constraints. Before the entrepreneur and accelerator enter into a contract, they will both forecast their equilibrium payoffs in the game and their equilibrium probability of raising financing from the VC. That will then generate their equilibrium payoffs given by $\widehat{EU}$ and $\widehat{E\pi_A}$ for the entrepreneur and accelerator, respectively. If these payoffs exceed their relevant outside options, then the entrepreneur and accelerator will enter into a contract.

We assume, without loss of generality, that the outside options are low enough that they will contract. Note that this is slightly different from the standard moral hazard contracting model with a linear contract that has a variable component that resolves the incentive constraint and a fixed component that resolves the participation constraint. A seed financing contract is necessarily more complex because the contract does not cleanly separate into two components, and so the compensation parameters cannot separately address each constraint. Even taking the investment amount I_A as endogenous will not lead to a clean solution because both the valuation cap and the investment amount each influence both the participation and the incentive constraints.

To understand the intuition behind the optimal contract, observe that there is a direct and indirect effect from a high valuation cap (from the accelerator's perspective). A low valuation cap will allow the accelerator to buy into the venture at favorable prices (relative to the VC), which will directly increase its profits. But a low valuation cap will also dampen incentives for the entrepreneur to exert effort, which is the indirect effect through incentives. A low valuation cap will increase the accelerator's profits conditional on raising money, but it affects the unconditional probability of raising money at all because of the effect on incentives. The optimal valuation cap will balance these direct and indirect effects. The intuition behind the proposition can be seen from the total derivative of expected profits:

$$\frac{dE\pi_A}{d\bar{v}} = \underbrace{\frac{\partial E\pi_A}{\partial \hat{e}} \frac{\partial \hat{e}}{\partial \bar{v}}}_{\substack{\text{Indirect} \\ \text{Effect}}} + \underbrace{\frac{\partial E\pi_A}{\partial \bar{v}}}_{\substack{\text{Direct} \\ \text{Effect}}} \tag{22}$$

This is the total derivative of the effect of the valuation cap on the accelerator's profits, written in terms of the twin partial effects. The direct effect is the second term, namely the effect of the cap on profits. This indirect effect is the first term, which runs through the effort of the entrepreneur. A change in the cap will change effort, and effort will then change the accelerator's profits through the probability of obtaining equity financing. The direct effect is positive while the indirect is negative: increasing the cap increasers effort from the entrepreneur which raises the likelihood of equity financing and consequently increases accelerator profits; this is the indirect effect. But increasing the cap also decreases the accounting profits of the accelerator; this is the direct effect. The optimal cap will balance these opposing direct and indirect effects. Under this optimal contract, we can examine how the optimal cap changes with respect to founder/firm types.

Corollary 1: The optimal valuation cap increases in the type of the entrepreneur and the firm.

Proof: Rewrite the optimal cap as

$$\bar{v} = \frac{\frac{vq_0}{(q_0 + q_{vc})} - \frac{vc_e}{c_a\beta\gamma^2\theta^2} + v_A}{\frac{I_{vc}}{I_A} - \frac{v_A q_{vc}}{I_A q_0}} \tag{23}$$

Let W be the denominator above. By $(SOSC)$, $W > 0$.

$$\frac{\partial\bar{v}}{\partial\theta} = \frac{2vc_e}{Wc_a\beta\gamma^2\theta^3} > 0 \text{ and } \frac{\partial\bar{v}}{\partial\gamma} = \frac{\partial vc_e}{Wc_a\beta\gamma^3\theta^2} > 0\ . \tag{24}$$

QED.

While proof of Corollary 1 is a straightforward derivative from the optimal contract, we can obtain more intuition by examining the direct and indirect effect of the cap on profits. The effect of the entrepreneur's type on the optimal cap is ultimately an application of the implicit function theorem and can be seen from differentiating the total derivative:

$$\frac{d^2 E\pi_A}{d\theta d\bar{v}} = \frac{\partial\hat{e}}{\partial\bar{v}}\frac{\partial^2 E\pi_A}{\partial\theta\partial\hat{e}} + \frac{\partial E\pi_A}{\partial\hat{e}}\frac{\partial^2\hat{e}}{\partial\theta\partial\bar{v}} + \frac{\partial^2 E\pi_A}{\partial\theta\partial\bar{v}} \tag{25}$$

A marginal change in the entrepreneur's type has positive impact on the indirect effect since $\frac{\partial E\pi_A}{\partial\hat{e}} = \gamma\theta\frac{q_A}{Q}v$. Because effort and type are complements in production, higher type managers will work more, which will marginally boost profits by a greater amount for the high types. At the same time, the direct effect of the cap on the accelerator's (accounting) profits increases in absolute value, i.e. the effect becomes more negative as the entrepreneur's type increases. Recall that the direct effect of the valuation cap on the accelerator's accounting profits is negative, as higher caps erode the accelerator's profits. The direct effect is given by $\frac{\partial E\pi_A}{\partial \bar{v}} = \rho v \frac{\partial\left(\frac{q_A}{Q}\right)}{\partial \bar{v}}$, which includes the change in the accelerator's ex-post ownership stake for a change in the level of the cap. This negative effect occurs when the entrepreneur raises money. Better entrepreneurs are more able to raise money, so in expectation have a larger (negative) direct effect on profits. The optimal valuation cap will balance the upward pressure from the indirect effect against the downward pressure from the direct effect. Corollary 1 states that the positive pressure outweighs the downward pressure, so increases in entrepreneur/firm types will lead the accelerator to increase the valuation cap.