Human Capital Breadth, Portfolio Choice and Performance in Venture Capital *

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Abstract

I examine how the breadth of venture capital (VC) partners' human capital influences investment selection, startup performance, and innovation. Partners with broader human capital are more likely to lead investments in novel startups with previously unexplored business models and significantly increase the likelihood of major success; however they underperform when leading non-novel deals. Exploiting plausibly exogenous variation in partner time constraints as a shock to the within-VC firm likelihood of leading a deal, I provide causal evidence for these effects. A theoretical model endogenizes startup creation, partner assignment, and investment to rationalize the findings and generate further predictions. The results highlight the nuanced value of human capital breadth in financing innovation.

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1 Introduction

Venture capital (VC) plays a critical role in fostering innovation and economic growth by financing high-risk, high-reward startups (Lerner, 2000; Samila and Sorenson, 2011; Kaplan and Lerner, 2010; Gornall and Strebulaev, 2021). The success of this model depends not only on financial capital but also on the human capital of VC investors, who leverage their expertise to identify, support, and scale promising startups (Kaplan and Strömberg, 2001; Gompers and Lerner, 2002; Casamatta, 2003; Kaplan and Strömberg, 2004; Chemmanur et al., 2011; Bernstein et al., 2016; Gompers et al., 2020). The literature on human capital and investment performance reveals a fundamental tension regarding the optimal composition of investors' skill sets. On the one hand, research in financial intermediation underscores the benefits of specialization, arguing that deep industry expertise leads to superior outcomes (Gompers et al., 2009; Cressy et al., 2007; Blickle et al., 2023; Spaenjers and Steiner, 2024). Conversely, the literature in labor economics and finance highlights benefits of breadth-often described as a "jack of all trades" advantage—arguing that individuals with broad, diverse experience are better equipped to adapt to uncertainty and facilitate innovation (Lazear, 2004; Custódio et al., 2013, 2019; Murphy and Zabojnik, 2007). This tension is especially pronounced in venture capital, given that VCs primarily invest in early-stage firms with uncertain prospects, sparse historical data, and radically novel business models that differ significantly from previously financed startups.

A key unresolved question is whether broader human capital enhances the ability to identify and support novel investments or whether deeper specialization consistently drives superior outcomes through domain-specific expertise. Ex-ante, the answer to this question is ambiguous. On the one hand, deep expertise may help VC partners assess the technological viability and potential of the startup, on the other hand, especially for early stage deals broader knowledge may be helpful in assessing the team or broader business model potential. In this paper, I address this question both empirically and theoretically.

Answering this question empirically is challenging. The first challenge relates to measurement. Quantifying startup novelty ex ante is difficult, and data on VC partners' human capital are not readily available. Second, even with perfect empirical measures, we are faced with an identification challenge. The matching process between startups and VC investors is non-random and there is ample evidence that ex ante higher quality startups prefer to match to more experienced VCs (Hsu, 2004; Sørensen, 2007). Even within VC firms, the literature has documented a large heterogeneity in skills among individual VC partners (Ewens and Rhodes-Kropf, 2015). In this paper, I tackle both challenges. On the measurement front, using startups' business descriptions, I construct and validate a new measure of ex ante startup novelty and rely on LinkedIn data accessed through Revelio Labs to construct measures of VC partners' human capital. I address the identification challenge in two ways. To rule out the first concern, i.e., ex ante matching between startup and VC investor, in all specifications I rely on within VC firm-year variation while also controlling for time-varying partner-level characteristics and granular fixed effects related to deal characteristics. To further address endogenous VC partner-venture matching within VC firms, I exploit plausibly exogenous variation in partners' time-varying time constraints, which serves as a probability shifter for partner assignment to deals, akin to a Bartik (1991)-style instrument (Abuzov, 2019).

Empirically, first in a reduced-form analysis, I document that, within VC firms, partners with broader human capital are more likely to lead investments in startups pursuing novel and previously unexplored business models. While these partners are associated with lower performance in non-novel deals, their involvement in novel investments is correlated with a significantly higher likelihood of major success. All specifications include fixed effects for VC firm, year of investment, deal stage, industry, and country. This setup allows me to compare partners with different levels of human capital breadth making investment decisions within the same VC firm and year, and within tightly defined deal characteristics. Second, to address concerns about endogenous partner-deal assignment within VC firms, I exploit plausibly exogenous variation in partners' time constraints. Following Abuzov (2019), I proxy time constraints using a "busyness" measure: a partner is considered busy if they are concurrently involved in a high-value exit event for another deal. Controlling for other partner-level characteristics, I confirm that busy partners are less likely to lead a new deal, consistent with busyness limiting assignment. I construct a time-varying measure of the availability of broad-background partners within each VC firm to serve as a shift variable in assignment: when more broad partners are available (i.e., not busy), the probability that a novel deal is led by such a partner increases. This instrument provides exogenous variation in the likelihood that a broad partner leads a given deal. Using this approach, I estimate the causal effect of partner human capital breadth on investment outcomes and find that it has a positive effect on the performance of novel firms and a negative effect on the performance of non-novel firms. Finally, I document two additional stylized facts: (i) the share of VC financing allocated to radically novel startups has declined substantially over the past two decades, and (ii) the human capital of VC investors has become increasingly specialized over the same period.

To rationalize the empirical findings and observed secular trends, I develop a three-stage model that jointly endogenizes entrepreneurial entry, the VC firm's partner assignment to projects, and partner screening effort. In the first stage, an entrepreneur chooses whether to produce a high or low quality novel project, with limited liability and a non-pecuniary benefit from receiving VC financing. In the second stage, the VC firm assigns a partner either specialized or broad, and the partner chooses how much costly effort to exert in screening the project. Screening produces a noisy signal of project quality, with broader partners having lower effort costs for novel projects but also lower fallback payoffs if the project is rejected. In the final stage, surplus is split between the VC and entrepreneur, conditional on project quality and financing. The model generates equilibrium predictions for partner specialization, screening effort, and project acceptance. It rationalizes the empirical finding that broader partners are more likely to finance novel projects and perform better when doing so showing that lower specialization reduces screening costs and raises acceptance rates and expected returns when the prior for high quality ventures is low. The model also accounts for the long-run decline in financing for novel startups and the rise in partner specialization: when the cost of producing high-quality novel ventures increases (e.g., due to rising complexity or "burden of knowledge" Jones (2009)), fewer entrepreneurs select into high-quality entry, lowering the prior for novel success. In response, VCs optimally hire more specialized partners with higher fallback payoffs, reducing screening effort and further discouraging high-quality entry—creating a feedback loop that drives both trends. A result of the model is that the share of novel ventures financed and specialization should co-move in opposite directions. The equilibrium reacts in a similar way if, instead of increasing the cost of creating high-quality novel ventures, the cost of entry is reduced for entrepreneurs, e.g., as argued by Ewens et al. (2018).

To study this question empirically, I combine three primary datasets: PitchBook, Revelio Labs, and the USPTO. From PitchBook, I collect information on VC investments and startup exits. From Revelio Labs, I gather detailed data on VC partners' human capital. To measure innovation among VC-backed startups, I use patent application, grant, and citation data from the United States Patent and Trademark Office (USPTO).

To measure the extent to which a VC-financed startup is novel, I leverage recent advances in the NLP literature and rely on business descriptions of VC-funded startups available in PitchBook.[1] For each startup I first construct an OpenAI LLM-based em-

[1] One concern with using business text descriptions is that startups may pivot from their original business plans. However, Kaplan et al. (2009) provide evidence that this is very rare, and business plans remain relatively sticky from the time a company receives its first round of venture financing to its public listing. This is also consistent with Paine (2024), who finds that around 87% of words that appear on

bedding vector from the startup's business description.[2] This allows me to compute the embedding-based distance between any two VC-funded startups using cosine similarity. The novelty proxy for a given startup is then computed as the maximum cosine-similarity distance between the focal startup and all startups financed by the VC industry in the five years before the focal startup receives its first VC financing.[3] The novelty measure captures how different a given startup's business model is relative to the closest venture financed by the VC industry in the past.

Using this measure, I present several new stylized facts about novel firms and aggregate novelty trends in the VC industry. First, I document two facts that also serve as checks on the validity and usefulness of the measure. The novelty measure is strongly correlated with the likelihood of achieving either major success or failure, and this result holds when including granular VC firm, deal stage, deal industry, financing year, and financed company country fixed effects. That is, novel firms financed by the same investor in the same industry, stage, deal year, and country have a higher likelihood of achieving a major successful exit or experiencing failure. In terms of magnitude, a one-standard-deviation increase in novelty is associated with a 0.8% increase in the probability of failure and a 4.5% increase in the probability of achieving a major success.

Second, I document that startup novelty correlates positively with both the number of forward patents granted and the number of forward patent citations (after receiving VC financing), suggesting that this measure can serve as an ex-ante proxy for future startup innovation output.[4] The magnitude is sizable, and a one-standard-deviation increase in novelty is associated with 7.5% higher expected patent counts and a 26% increase in the expected number of forward citations.

When analyzing time trends of novelty, I document a steadily declining trend in the average novelty of VC-financed startups over the sample period (2003–2021)).[5] The trend does not seem to be driven by a decline in absolute novelty among all VC-financed star-

startups' webpages during their first rounds of financing are also present on their IPO prospectus.

[2] Duevski and Bazaliy (2025) compare the performance of different embedding models and argue that OpenAI-based embedding models achieve superior performance for VC data.

[3] This measure is related to but distinct from Bonelli (2022)'s "backward similarity" measure, which is computed as the average past similarity between a focal startup and what the VC industry has financed in the past in the same industry. Bonelli (2022)'s "backward similarity" measure captures startup nicheness and is well suited as a proxy for VC firms' ability to predict future outcomes from past data.

[4] This measure has several advantages over using patent data directly: (i) very few early stage VC financed firms patent, (ii) patenting by early stage firms is concentrated in very few sectors e.g., life sciences and biotech.x

[5] Notice that this trend is not purely mechanical and simply an simply an artifact of the proliferation of VC activity, since (i) the measure is constructed using a rolling-window look-back and (ii) in robustness analysis, I construct an alternative novelty measure where each focal firm is compared to the same number of random VC-financed firms, i.e., the number of firms used as a benchmark is fixed.

tups; instead, it is driven by a decline in the share of highly novel startups receiving financing each year.

To measure human capital breadth of VC partners, I rely on Revelio Labs, a workforce database provider that has collected an extensive set of LinkedIn profiles. I first match partners listed in PitchBook to Revelio Labs. For the subset of matched partners, I extract detailed educational and work histories of VC partners before they joined the VC industry.[6] To measure human capital breadth, I closely follow Custódio et al. (2013) and construct four proxies of human capital breadth: the ratio of distinct job categories a partner has held in the past to total employment spells; the ratio of distinct roles a partner has held in the past to total employment spells; the ratio of distinct industries a partner has worked in to total employment spells and the total number of distinct educational degrees a partner has obtained. I construct a human capital breadth index from these measures by Principal Component Analysis (PCA), similar to Custódio et al. (2013). In the empirical analysis, I use this index as the main measure of human capital breadth, and conduct robustness checks for each individual measure. Using this index, I document a decrease in human capital breadth in the VC industry over my sample period (2003–2021). This fact is robust to measurement choices, and one can observe a secular decline even when using a simple educational measure such as the fraction of MBA-educated partners relative to partners with a PhD or a STEM degree.

First, without claiming to establish causality, using investment-level data, I document that within a VC firm, partners with broad backgrounds are more likely to be lead partners on novel deals. A one-standard-deviation increase in a partner's breadth index is associated with a 0.1-standard-deviation increase in deal novelty. This relationship is stronger for investments where the VC firm is a lead investor, for non-syndicated deals, and for deals led by partners earlier in their VC careers.

I also find that the interaction between startup novelty and lead partner breadth is positively associated with performance, measured by the likelihood of a major success.[7] However, the baseline coefficient of human capital breadth is negative, implying a negative correlation between human capital breadth and performance for non-novel firms. In these specifications, I control for granular fixed effects at the deal stage, deal indus-

[6] PitchBook, through WRDS, does not provide information about the date a partner joined a particular VC firm. I proxy for VC industry entry by using the date of the earliest deal done by a given partner in PitchBook and ensuring that the job history identified is before the partner joined the firm where they made their first investment.

[7] Following prior literature, I define major success to be an exit via IPO or a high value acquisition. The effect is robust for various thresholds of defining a high value acquisition and also holds when only including IPO exits (Gompers et al., 2020).

try, deal year, and VC-firm levels. This ensures that the observed association is not driven by VC-firm-specific quality, project deal flow, specialization in a particular sector or investment style, or systematic differences in novelty trends across sectors and deal stages. Additionally, the granular fixed effects account for time-varying macroeconomic and industry shocks that could influence performance outcomes. In terms of economic magnitude, for non-novel firms (those with novelty one standard deviation below the mean), a one-standard-deviation increase in human capital breadth is associated with a 1.5 percentage point decrease in the likelihood of a major success. For novel firms (one standard deviation above the mean), the corresponding increase in breadth is associated with a 1.5 percentage point increase in this likelihood.

To study the causal impact of human capital breadth on startups' performance, I first restructure the data following Ewens and Rhodes-Kropf (2015). For each deal made by a VC firm, I construct a set of potential lead partners, defined as those employed by the same firm within a three-year window around the deal (-3 to +3 years). For each potential lead, I incorporate a busyness proxy, following Abuzov (2019), which equals 1 if the partner is involved in a major exit event—either a high-value acquisition or an IPO—within a 90-day window (-90 to +90 days) around the focal deal. First, using this data structure, I show that busy partners are less likely to lead concurrent deals. In terms of economic magnitude, in the baseline, being busy reduces the likelihood of leading a concurrent deal by around 1.9%, which is about a 10% relative reduction (compared with 20% unconditional probability of being an investment lead); if we focus solely on deals where the VC firm is a lead investor, this magnitude doubles and further increases if I focus on early-stage deals only. This suggests that time constraints of VC partners become more important for deals where the VC firm takes the lead and early-stage investments. This is intuitive and consistent with the fact that time constraints of partners are more binding when the screening or monitoring effort required by the VC firm is larger. This data structure also allows me to provide further evidence on the fact that higher human capital breadth partners are more likely to lead novel deals. Using this data structure, I can formally estimate the effect of the interaction between partner human capital breadth and deal novelty on the likelihood of leading a deal, while including granular partner and deal fixed effects. Intuitively, this means that the interaction term will be estimated by within partner variation across deals of different novelty where the partner is chosen or not to be a lead partner and within deal variation of partners of different human capital breadth. I find a positive and economically large interaction term. For deals of one standard deviation above mean novelty a one standard deviation increase in human capital breadth raises the likelihood of leading a deal to around 51% which is large relative to the unconditional mean of 20% and the estimate is even larger for deals where the VC firm is a lead investor. I run several robustness checks. (1) I construct a Busy Partner placebo by reshuffling the busy indicator across partners while keeping the within deal distribution of busy and non-busy partners the same and I find no effect. (2) I vary the construction of the busyness proxy (e.g., including only IPO events where partners are arguably more time-constrained). (3) different time windows (± 60, ± 45 days).; the effects remain robust.

This data structure also underpins my identification strategy for estimating the causal effect of human capital breadth on performance. The central challenge is endogenous partner-deal assignment within VC firms: partner selection may correlate with unobserved deal quality or partner traits. To address this, I construct an instrument based on idiosyncratic fluctuations in partner availability driven by exit events in a partner's existing portfolio. These events reduce a partner's availability for new investments, generating plausibly exogenous variation in who leads a given deal. Specifically, I use the average human capital breadth of all available (i.e., non-busy) partners in a firm at the time of each deal to instrument for the breadth of the lead partner. This shift-share instrument varies within VC firm and year, capturing changes in partner availability across deals rather than cross-sectional differences across VC firms. Crucially, because partner exits are driven by factors unrelated to the specific startups under consideration (within a given VC firm), the average available human capital breadth at the time of a deal is plausibly exogenous to future startup performance. By exploiting this within-VC firm-year variation, I mitigate concerns about endogenous matching based on unobserved startup quality or partner-specific characteristics. The exclusion restriction is reasonable because variations in partner availability driven by unrelated exit events should influence startup performance only through their effect on the selection of a broad or narrow-background partner, rather than through other omitted channels.[8]

The intuition behind this instrument is that, within a given VC firm in a given year, the probability of assigning a broad-background (narrow-background) partner to a deal increases (decreases) with the average availability of broad human capital. I use average human capital breadth availability to instrument for the chosen partner's human capital breadth and the interaction of average breadth availability and deal novelty to instrument for the interaction of the chosen partner's breadth and deal novelty. The relevance condition is strongly supported by the data, with F-statistics exceeding 100, and is eco-

[8]This is likely to be valid for early-stage investments, since, as argued by Malenko et al. (2024), individual partners play a vital role in the selection process of startups, and many VC firms apply a champion rule during investment-committee voting. I also provide further evidence that team diversity measured at a fund level does not seem to play a role in the likelihood of financing novelty.

nomically meaningful: a one-standard-deviation increase in average breadth availability is associated with a 0.3-standard-deviation increase in the human capital breadth of the selected partner, demonstrating a strong first-stage relationship. The IV estimates imply that, at very low novelty, an additional standard deviation of breadth reduces the probability of major success by about 11%, representing a negative baseline effect. For firms with novelty of one standard deviation above the mean, a one-standard-deviation increase in human capital breadth leads to an 8.2% increase in the probability of a major exit. The IV estimates are similar in magnitude to the OLS estimates in the same sample.

The empirical findings and the construction of the tests in the paper are consistent with both selection, whereby broad-background partners are better at screening novel firms (but not non-novel firms), and monitoring, whereby their involvement helps novel firms achieve a successful exit. The IV strategy employed does not allow me to separate the two channels, since when a partner is busy this may reduce both (i) the likelihood of the partner screening the project (e.g., not participating during pitches or committee voting due to time constraints) and (ii) the likelihood of the partner being involved with the startup after financing.

Overall, my findings highlight the critical role of human capital breadth in fostering exploration and financing novel ventures. The observed decline in aggregate novelty among VC-financed startups over time can be explained by two potential factors. One perspective, consistent with Bloom et al. (2020), would suggest that as startup business models become less novel, VC firms adapt by specializing, which leads to a decline in broad expertise among partners. Alternatively, as Lerner and Nanda (2020) argue, the VC industry has increasingly focused on narrower investment scopes, prioritizing ventures that align with institutional investors' preferences and risk profiles. This shift may constrain support for a broader range of innovative opportunities and limit financing for novel business models. From this perspective, my findings suggest that policy interventions supporting the development of human capital breadth could be beneficial. Policies that encourage cross-sector job mobility or promote interdisciplinary education, particularly in business and technical fields may enhance the capacity of investors to evaluate and support innovative ideas. Business schools and executive education programs could play a role by embedding cross-disciplinary training into their curricula.

2 Related Literature

My primary contribution is to the literature studying the drivers of portfolio choice by venture capitalists and outcomes of funded startups. A substantial body of research underscores the critical role that venture capitalists play in financing and nurturing innovative startups. Two primary mechanisms of value creation recur throughout this literature: the ability to attract or select high-potential ventures (Sørensen, 2007; Howell, 2020) and the monitoring that VCs provide post-investment (Hellmann and Puri, 2000; Lindsey, 2008; Bernstein et al., 2016; Ewens and Marx, 2018). While much of the early literature on venture capital focuses on firm-level attributes such as reputation, syndication networks, and overall fund size (Hochberg et al., 2007; Gompers et al., 2008), recent research has begun to zero in on the partner-level drivers of performance. Studies examining how individual venture capitalists' skills and backgrounds influence deal success frequently emphasize the significance of partner-level human capital. Ewens and Rhodes-Kropf (2015), for example, show that differences among partners within the same VC firm have a substantial impact on investment outcomes. Likewise, Nahata (2008) links partner experience to investment performance, suggesting that personal track records and industry knowledge play a vital role in building VC reputation. My primary contribution to this literature is to show that individual VC partners' human capital breadth is particularly important for the selection and monitoring of startups with novel (previously unexplored) business models.

In addition to contributing to the literature on venture capital and portfolio choice, I also build on research in labor economics and finance by highlighting instances where a broad, generalized skill set can be advantageous. Lazear (2004)'s "Jack of all trades" theory argues individuals with more balanced skill set are more likely to become successful entrepreneurship. Lazear (2012) argues that leaders are more likely to be generalists in both their innate characteristics and in their pattern of skill acquisition. In the context of executive leadership, Murphy and Zabojnik (2004) and Murphy and Zabojnik (2007) argue that the shift from firm-specific to general managerial skills has contributed to rising executive compensation and increased competition for top talent. Similarly, Custódio et al. (2013) and Custódio et al. (2019) find that generalist CEOs earn higher salaries, manage more complex firms, and drive greater innovation. I extend this literature by showing that venture capitalists with broader human capital are more likely to identify and finance novel startups and to facilitate their successful exits.

I also contribute to the literature on performance heterogeneity between specialist and generalist private equity and venture capital (VC) firms. A strand of literature argues that specialist private market intermediaries tend to outperform their diversified counterparts (Cressy et al., 2007; Spaenjers and Steiner, 2024), while Humphery-Jenner (2013) argue that there is a premium for more diversified PE funds. A seminal study by Gompers et al. (2009) finds that industry investment specialization at the partner level is positively associated with performance. I extend this literature in two key ways. First, I introduce a critical distinction between two dimensions of specialization: the breadth of human capital individual VC partners accumulate before entering the VC industry—an inherent personal characteristic—and their investment focus after becoming startup investors. Second, I demonstrate that while broad human capital does not confer an advantage for the average VC-financed firm, it plays a crucial role in supporting early stage novel projects within a given sector. My findings refine the existing understanding of specialization in venture capital by highlighting the nuanced role of human capital breadth in fostering the financing of novel ventures.

3 Data sources, Measurement and Stylized Facts

3.1 Data Sources

This paper examines how the human capital breadth of Venture Capitalists (VCs) affects their investment choices, performance, and the innovation output of funded startups. To investigate this, I employ detailed data on VC portfolio allocation, exits of startups funded by VCs, patent applications and citations of VC-funded companies, and the human capital of VC investors. Specifically, I integrate data from several sources: PitchBook, which provides detailed data on VC investments and the subsequent exits of funded startups; a combined dataset from PitchBook and Revelio to construct measures of human capital by VC partners; and USPTO data to evaluate innovation output through patents and citations of VC-funded startups.

3.1.1 PitchBook

I obtain information on VCs' portfolio choices and performance from PitchBook, accessed via WRDS. The data vendor provides information on deals done by VC firms and VC-financed company characteristics, including textual descriptions, VC investor information, as well as exit types of VC-financed companies. I restrict my main sample to the period between 2003 and 2021, where deal coverage in PitchBook is representative and where business descriptions of VC-financed ventures are readily available (Retterath and Braun, 2020). Garfinkel et al. (2021), for instance, show that during the sample period analyzed in this paper, PitchBook data provides the most comprehensive data coverage when compared with other commercial databases (e.g., Crunchbase or VentureXpert).

Since I focus on investments made by institutional venture capitalists (as opposed to angel investors or corporate venture capital, for instance), I include in my sample deals with the DealClass label "Venture Capital" in PitchBook and the following deal type labels: "Seed Round," "Early Stage VC," "Later Stage VC," "Restart - Later VC," and "Restart - Early VC." To obtain a representative sample of VC investors, I also restrict the sample to VC investors who have made at least five investments in different companies over the entire sample period (2003–2021).

For each financed startup, I classify the exit types using the data provided by PitchBook, where I can observe exits up until July 2025, as "IPO" exits, "M&A" exits, and "Major Success." I classify a startup's exit as an "IPO" exit for a given VC investor–portfolio company pair if the given VC firm has exited the company via an IPO. Similarly, I classify the VC investor–portfolio company pair as an "M&A" exit if the given VC investor has exited the company via an M&A.[9] I define a "Major Success" as an outcome if the deal has exited via an IPO or a very profitable acquisition. For most of my tests I define a profitable acquisition as one with an exit value of at least five times total VC invested capital. I run sensitivity checks and robustness analyses for 1x and 3x thresholds (Ewens and Rhodes-Kropf, 2015; Bonelli, 2022). All results are also robust when using only IPO as a measure of successful exit.

3.1.2 Revelio

To collect detailed educational and job histories of VC partners, I supplement the PitchBook dataset with Revelio. Revelio is a leading workforce database provider that has collected the near-universe of LinkedIn profiles. Their resume data includes comprehensive detail on individuals' work and educational histories. The use of Revelio data has been rising in the finance literature (e.g., (Hampole et al., 2025; Dorn et al., 2025)). Since Revelio does not provide an identifier that can be used to match directly with PitchBook data in order to obtain human capital characteristics of VC partners, I utilize the following matching strategy.

First, I match PitchBook VC firms to Revelio firm-level data. To do so, I first clean both Revelio and PitchBook firm names by removing common suffixes (e.g., Ltd, GmbH) and converting the names into lowercase. Then I proceed with matching in four steps.

[9] An exit is classified as an M&A exit if the exit type is labeled as "Merger/Acquisition" or "Merger of Equals" in the exit data provided by PitchBook. To focus on successful M&A exits, I remove exits labeled as "Corporate Divestiture" or "Distressed Acquisition."

First, I match directly on firm name and website domain—i.e., requiring both firm name and website to be the same in both databases. Then, for the unmatched VC firms, I use information on their headquarters in PitchBook and require that the firm name and the headquarter country be the same.[10] As a third step among unmatched firms, I match only on firm name. Finally, as a fourth step among unmatched firms, I match on website domain and headquarters but not on VC name, and I manually verify the correctness of those matches.

Once I obtain a sample of matched VC firms to Revelio, I use Revelio's jobs data to match the partners available in PitchBook and Revelio directly on first and last name. For the final sample, I require that at least one of the background characteristics (e.g., ethnicity, gender, educational background, work history) for a given partner be available in Revelio.

3.1.3 USPTO

To measure innovation by VC-financed companies, I supplement the data with deal-level data on patent applications and grants from the USPTO (United States Patent and Trademark Office). The USPTO also includes patent applications that are still pending, as well as those that have been abandoned, rejected, or canceled. It provides each patent's unique identifier, as well as information on its assignee, its technology class, its application year, and, when applicable, its grant year. I match the VC-financed startups from PitchBook to USPTO data using fuzzy matching, similar to Bernstein et al. (2016).

3.1.4 Summary Statistics

Table 2 about here.

Table 2 presents summary statistics for the main deal-level sample of the data. Each observation represents a deal–investor–company–lead partner, if the lead partner is available. There are a total of 232,130 new financing rounds during the sample period (2003–2021). These are financing rounds of 92,740 distinct ventures, financed by 8,521 distinct VC investors. Out of those 232,130, for a subset of 81,386, PitchBook also provides the identity of the partner involved in the deal (16,946 distinct partners in total). Out of those 232,130 deals, around 4% have successfully exited to the public market, and

[10] Revelio Labs' company data does not contain information on firm headquarters. I construct a proxy for this by assuming that the firm's headquarters is the state or country where the largest number of employees are located which is a reasonable assumption for venture capital firms.

around 7% have achieved a major exit. Out of those 16,946 available on PitchBook, I am able to match and retrieve at least one background characteristic from Revelio for 9,880 partners. These partners lead around 47,561 deals, so the match rate is approximately 58%.[11]

In terms of background characteristics of partners assigned to a given deal, around 11% of deals are led by female partners, around 43% of deals are led by partners who have an MBA degree, and only 6% of deals are led by partners who have an advanced PhD degree. 31% of deals are led by partners with a STEM education, and around 63% of deals are led by partners with a Social Science and Humanities education. Around 50% of deals are led by partners who have completed at least one degree at a top educational institution.[12]

Table 3 about here.

Table 3 presents the summary statistics for individual partners i.e., where each observation is a unique partner who has led at least one deal over the sample period. The summary statistics at individual partner level present a similar picture to the deal level summary statistics.

3.2 Measurement and Stylized Facts

3.2.1 Measurement of Novelty

To measure the extent to which startups are novel, I rely on startups' business descriptions provided by PitchBook. I rely on recent advances in Natural Language Processing (NLP) and use the business text description of a startup to construct an embedding vector using state-of-the-art OpenAI embeddings. Embeddings generated by large language models (LLMs) possess the property that similar texts are represented by vectors that are closest in vector space. OpenAI embeddings are particularly suitable for analyzing VC

[11]This is the match rate computed both in terms of overall partner coverage and deal coverage, which means that matched partners are not more or less likely to be leads on investments than unmatched partners suggesting that the sample is representative.

[12]The definition for a top educational institution follows Calder-Wang and Gompers (2021). Specifically, top institutions are: 'Brown University', 'Harvard University', 'Columbia University', 'Cornell University', 'Dartmouth College', 'University of Pennsylvania', 'Princeton University', 'Yale University', 'Duke University', 'Massachusetts Institute of Technology', 'University of Chicago', 'Caltech', 'Stanford University', 'Northwestern University', 'University of California, Berkeley', 'Williams College', 'Cambridge University', 'INSEAD', 'HEC Paris', 'London Business School', 'London School of Economics', 'Oxford University'.

data, as shown by Duevski and Bazaliy (2025). Importantly, when constructing the text embeddings from business descriptions from PitchBook, I do not include any firm-level information (such as the name of the financed company, for instance) that may introduce a look-ahead bias, as documented by He et al. (2025).

I construct my main proxy for the novelty of the startup in the following way. For each deal d for company c made at time t, I define the novelty of startup c at date t as:

$$N_{c,t} = 1 - \max_{j \in (t-5,t)} \text{CosSim}(C_c, C_j), \tag{1}$$

where $\text{CosSim}(C_c, C_j)$ is the cosine similarity between the embedding vector of focal company c and company j, and $\max_{j \in (t-5,t)} \text{CosSim}(C_c, C_j)$ specifies that I take the maximum cosine similarity of the focal company c to any other startup that has received venture financing in the five years prior to year t. In particular, note that according to this definition, $N_{c,t} = 0$ if company c has received venture-backed financing in the past five years. Equation (1) uses a five-year rolling window to avoid mechanical issues related to, for example, the proliferation of VC activity over time.[13]

Intuitively, (1) captures how distinct the business model of company c is from any other company that has received venture financing in the past five years. This proxy evaluates the extent to which the focal company c is novel relative to what the venture capital industry has financed in the past. This definition is related to, but different from, Bonelli (2022)'s "backward similarity measure," which captures how similar a startup is, on average, to what the venture capital industry has financed in the past five years. In particular, $N_{c,t}$ captures how distinct the focal startup is from the financed firm with the closest business model and, arguably, it is better suited to identify the true novelty of the business model, as opposed to, for example, whether the business model is niche. I term the measure $N_{c,t}$ Novelty (Distance to Closest Firm).

One additional advantage of constructing startup novelty via (1) is that one can explicitly retrieve the closest firm to any given firm receiving VC financing in the past. In Appendix Table A1, I provide the explicit novelty measure for some well-known startups, their percentile ranking in terms of novelty, as well as the firm that is identified to be the closest to them in terms of business description.

[13] For example, firms appearing less novel over time simply because the benchmark comparison set is larger.

3.2.2 Stylized Facts About Novel Startups

In this subsection, I present several stylized facts about novel startups.

Figure 1 about here.

In Figure 1, in the left panel, I plot the distribution of the Novelty (Distance to Closest Firm) measure conditional on $N_{c,t} > 0$, i.e., for startups receiving their first round of venture financing. The median startup's novelty is 0.25. In the right panel of Figure 1, I plot the time evolution of the mean of the Novelty (Distance to Closest Firm) measure and document a decreasing mean novelty over time. Note that these plots are conditional on $N_{c,t} > 0$, so they capture the evolution of novelty for startups receiving their first venture financing, i.e., the pattern is not driven by later financing rounds of the same venture. Note that (1) applies a five-year rolling window to the novelty measure, which means that the decline in novelty presented in Figure 1 is not simply driven by the fact that, as time passes, VC activity proliferates and each benchmark firm is compared to more firms, naturally driving novelty down over time.

To strengthen this argument even further, in Figure A2, I plot graphs using an alternative novelty measure where all focal firms are compared to the same number of random firms (300 in the left panel and 500 in the right panel) in each year, and I show that the decline in novelty presented in Figure 1 is robust to this alternative way of constructing the measure. In Figure A1, I construct an alternative novelty measure where, instead of using the closest firm, I use the top five closest firms in terms of business description similarity and show that the decline in novelty is robust. In Figure A3, I use PitchBook descriptions from a different data vintage (PitchBook data vintage 2025) and show: (1) Very few startups have had meaningful changes to their business descriptions (less than 10% of firms have had any meaningful semantic changes); (2) The documented decline in novelty is robust to using business descriptions from a different data vintage.

Figure 2 about here.

To better understand the time evolution of novelty, in the top-left panel of Figure 2, I plot the number of distinct firms financed by the VC industry with positive novelty over time, which shows an increasing trend. In the top-right panel, I plot the raw number of firms with novelty above 0.3—that is, financed firms with a novelty measure above the top quartile for the entire sample—and document that the number of firms financed with relatively high novelty has also been increasing. In the bottom-left graph, I plot the share of firms with a novelty measure above 0.3 and document a declining trend over time. That is, the decline in average novelty observed in Figure 1 is driven by a decline in the share of financed firms with high novelty (even if their absolute number is going up). Finally, in the bottom-right panel, I plot the median novelty measure for the top 100 most novel VC-financed firms in each year and document a declining trend; however, this decline starts later than the general decline in novelty.

Overall, the time trends observed are consistent with the fact that the decline in average financed novelty is primarily driven by a steady decline in the share of VC financing going to high-novelty startups.

In a regression setting, I document two stylized facts about novel startups that also serve as validation for the novelty measure. First, novel startups are more likely to fail or achieve a major exit. Second, novel startups contribute more to innovation output. The second fact is particularly useful and shows that even though novelty is constructed from business descriptions—which arguably capture more about the startup's product and business design—they are still correlated with ex-post innovation outcomes and therefore can be used as an ex-ante proxy for the startup's innovation output or social value.

Novelty and Performance: I document that novel startups are more likely to fail or achieve a major success. Specifically, I estimate the following model using a deal-level data structure, where each observation is a deal–investor–company:

$$P_{d,i,t,s,k} = \alpha + \beta N_d + \eta_{i\times t\times s\times k\times c} + \epsilon_{d,i,t,s,k}, \tag{2}$$

where d denotes a deal, i the industry of the deal, t the year the deal is made, s the stage of the deal, k the investor (VC firm) financing the deal, and c the country of the financed company. $P_{d,i,t,s,k}$ is a performance outcome indicator, which can be Failure or Major Success. N_d is the novelty of the deal, and $\eta_{i\times t\times s\times k\times c}$ denotes granular industry $\times$ time $\times$ deal stage $\times$ country $\times$ investor (VC firm) fixed effects. The coefficient of interest, β, captures the association between deal novelty and deal performance.

Table 5 about here.

The results are presented in Table 5. More novel startups are significantly more likely to both fail and achieve a major success. Note that the variation in columns (3)–(4) comes from within an industry $\times$ time $\times$ deal stage $\times$ country $\times$ investor; that is, we are comparing the performance of more or less novel startups financed by the same investor in the same stage, deal year, industry, and country. This suggests that the results of this stylized fact are not simply driven by certain investor characteristics that have been shown to be associated with startup success (e.g., VC firm reputation, experience, deal flow). Similarly, the performance is not merely driven by time-varying industry or overall economic conditions (e.g., the hotness of the M&A and IPO market in general, industry-specific shocks, and varying country-level economic shocks). In terms of economic magnitude, estimates in columns (3) and (4) imply that a one standard deviation increase in novelty is associated with a 0.8% increase in the probability of failure and a 4.5% increase in the probability of a major success.[14]

Table 6 about here.

In Table 6, I estimate a similar model as in (2), but I split startups into yearly novelty quartiles. The baseline is Novelty (Distance to Closest Firm) = 1, which represents the least novel startups in each year. Estimates in columns (3)–(4) imply that the probability of failure increases by 3% and the probability of a major success exit increases by 9% when moving from the bottom to the top quartile of novelty. Intuitively, in columns (3)–(4), I evaluate the performance of startups financed by the same investor in the same year, industry, deal stage, and country, relying on variation in startup novelty.

I run several robustness analyses to confirm these stylized fact. First, in Table A2, I re-estimate model (2) with an alternative novelty measure defined as one minus the average cosine similarity between the textual description of the startup financed in the deal and the top five closest startups receiving venture capital financing within five years before the deal in the same deal stage. Second, in Table A3, I re-estimate (2) using a sample that includes only firms with first financing rounds between 2018–2021, where the business description likely captures the startup's product description close to its creation. In Table A4, instead of using Major Success as an outcome (which includes high-value acquisition exits), I re-estimate the model using only IPO as a measure of success. In Table A3, I also show that novelty positively correlates with both IPO valuation and IPO multiple for the subsample of deals that have exited via the public market.

Novelty and Innovation: To assess the association between novelty and the innovation output of a given startup, I estimate the following model using a deal-level data structure where each observation is a deal–investor–company:

[14] Calculated as Point Estimate × SD in Novelty (Distance to Closest Firm Measure)

$$I_{d,i,t,s,k} = \alpha + \beta N_d + \eta_{i \times t \times s \times k \times c} + \epsilon_{d,i,t,s,k}, \tag{3}$$

where $I_{d,i,t,s,k}$ is a forward-looking innovation measure. Specifically, for each deal made, I count the number of forward patents (patents granted after the deal is made) and forward citations (citations of patents granted after the deal is made).[15] N_d is the novelty of the deal, and $\eta_{i \times t \times s \times k \times c}$ denotes granular industry × time × deal stage × country × investor fixed effects. The coefficient of interest, β, captures the association between deal novelty and innovation.

Table 7 about here.

The results are shown in Table 7. I use (3) and estimate a Poisson count model (to avoid well-known issues with using the log(1+) model; see Chen and Roth (2024)). Estimates in column (4) imply that a one standard deviation increase in novelty is associated with a 26% increase in expected forward citations.[16]

I conduct several robustness checks. First, in Table A6, I re-estimate (3) using an alternative novelty measure defined as one minus the average cosine similarity between the textual description of the startup financed in the deal and the top five closest startups receiving venture capital financing within five years before the deal in the same deal stage. In Table A7, I use a log(1+) model instead of a Poisson count model for the right hand side variable. In Table A8, I use a novelty quartile measure and show that the effect is monotonic.

3.2.3 Measurement of Breadth of Human Capital and Stylized Facts

To measure human capital breadth, I rely on the educational and work histories of VC partners obtained from Revelio. For each partner that I match to Revelio, I first obtain the year of their deal as recorded by PitchBook. Then, when constructing their work history, I include only those jobs with an end year prior to their first recorded deal. Using their work histories and educational background, I construct four main proxies for human capital breadth. The first three proxies closely follow (Custódio et al., 2013):

1. Ratio of job categories: This is defined as the ratio between distinct job categories ("job category" variable in Revelio) and the number of employment spells.[17]

[15] I adjust the citation number by year and NBER subcategory, as is standard in the literature (e.g., Lerner and Seru (2022)).

[16] Calculated as $e^{3.292 \times 0.07} - 1 = 0.26$.

[17] Job Category is a broad classification of the types of jobs an individual has done into 7 categories: Admin, Finance, Engineer, Scientist, Operations, Marketing, Sales

2. Ratio of job roles. This is defined as the ratio between distinct job roles ("role k1500" variable in Revelio) and the number of employment spells.

3. Ratio of industries: This is defined as the ratio between the number of distinct industries an partner has worked in and the number of employment spells.

4. Educational breadth: This is a count of the distinct types of degrees an individual has obtained in the past. Distinct types of degrees are: STEM education, Social Science or Humanities Education, IT Education, Medicine, MBA and PhD.

Following Custódio et al. (2013) using PCA, I combine these measures into a single time-invariant index for each individual partner. The PCA weights that form the index are given in the equation below:

$$\text{BreadthIndex}_i = 0.0975\, z_{i,\text{edu}} + 0.5413\, z_{i,\text{ind}} + 0.5795\, z_{i,\text{cat}} + 0.6014\, z_{i,\text{role}} \tag{4}$$

In the PCA, I obtain only one eigenvalue higher than 1 and thus retain only the first principal component, which explains around 60% of the variation (similar to (Custódio et al., 2013)). As expected, all individual components load with the same sign when constructing the measure, which means that they are positively correlated with the underlying concept we are trying to proxy for—namely, human capital breadth. A scree plot of the PCA and the cumulative variance explained is given in Figure A4. I use the measure defined by (4) in the main test and run robustness analyses for each individual component.

Figure 3 about here.

In Figure 3, I plot the distribution of the breadth index measure (left panel) and the time evolution of the breadth index measure. I document a decline in average breadth in human capital among VC partners. This trend is robust even when using simple educational proxies to measure human capital breadth. This is shown in Figure A5. In the top panel of the figure, I plot the share of partners with an MBA degree relative to the share of partners with a PhD or STEM degree only. This share has declined from roughly 80% in the early 2000s to below 70% around 2020. In the bottom-left panel, I plot the share of partners with interdisciplinary education and document a decline over time.[18] In the bottom-right panel, I plot the average number of distinct degrees per partner over time and document an average decline.

[18] A partner has interdisciplinary education if they have: 1) an MBA degree and a STEM degree; or 2) Social Science or Humanities education and a STEM degree; 3) an MBA degree and a PhD degree; 4) medical education and an MBA degree.

4 Empirical Results

In this section I present the main empirical findings of the paper.

4.1 Partner level Human Capital Breadth and Novel Startups

First, without claiming causality, I present two novel facts that link individual partners' human capital breadth to the selection and performance of novel startups.

4.1.1 Association between Lead Partner Human Capital Breadth and Startup Novelty

First, I document an association between the human capital breadth of an individual lead partner on a deal and the deal's novelty. To do so, I estimate the following empirical specification at the deal level:

$$N_{j,k,p,t} = \alpha + \beta B_p + X_{t,p} + \eta_{i \times t \times s \times c} + \rho_{t \times j} + \epsilon_{j,k,p,t}, \tag{5}$$

where $N_{j,k,p,t}$ is a deal level novelty of deal made by investor j in startup k with a lead partner p in year t. B_p is a partner level human capital breadth index, $X_{t,p}$ are time varying partner level controls measured at the time the deal is made, $\eta_{i \times t \times s \times c}$ represents industry $\times$ deal year $\times$ deal stage $\times$ country of financed company fixed effects and $\rho_{t \times j}$ is an investor$\times$ deal year fixed effect. The coefficient of interest is β, which captures the association between lead partner's breadth index and deal novelty. In all specifications in this section standard errors are double clustered at an investor and financed company level.

Table 8 about here.

The results are presented in Table 8. Across all specifications, the lead partner's breadth index is positively associated with startup novelty. The granular fixed effects show that within a VC firm $\times$ deal year, partners with broader human capital lead more novel startups. Intuitively, the coefficient β is estimated by relying on variation in breadth across different partners financing startups of different novelty within a given VC firm making investments in the same year. In column (3) in Table 8, which is the strictest specification we add investor $\times$ deal year $\times$ partner VC industry entry year. In this specification intuitively we compare the novelty of investments made by two partners who differ based on the human capital breadth index making investments in the same year and joining the VC industry in the same year, the other granular high dimensional fixed effect industry × deal year× deal stage × country controls for observable deal characteristics that may be correlated with novelty. Notice that, even though the effect we estimate is not strictly causal, the granular fixed effects are helpful in ruling out several potential explanations. Firstly, the industry × deal year× deal stage × country show that the effect is not driven by broader partners choosing more novel sectors, simply investing in times when novelty is higher, investing in different stages in the firm's lifecycle or in different countries. Secondly the granular VC firm × year *times* Partner entry year shows that the effect is not driven simply by more novel firms selecting different types of VC firms and presumably also more experienced VC partners.[19] The estimates in column (3) imply that a one standard deviation increase in human capital breadth is associated to 0.1 standard deviation increase in the deal novelty financed.

Table 9 about here.

In Table 9 I estimate specification (5) 1) Separately for lead (columns (1) and (3)) and non-lead (columns (2) and (4)) investment, and in columns (5) and (6) I include an interaction term between the lead partner's human capital breadth and a dummy Lead Investment that takes a value of 1 if the VC firm of the partner is a lead investor on the deal. Since lead VC firm typically do the investment screening as well as assign partners to the board of directors the association between the human capital and startup characteristics should be greater for deals where the given VC firm is a lead investor. The results in Table 9 confirm this. First the effect size of lead partner's human capital breadth on startup novelty is economically higher and statistically more significant for deals where the VC firm is a lead investor (columns (1) and (3) versus columns (2) and (4)). Secondly the interaction term between lead partner breadth and VC firm lead investor indicator dummy is positive (columns (5) and (6)).

I conduct several robustness checks. First, in Table A9 I estimate specification (5) by using an alternative novelty measure defined as one minus the average of the cosine similarity of the textual description of the startup financed in the deal and top five closest startups receiving venture capital financing within five years before the deal in the same deal stage. In Table A10 I estimate the same specification but split the deals by non-syndicated deals (deals where the VC firm is a sole investor) and syndicated deals (deals where there are multiple VC firms investing) and show that the effect is larger for deals

[19]The deal year × VC Partner Entry Year controls for the number of years a given partner has spent in the VC industry, The VC Experience is an additional control for the number of deals a partner has done before the focal deal.

where the VC firm is a sole investor. In Table A11 I estimate the same specification for the four measure of human capital breadth used in the construction of the human capital breadth index separately. In Table A12 I estimate the same specification for the four measure of human capital breadth used in the construction of the human capital breadth index separately and I include only deals where the VC firm is a lead investor and show that the effect size is larger. Finally, in table A13 I do a sample split based on the distance of the year when the deal is made and the partner entry year and show that the effect is stronger for deals made closer to partner's industry entry (column (1) vs. column (2)).

4.1.2 Interaction between lead partner breadth with deal novelty and performance

Second, I document a positive interaction between the lead partner's human capital breadth and deal novelty on performance. Specifically, I estimate the following model at the deal level:

$$P_{j,k,p,t} = \alpha + \beta B_p + \gamma N_{j,k,p,t} + \delta B_p \times N_{j,k,p,t} + X_{t,p} + \eta_{i\times t\times s\times c} + \rho_{t\times j} + \epsilon_{j,k,p,t}, \quad (6)$$

where $P_{j,k,p,t}$ is a deal level performance measure for an investment made by firm j in startup k with lead partner p at time t. $N_{j,k,p,t}$ is the deal novelty and B_p is a lead partner breadth index measure, $B_p \times N_{j,k,p,t}$ is an interaction term between lead partner breadth index and startup novelty. $X_{t,p}$ are time varying partner level controls measured at the time the deal is made, $\eta_{i\times t\times s\times c}$ represents industry $\times$ time $\times$ deal stage $\times$ country fixed effects and
$rho_{t\times j}$ is an deal year $\times$ investor fixed effect.

Table 10 about here.

The results are presented in Table 10. Intuitively, in column (3), the coefficients are estimated by relying on variation in the partner breadth index and novelty across deals made by the same VC firm, in the same industry, deal stage, and year. The granular fixed effects rule out a story where the effect is driven by any VC firm-specific factors, such as VC firms attracting better deal flow while simultaneously hiring better partners. The fixed effects also rule out time-varying macroeconomic or industry-wide shocks that may influence certain performance outcomes, making them more or less likely and thus driving up novelty. First, the baseline coefficient β on the lead partner breadth index is negative, which suggests that non-novel deals lead by broad partners perform worse than non-novel deals led by narrower partners. The economic magnitude of β in column (3) implies that non-novel deals financed by broad partners perform worse than non-novel deals financed by narrow partners. At zero novelty, a one standard deviation increase in the breadth index is associated with a 5% decrease in the probability of a Major Success (specification (3)). The interaction term between human capital breadth and novelty δ is positive and statistically significant. As novelty increases, the positive interaction term implies that the probability of an Major Success for deals led by broad partners increases with deal novelty. For each 0.1 increase in novelty, the effect of the breadth index increases by 2%. These estimates, in particular, imply that the association between the breadth index and Major Success is negative for below-median novelty deals (median of 0.24); however, it turns positive for above-median novelty firms.

I conduct several robustness tests. First, in Table A14, I re-estimate specification (5) by using an alternative novelty measure defined as one minus the average of the cosine similarity of the textual description of the startup financed in the deal and top five closest startups receiving venture capital financing within five years before the deal in the same deal stage. In Table A16, I estimate the specification separately for all components contribution to the human capital breadth index. In Table, A15 I estimate the specification separately for lead and non-lead investments. In Table A18 I re-estimate the same specification by using only IPO as a proxy for successful exit. Finally in tables A19 and A20 I show that the results are robust to using different cut-offs of successful acquisition value.

In Table A17, I estimate the direct association between human capital breadth and investment performance i.e. I estimate:

$$P_{j,k,p,t} = \alpha + \beta B_p + X_{t,p} + \eta_{i\times t\times s\times c} + \rho_{t\times j} + \epsilon_{j,k,p,t}, \tag{7}$$

I find a clear null results - that is human capital breadth is not associated with deal performance in general.

5 Causal impact of Lead Partner Breadth on Performance of Novel Startups

Overall, the two reduced form results highlight (i) the human capital breadth of the lead partner is positively associated with deal novelty (ii) for low novelty deals, higher human capital breadth is negatively associated with performance and for high novelty deals human capital breadth is positively associated with performance. Even with granular fixed effects that isolate deal-level characteristics and the inclusion of VC investor $\times$ deal year fixed effects, the deal–lead partner assignment—even within the same VC firm—is endogenous. This can result in a bias in the OLS estimates in specification (6). For example since the lead partner human capital breadth assignment is endogenous, if broader partners are more likely to get the most difficult to execute non-novel deals the baseline estimate β may be downward biased, similarity if due to access and network advantages they get most promising novel deals, the estimate for the interaction effect of partner breadth and deal novelty δ can be upward biased.[20]

The ideal experiment would compare the performance of two startups with the same novelty and quality, one having a broad lead partner and the other a narrow lead partner of the same quality. In the absence of such an experiment, one approach is to utilize an instrumental variable strategy that exogenously shifts the likelihood of a partner being a lead on a specific deal. A natural candidate for such an instrument is the time-varying availability of partners within the same VC firm. Intuitively, if partners face time constraints, during periods of high workload they should be less likely to lead a new investment. One proxy for time-varying partner busyness is the partner's involvement in an exit event of another deal made by the VC firm. Specifically, Abuzov (2019), for instance, finds that partners' deals made during periods when the partner is concurrently involved in an exit event perform worse than deals made by the same partner when the partner is less busy. If VC firms internalize this effect, it would imply that busy partners are ex ante less likely to be assigned as lead partners on deals made during periods of high workload. Thus, a natural shifter for the probability of a partner being a lead on a specific deal is whether the partner is concurrently involved in an exit event for another deal.

Before proceeding with causal estimation, I show that a partner's busyness reduces the likelihood of that partner being the lead partner on a new deal made by the same VC firm. To do this, I first restructure the dataset at the deal level in the following way: for each deal d made by VC firm j, I construct a set of potential partners who could have led this deal. As a baseline, I select all partners who have led deals at the same VC firm within a $[-3, +3]$ year window around the deal. For each partner, I construct a busyness proxy at the time of the deal. Following Abuzov (2019), I define a partner p to be busy at time t if the same partner p is involved in a major exit (via a high-value acquisition or

[20] The direction of the OLS bias in specification (6) can go either way, the hypothetical bias highlighted in the paragraph is the bias one should worry about i.e., the bias that would make the results statistically significant without a causal interpretation.

IPO) for another deal in a $(-90, +90)$ day window around the focal deal date t. Using this data structure, I first show a negative association between partner busyness and the likelihood of leading a new deal:

$$PartnerChosen_{d,j,p} = \alpha + \beta BusyPartner_{p,t} + X_{p,t} + \eta_d + \rho_j + \epsilon_{d,j,p}, \quad (8)$$

where $PartnerChosen_{d,j,p}$ is an indicator variable equal to 1 if partner p working for investor j leads deal d, and 0 otherwise. $X_{p,t}$ is a set of partner-level controls measured at the time the deal is made. $BusyPartner_{p,t}$ is an indicator equal to 1 if the partner is involved in an exit event in the $(-90, +90)$ day window around the focal deal. η_d is a deal fixed effect, and ρ_j is an investor fixed effect. Standard errors are clustered at the deal level.

Table 11 about here.

The results are shown in Table 11. In column (1), I estimate the coefficient of interest β for the full sample (i.e., not conditioning on positive novelty), and find a statistically significant negative effect. In columns (2) and (3), I split the sample between lead and non-lead investments of the VC firm. If partner time availability matters, it should matter more for investments where the VC firm is the lead investor. This is precisely what we find: the estimated β in column (2) (lead investment sample) is more than twice the size of that in column (3).

In column (4), I restrict the sample to investments receiving their first rounds of VC financing (i.e., investments with positive novelty). We find a larger magnitude of the estimated β relative to column (1), since partner time constraints are arguably more important for firms receiving their first VC financing.[21] In columns (5) and (6), I estimate β separately for lead and non-lead investments in the sample of firms receiving first-time VC financing, and show that the magnitude of the coefficient is much higher for investments where the VC firm is a lead investor.

This data structure also allows me to provide further evidence on the association between lead partner human capital breadth and deal novelty. Specifically, since I now have a set of potential partners who could have led each deal, the data structure allows for the inclusion of granular deal and partner-level fixed effects. Specifically, it allows me to estimate the following model:

$$PartnerChosen_{d,j,p} = \alpha + \beta N_d \times B_p + \gamma BusyPartner_{p,t} + X_{p,t} + \eta_d + \rho_j + \sigma_p + \epsilon_{d,j,p}, \quad (9)$$

[21] Either because screening is more costly or requires more effort for these firms, or because monitoring may be more valuable.

where N_d is the focal deal's novelty, B_p is the partner's human capital breadth index, and σ_p is a partner fixed effect. The coefficient of interest is β which is the interaction between partner human capital breadth and deal novelty. The specification (9) allows me to include both partner and deal fixed effects which allow me to absorb all deal characteristics that may correlate with specific partner choice as well as all time invariant partner characteristics. Intuitively, the interaction term is estimated by within partner variation across deals of different novelty where the partner is or is not chosen to be a lead partner **and** within deal variation of available partners of different breadth index. Specification (9) also allows me to estimate the busy partner coefficient relying on within partner variation leveraging times where the same partner is busy versus available (all time invariant partner characteristics are controlled for).

Table 12 about here.

The results are presented in Table 12. Column (1) provides estimates for the full sample, column (2) for a subset of deals where the VC firm is a lead investor and column (3) for a subset of deals where the VC firm is a non-lead investor. The coefficient is on the interaction term between human capital breadth is positive, statistically significant and economically large. A one standard deviation (sd) increase in the interaction, i.e., a one sd. increase in partner human capital breadth when the deal is at one sd. above mean novelty raises the likelihood of leading a deal to around 51% which is large relative to the unconditional mean of 20%. The estimates are larger (smaller) when we split the sample between lead vs. non-lead investments. The magnitude of the coefficient on Busy Partner is similar to the one in model (8), except that now the variation we rely on is within partner across deal variation.

Similar to the previous subsections, we conduct a battery of robustness tests. First, in Table A21 I conduct a placebo test whereby I reshuffle the busy indicator randomly across partners while keeping the within deal distribution of busy vs. available partners the same. I do not find any association between the placebo and the likelihood of a partner leading a deal. Then, in Table A22 we use only IPO exit busyness as a proxy and show that the estimated β is statistically significant and consistently larger than the β estimated in the main table.[22] In Table A23 I use an alternative shorter (-60, 60) days time window around the concurrent deal to define a busy partner, In A24 I use an alternative shorter (-60, 60) days time window around the concurrent deal to define a busy partner and only include IPO exit busy partners. In Table A23 I use an alternative

[22]IPOs are much harder to execute and arguably strain the partner's involved more

shorter (-45, 45) days time window around the concurrent deal to define a busy partner, In A24 I use an alternative shorter (-45, 45) days time window around the concurrent deal to define a busy partner and only include IPO exit busy partners.

The evidence presented suggests that (i) the time constraints of individual VC partners are significant, and (ii) the estimated effect sizes are economically meaningful and become more pronounced when time constraints are likely to matter most—specifically, in investments where the VC firm acts as the lead investor.

5.1 IV Estimates and the causal impact of human capital breadth for novel and non-novel firm performance

In Section 4.1.2, we presented a positive association between the interaction of human capital breadth and deal novelty with performance. Even though specification (6) includes granular VC firm fixed effects and various fixed effects related to startup characteristics (industry × year × deal Stage), the assignment or selection of startups, even within a VC firm, is non-random. For example, if deal quality and partner quality within a VC firm are heterogeneous, one may worry that the interaction effect captures a pure quality-matching story—i.e., better-suited partners for novel firms are matched with the highest-quality novel firms, which drives the increase in the probability of a Major Success. To capture the causal effect, one would need an instrument that randomly shifts the assignment of a given partner to a deal within a VC firm. In other words, one would like to compare how the same novel deal would perform given that it is randomly assigned to a broad versus a narrow partner and then compare the outcome. As argued in the previous subsection a natural candidate of such an instrument is the time varying availability of partners. The results presented in Table 11 suggest that, controlling for other partner characteristics, busy partners are less likely to be assigned to lead a deal. To shift the probability of a partner with high (low) human capital breadth being assigned to a given deal, I propose an instrument that relies on time variation in human capital breadth availability within a given VC firm, called the average available breadth index.

I define the average available breadth index at time t in VC firm j as the sum of breadth indices of non-busy partners employed by VC firm j scaled by the number of non-busy partners employed by firm j at time t. Specifically, I define the average available breadth index of a VC firm j at time t as :

$$AvgB_{j,t} = \frac{\sum_{p \in j} B_p \times I_{p,t}}{\sum_{p \in j} I_{p,t}}, \tag{10}$$

where j denotes a VC firm, p denotes a partner. The sum $p \in j$ is taken over partners who work at VC firm j at time t, B_p is a breadth index measure at a partner level, $I_{p,t}$ is an indicator variable taking a value of 1 if the partner is non-busy at time t. Intuitively, at times when broad partners are busy the measure decreases, but at times when broad partners are more available relative to narrow partners the measure increases. A hypothesis is that at the time a deal is made a high average breadth availability should increase the probability a high breadth index partner being assigned to a deal and vice versa. So the average available breadth index is a natural candidate for an instrument of the chosen partner's breadth.[23]

To study the effect of the interaction between breadth and novelty we need another instrument for the breadth × novelty interaction which will be the average available breadth index × deal novelty. Given these two instruments, I estimate the following model via a 2SLS:

$$\textbf{First Stage: } B_{d,p,j,t} = \alpha + AvgB_{j,t} + AvgB_{j,t} \times N_{d,t} + X_{p,t} + \eta_{i\times t\times s} + \rho_j + \epsilon_{d,p,j,t} \quad (11)$$

$$\textbf{First Stage: } N_{d,t} \times B_{d,p,j,t} = \alpha + AvgB_{j,t} + AvgB_{j,t} \times N_{d,t} + X_{p,t} + \eta_{i\times t\times s} + \rho_j + u_{d,p,j,t} \quad (12)$$

$$\textbf{Second Stage: } P_{d,p,j,t} = \alpha + N_{d,t} + \widehat{B_{j,t}} + \widehat{B_{j,t} \times N}_{d,t} + X_{p,t} + \eta_{i\times t\times s} + \rho_j + s_{d,p,j,t}, \quad (13)$$

where in $B_{d,p,j,t}$ is the breadth index partner p chosen for deal d made by investor j at time t. $AvgB_{j,t}$ is the average available breadth at investor j at time t,$AvgB_{j,t} \times N_{d,t}$ is the interaction between deal novelty and the average available breadth, $X_{p,t}$ is a set of time varying chosen partner level controls, $\eta_{i\times t\times s}$ are industry × year × deal stage fixed effects and ρ_j is an investor fixed effect. $P_{d,p,j,t}$ is a performance outcome.

Table 13 about here.

The results are presented in Table 13. Columns (1) and (2) present the first-stage estimates from specifications (11) and (12). In column (1), the Avg. Available Breadth is a strong predictor of the Breadth Index of the chosen partner, and in column (2) the interaction between the Avg. Available Breadth and Novelty is a strong predictor of the interaction between the Breadth Index and Novelty. The first-stage estimate in column

[23]Another approach is to scale the nominator by the total number of partners instead of the total number of available partners. Then in the IV regression, one would need to condition on at least one partner being busy or available since the coefficient will be identified only from those deals where such a variation is present.

(1) implies that a one standard deviation increase in the average availability of breadth at a given VC firm is associated with an increase of 0.3 standard deviations in the Breadth Index of the partner actually chosen to lead the deal. Column (3) presents the IV estimates from specification (13), where the performance outcome is Major Success. First, the F-statistic for the instrument passes the weak instrument threshold (as show in table (3) and explicitly seen in the first stage results presented in columns (1) and (2)). In column (3), the coefficient on the Breadth Index is negative and significant, whereas the coefficient on the interaction between the Breadth Index and Novelty is positive and significant.

I perform several robustness tests. In Table A27 I estimate the same 2SLS model, but using only IPO as a measure for success. In Table A29 I vary the time window over which the busyness measure is constructed and in table A30 I vary the time window over which the busyness proxy is constructed and I use only IPO as a measure for successful exit. The conclusions remain.

6 Theoretical Framework

In this section I present a stylized model that jointly endogenizes the project selection and partner assignment choice of VC firms and the novel venture creation process by entrepreneurs. The theoretical model is written to explain the decision of VC firms to assign a generalist or specialist partners and how this choice interacts with the entrepreneurial incentives for creating novel ventures. I focus on novel venture sector where ventures of uncertain quality are created, screened and funded. The "known" sector of the economy is treated as a passive fallback option: If a novel venture is rejected by the VC firm, the VC firm finances a project from the "known" pool of ventures and earns an exogenous return $R_k(\gamma)$ which we assume increases with partner specialization but is otherwise exogenous.

Figure 4 about here.

The timeline of the model is presented in Figure 4 and described as follows:

1. **Entrepreneur stage**

   (a) An entrepreneur is born with skill $\eta \sim Uniform[0, 1]$.

(b) Given η a founder chooses to enter or not and if she enters she can create a high quality (h) or low quality (l) venture.

(c) The baseline cost for creating a high (low) quality venture for a founder with no skill $\eta = 0$ is c_h (c_l), where $c_h > c_l$. Given a positive $\eta > 0$ the cost of creating a high (low) quality venture is given by:

$$\mathrm{Cost}(h) = c_h - \eta, \qquad \mathrm{Cost}(l) = c_\ell - \lambda\eta, \quad 0 < \lambda < 1.$$

(d) If a project is created and financed, returns to the VC are R_h or $R_l < 0$ if the project is high (low) quality; the entrepreneur receives share an exogenous share ε of the surplus and non-pecuniary private benefit $b > 0$.

2. **VC stage**

(a) Observing the parameters of the model, but not the exact η drawn by the entrepreneur the VC firm forms a prior π on the probability of the novel being high quality project and assigns a partner with a specialisation level γ to screen the project.

(b) The partner exerts observable and contractable effort e which costs $\frac{1}{2}\gamma e^2$ and observes a signal about the quality of the project created by the entrepreneur

$$s = \theta + \varepsilon, \qquad \varepsilon \sim \mathcal{N}\big(0, \tfrac{1}{\tau}\big), \quad \tau = \kappa e.$$

(c) Investment rule: Invest in novel project if $s \geq s^*$ otherwise invest in fallback option in known sector that yields $R_k(\gamma)$ which is concave increasing function of specialization level γ.

3. **Surplus-sharing stage**

(a) After the investment decision, cash surplus is split via Nash bargaining: VC gets $1 - \varepsilon$, entrepreneur gets ε.

6.1 Surplus-sharing stage

We assume that the surplus sharing stage is completely exogenous and if a high quality venture is created and financed the VC gets $1 - \epsilon$ of the surplus (which is $R_h - R_k(\gamma)$) and the entrepreneur gets a fraction ϵ. If a low quality venture is created and financed then since the low quality venture has a negative payoff and the entrepreneur is protected by limited liability the VC bears the full cost of funding such a venture $R_l - R_k(\gamma)$.

6.2 VC stage: Optimal effort and VC assignment rule

Once the surplus sharing stage is completed. We solve the model backwards. Let π be the prior probability that the project is of high quality. To screen the project the VC firm will hire a partner of type γ who will exert costly effort to acquire a signal about the quality of the project. The partner can exert effort e to get an informative signal about the project quality. Exerting effort is costly and the partner pays a convex cost $C = \frac{1}{2}\gamma e^2$.

We assume that the effort exerted by the partner is observable and contractable. To compensate the assigned partner the VC firm will pay the partner a a wage w which is enough to cover the partner's effort cost and the partner's outside opportunity cost $u(\gamma)$ which is an exogenous parameter that depends on the partner type γ.[24]

6.2.1 Information acquisition and VC payoff

The partner hired by the VC firm can exert costly effort to acquire an informative signal about the project quality. The observed signal is given by:

$$s = \theta + \epsilon \text{ where } \epsilon \sim N(0, \frac{1}{\tau}), \tag{14}$$

where $\theta = 1$ if the project is of high quality and $\theta = 0$ if the project is of low quality. The parameter τ is the signal informativeness and we assume that it increases with effort e. In particular we assume that $\tau = \kappa e$, where $\kappa > 0$ is a screening efficiency parameter. If the partner decides to not invest in the project the partner can invest in the "known" sector where there is a fallback option that returns $R_k(\gamma)$ that depends on the partner type γ.

After observing a signal the VC partner applies a simple threshold rule for investments. The partner accepts the investment if the signal $s \geq s^*$ there s^* is a threshold above which the signal is valuable. If the signal observed by the partner is below the threshold then the VC firm gets the fallback option $R_k(\gamma)$.

Assumption 1 (Information is valuable)**.** *We assume that for all $\gamma \in [\gamma_{min}, \gamma_{max}]$ it holds:*

$$\pi R_h + (1-\pi)R_l < R_k(\gamma) \tag{15}$$

Intuitively, (15) states that without information acquisition it is optimal to invest in the fallback option, that is for any partner type γ the fallback option dominates the

[24]The outside option of the partner is treated as exogenous in the model and set in a competitive labor market for VC partners. In principle we can let $u(\gamma)$ be a differentiable function of the partner's specialization level.)

expected value before acquiring additional information about the type of project faced in the unknown pool.[25]

Lemma 1 (Signal cut-off at which project from the unknown pool is accepted). *The cut-off signal at which investment in the unknown pool of projects becomes acceptable is given by:*

$$s^* = \frac{1}{2} + \frac{\Lambda}{\tau}, \tag{16}$$

where:

$$\Lambda = ln\left(\frac{(R_k(\gamma) - R_l)(1-\pi)}{(R_h - R_k(\gamma))\pi}\right) \tag{17}$$

Proof. See Appendix E. □

Notice that assumption 1 on the value of information in fact guarantees that $\Lambda > 0$. Notice that with $\Lambda > 0$, $s^* > \frac{1}{2}$ which implies that in most cases the project from the novel sector is rejected and the fallback option is preferred.[26] In this case the following comparative statics regarding the signal threshold are true and trivial to show:

Proposition 1. *The threshold signal satisfies the following comparative statics:* $\frac{\partial s^*}{\partial \pi} < 0$, $\frac{\partial s^*}{\partial (R_k - R_l)} > 0$, $\frac{\partial s^*}{\partial (R_h - R_k)} < 0$.

Proof. Trivial differentiation with respect to parameters of (16). □

The intuition behind proposition 1 is clear. If the prior probability of a good venture becomes higher, the signal investment threshold for accepting the project becomes lower. $R_k - R_l$ is the opportunity cost of investing in low quality venture, the higher the opportunity cost the higher the threshold for acceptance.[27] $R_h - R_k$ is the payoff difference between the high quality projects and the fallback option, the higher this difference the lower the acceptance threshold.

Given the signal informativeness τ we define the true positive rate $\alpha(\tau)$ i.e., the probability a venture is high quality and accepted and the false positive rate $\beta(\tau)$ i.e., the probability a venture is of low quality and is accepted:

$$\alpha(\tau) \ = \ \Pr\big[s \geq s^\star \ \big| \ \theta = 1\big] \ = \ 1 - \Phi\big((s^\star - 1)\sqrt{\tau}\big) \tag{18}$$

[25] Note that for (15) to hold we need to have $\pi < \frac{R_k(\gamma) - R_l}{R_h - R_l}$. π is determined endogenously in equilibrium and later we will show that (15) will hold in equilibrium. Intuitively, the prior probability of facing a high quality venture should not be high enough, otherwise screening is not valuable.

[26] This result resonates with the fact that in the VC context very few firms seeking financing eventually obtain financing, unlike for instance in the case of more mature projects applying for bank loans.

[27] $R_k - R_l$ is the difference between the fallback in case a venture is rejected and the payoff in case a low quality venture is financed, hence it is the opportunity cost of financing in the unknown sector and ending up with a low quality venture.

$$\beta(\tau) \;=\; \Pr\big[s \ge s^\star \;\big|\; \theta = 0\big] \;=\; 1 - \Phi\big(s^\star \sqrt{\tau}\big) \tag{19}$$

Here $\Phi(\cdot)$ is the standard normal cdf, π is the prior $P[\theta = 1]$, and κe converts effort e into signal precision $\tau = \kappa e$. The VC expected profit of the VC firm if the VC firm hires a partner of type γ before paying the partner and before surplus is shared between the VC firm and the entrepreneur is then is given by:

$$\begin{aligned}\Pi(e) = \quad & \underbrace{\pi\, \alpha(\tau)\, R_h}_{\substack{\text{high quality venture}\\ \text{accepted}}} \quad + \underbrace{(1-\pi)\, \beta(\tau)\, R_l}_{\substack{\text{low quality venture}\\ \text{accepted}}} \\ & + \underbrace{\pi\, [1-\alpha(\tau)]\, R_k(\gamma)}_{\substack{\text{high quality venture}\\ \text{rejected}}} + \underbrace{(1-\pi)\, [1-\beta(\tau)]\, R_k(\gamma)}_{\substack{\text{low quality venture}\\ \text{rejected}}}\end{aligned} \tag{20}$$

The contribution of each term in (20) is also explained in Table 1.

Project quality	**VC decision**	**Probability**	**Contribution to** $\Pi(e)$
$\theta = 1$ (good)	Accept $(s \ge s^*)$	$\pi\, \alpha(\tau)$	$\pi\, \alpha(\tau)\, R_h$
$\theta = 0$ (bad)	Accept $(s \ge s^*)$	$(1-\pi)\, \beta(\tau)$	$(1-\pi)\, \beta(\tau)\, R_l$
$\theta = 1$ (good)	Reject $(s < s^*)$	$\pi\, [1-\alpha(\tau)]$	$\pi\, [1-\alpha(\tau)]\, R_k$
$\theta = 0$ (bad)	Reject $(s < s^*)$	$(1-\pi)\, [1-\beta(\tau)]$	$(1-\pi)\, [1-\beta(\tau)]\, R_k$

Table 1: Building blocks for the VC's expected payoff $\Pi(e)$ before deducting compensation of the hired partner. Here π is the prior probability a venture is of high quality, $\alpha(\tau)$ is the true-positive rate, $\beta(\tau)$ the false-positive rate, R_h the payoff from backing a high quality venture, R_l from backing a low quality venture, and R_k the fallback return from rejecting.

The VC firm will hire a partner type γ and will pay the partner a wage $w(e, \gamma)$ to compensate the partner for her effort $\frac{1}{2}\gamma e^2$ and her outside option $u(\gamma)$.[28] The partner's participation constrain is given by:

$$w(\gamma, e) - \frac{1}{2}\gamma e^2 \ge u(\gamma) \tag{21}$$

The VC firm will pay the partner of type γ a wage to exactly compensate the partner for her effort cost and outside option hence:

$$w(\gamma, e) = \frac{1}{2}\gamma e^2 + u(\gamma) \tag{22}$$

[28]The outside option of the partner is a function of partner type γ but it is determined outside of the model by a competitive labour market. We do not make any parametric assumptions on $u(\gamma)$ except that it is differentiable on the relevant range of γ.

6.2.2 Optimal Effort Choice

Proposition 2. *Given a partner type γ the VC firm will choose optimal effort to maximize:*

$$\max_{e \geq 0} U(e) \;=\; \underbrace{R_k + (1-\epsilon)\pi\, \alpha(\tau)\,(R_h - R_k) + (1-\pi)\,\beta(\tau)\,(R_l - R_k)}_{\Pi(e)\ \textit{(expected return to VC firm)}} \;-\; \underbrace{\left(\frac{\gamma\, e^2}{2} + u(\gamma)\right)}_{\textit{partner's compensation}} \tag{23}$$

Given (π, γ) the condition below (24) defines the optimal level of effort $e^* > 0$ which is a maximum of (23) and satisfies $\tau^* > 2\Lambda$.

$$\big\{(1-\epsilon)\pi\,(R_h - R_k)\,\alpha'(\tau) + (1-\pi)\,(R_l - R_k)\,\beta'(\tau)\big\}\,\kappa \;=\; \gamma\, e^{\star} \tag{24}$$

Proof. See Appendix E. □

Intuitively, condition (24) equalizes marginal screening benefit (right hand size) to marginal screening cost (left hand side). Marginally increasing effort rises the true positive rate $\alpha(\tau)$ and lowers the false positive rate $\beta(\tau)$, since α and β are concave the linear marginal cost will (left hand side) will cross the right hand side once for an interior effort defined by (24).

As a corollary we have the following comparative statics results:

Corollary 1 (Comparative statics of optimal effort). *Suppose parameter values are such that $R_k(2-\epsilon) \geq R_h + (1-\epsilon)R_l$ then optimal effort e^* is decreasing with respect to γ i.e., $\frac{\partial e^*}{\partial \gamma} < 0$. Optimal effort is increasing with respect to π i.e., $\frac{\partial e^*}{\partial \pi} > 0$.*

Proof. See Appendix E. □

We can derive an analytical solution for the optimal effort exerted and analyse comparative statics under two simplifying assumptions:

Assumption 2. $\Lambda \approx 0$ *We assume that under the prior expected value of a financing a high quality venture relative to the fallback is roughly the same as the expected value to the loss occurred from financing a bad project, which is the outside opportunity cost minus the return from the low quality project.*

Given assumption 2 it is straightforward to show that the true positive and false positive rates take a simple symmetric form:

$$\alpha(\tau) = 1 - \Phi\left(\frac{-\sqrt{\tau}}{2}\right) \tag{25}$$

$$\beta(\tau) = 1 - \Phi\left(\frac{\sqrt{\tau}}{2}\right) \tag{26}$$

We can use this as well as well known properties of the cdf and pdf of a normal distribution to rewrite the FOC:

$$\frac{\phi(\frac{\sqrt{\tau}}{2})}{4\sqrt{\tau}}\Delta\kappa = \gamma e, \tag{27}$$

where $\Delta = (1-\epsilon)\pi(R_h - R_k) - (1-\pi)(R_l - R_k) > 0$.

Now we will make an additional assumption that τ is small and we will approximate the exponential in the pdf $\phi(\frac{\sqrt{\tau}}{2})$ with 1 i.e., $\phi(\frac{\sqrt{\tau}}{2}) \approx \frac{1}{\sqrt{(2\pi)}}$ (0th order Taylor expansion). Finally, for the optimal effort we obtain:

$$e^* \approx \left(\frac{\Delta^2\kappa}{32\gamma^2 3.14}\right)^{1/3} \tag{28}$$

So optimal effort increases with the screening gain Δ (and π), the screening efficiency κ, and decreases with the screening cost γ and N. We will use equation (28) only as an illustration.

Define the likelihood of accepting a project in the novel sector $L_N(e^*(\gamma))$ as:

$$L_N(e^*(\gamma)) = \pi\alpha(\tau^*) + (1-\pi)\beta(\tau^*) \tag{29}$$

Define the expected return in the novel sector under optimal effort $E_N(e^*(\gamma))$ and the expected return in the known sector $E_K(e^*(\gamma))$

$$E_N(e^*(\gamma)) = \alpha(\tau^*)R_h + \beta(\tau^*)R_l \tag{30}$$

$$E_K(e^*(\gamma)) = R_k(\gamma)q^r(\tau^*), \tag{31}$$

where $q^r(\tau^*) = 1 - (1-\epsilon)\pi\alpha(\tau) - (1-\pi)\beta(\tau)$ is the probability that a novel project is rejected and the fallback is financed. We have the following two propositions that are the theoretical counterparts of the empirical findings:

Proposition 3 (The likelihood of financing a novel project decreases with specialization)**.** *At optimal effort provided* $R_k > \frac{R_l + R_h}{2}$ *the likelihood of accepting a novel project decreases with specialization i.e.,* $\frac{\partial L_N(e^*(\gamma))}{\partial\gamma} < 0$.

Proof. See Appendix E. □

Proposition 4. *Suppose $R_h \geq |R_l|$ i.e., the upside of investing in a novel project is higher then the downside, then the expected return in the novel sector decreases with the level of specialization i.e. $\frac{\partial E_N}{\partial \gamma} < 0$. The expected return in the known sector rises with specialization, $\frac{\partial E_K}{\partial \gamma} > 0$.*

Proof. See Appendix E. □

The last two propositions clearly speak to the empirical findings of the paper. One way to interpret the variation in γ in this setting is as a variation in local time constants (i.e., busyness). In particular, proposition 3 states that in a partial equilibrium setting, provided the return in the known sector is high enough, the likelihood of accepting a novel project decreases with specialization (increases with human capital breadth). Similarly, proposition 4 states that if the upside of financing a novel project is higher than the downside, the expected return in the novel sector rise with human capital breadth which provides a rigorous theoretical argument for causal relationship established in the instrumental variable setting, namely human capital breadth is helpful for financing novel firms but hurtful for financing non-novel ventures.

6.2.3 Optimal Hiring Rule

In this section we endogenize the VC hiring rule. In the previous subsection we optimized effort given γ. Now we solve for the optimal partner type γ. Recall that γ represents the specialization of the partner and we have assumed that the higher the specialization of the partner i.e., the higher the γ the higher the partner's screening cost, but also the higher the fallback option if the project is rejected. Specifically, motivated by the empirical evidence we assume that a generalist has a lower screening cost, and that the specialist has a larger fallback investment in the known sector. We assume $R_k(\gamma)$ is differentiable, increasing and concave i.e., $R_k'(\gamma) > 0$ and $R_k''(\gamma) < 0$.

We have the following proposition:

Proposition 5 (Optimal hiring rule)**.** *Given π the VC firm maximizes the total expected profit and hires a partner of type γ s.t.*

$$\max_{\gamma \in [\gamma_{min}, \gamma_{max}]} V(\gamma) = \Pi(e^*(\gamma), \gamma) - C(e^*(\gamma), \gamma) - u(\gamma) \tag{32}$$

Given π the condition below defines the optimal partner specialization γ which maximizes (32).

$$R_k(\gamma^*)' q^r = \frac{1}{2} e(\gamma^*)^2 + u'(\gamma), \tag{33}$$

where $q^r = 1 - (1-\epsilon)\pi\alpha(\tau) - (1-\pi)\beta(\tau)$ is the rejection probability.

Proof. See Appendix E. □

The intuition is straightforward, the LHS is the marginal benefit of raising γ (hiring a specialist) which is the marginal return of a fall back deal which the firm gets in case the deal from the unknown sector gets rejected. The right hand side is the marginal cost which is lower screening and the marginal wage to be paid at each γ.

Corollary 2 (Comparative statics of optimal specialization with respect to π)**.** *Assume payoffs are such that* $(2-\epsilon)R_k \geq R_h + (1-\epsilon)R_l$ *then optimal specialization decreases with* π *i.e. we have* $\frac{\partial \gamma}{\partial \pi} < 0$.

Proof. See Appendix E. □

Under the parameter conditions specified when π increases the VC firm is incentivized to hire a more generalized partner. Intuitively when π increases the threshold for acceptance a project drops, since in most cases it is optimal to reject a project an increase in π incentives the PE firm to hire a partner that can generate an informative signal that can bring the signal for the project above the threshold - this incentivizes the hiring of a specialist since specialist have a lower cost of effort.

6.2.4 Entrepreneur

In the first period of the model an entrepreneur is born with a skill level $\eta \sim F(\eta)$ where $F(\eta)$ is a CDF. The VC firm does not know the skill of the entrepreneur, but knows the distribution of entrepreneurial skill. The entrepreneur knows her skill. If the entrepreneur is sufficiently skilled to enter the market she can either work to produce a high quality venture or a low quality venture. The cost of producing a high quality venture is $c_h > c_l$ the cost of producing a low venture for an unskilled entrepreneurs. If the entrepreneur enters the market, produces a venture and the venture gets VC financing in the later periods the entrepreneur gets an additional private benefit of being entrepreneurs b.[29].The entrepreneur's skill η can help the entrepreneur lower the cost of working on a given venture via. :

$$c_h(\eta) = c_h - \eta \tag{34}$$

$$c_l(\eta) = c_l - \lambda\eta \tag{35}$$

where $\lambda < 1$. We make this assumption that skill helps reduce the cost of working on a good venture more than it helps to reduce the cost of working on a bad venture to make sure that there is sorting on skill. The expected utility of producing a low venture for a

[29]We assume that this private benefit is constant and does not vary by type of venture

type η entrepreneur is :

$$U_l(\eta) = \beta(\tau)b - c_l + \lambda\eta \tag{36}$$

In case the venture gets financing payoff is the private benefit b. Hence the expected payoff in case the entrepreneur produces a low quality venture is the probability of financing (probability of a false positive error by the VC) $\beta(\tau)$ times the private benefit b. The net cost the entrepreneur of skill η needs to pay is $c_l - \lambda\eta$ The utility for producing a high quality venture is:

$$U_h(\eta) = \alpha(\tau)(\epsilon(R_h - R_k) + b) - c_h + \eta \tag{37}$$

In this case the probability of financing is the true positive rate $\alpha(\tau)$ and the entrepreneur gets a fraction ϵ of the surplus plus her private benefit b. The entrepreneur produces a high quality venture whenever:

$$U_g(\eta) \geq U_b(\eta) \tag{38}$$

From the last equation we define the quality choice threshold:

$$\eta^h = \frac{(c_h - c_l) - (\alpha(\tau)(\epsilon(R_h - R_k) + b) - \beta(\tau)b)}{1 - \lambda} \tag{39}$$

So the entrepreneur chooses to produce a good venture whenever she is born with $\eta \geq \eta^h$. The condition for entry into entrepreneurship is determined by a participation constant for working on a low quality venture:

$$U_b(\eta) \geq 0 \tag{40}$$

This defines the entry into entrepreneurship threshold

$$\eta^l = \frac{c_l - \beta(\tau)b}{\lambda}. \tag{41}$$

whereby if the entrepreneur is born with an $\eta \geq \eta^l$ she enters entrepreneurship.

Hence the probability of entry into entrepreneurship assuming $F(\eta) = Uniform[0, 1]$ is given by:

$$1 - \eta^l \tag{42}$$

The probability of entry into entrepreneurship and producing a high quality venture is then:

$$1 - \eta^h, \tag{43}$$

so π is determined by:

$$\pi = \frac{1 - \eta^h}{1 - \eta^l} \tag{44}$$

The following conditions need to hold:

1. High entry threshold higher than low entry threshold $\eta^h \geq \eta^l$
2. Positive low entry threshold $\eta^l \geq 0$.
3. Consistency $\eta^h \leq 1$.

It is obvious that if 3. and 1. hold then also $\eta^l \leq 1$. This defines conditions on parameter values:

$$c_l \geq \beta(\tau)b \tag{45}$$

$$1-\lambda+c_l-\beta(\tau)b+\alpha(\tau)(\epsilon(R_h-R_k)+b) \geq c_h \geq \frac{c_l-\beta(\tau)b}{\lambda}+\alpha(\tau)(\epsilon(R_h-R_k)+b) \tag{46}$$

6.3 Equilibrium Definition and Existence

We now define the equilibrium of the model and prove its existence. The equilibrium consists of three endogenous variables: the fraction of high-quality projects π, the partner specialization level γ, and the screening effort e. These must satisfy the following conditions simultaneously:

Equilibrium A tuple (π^*, γ^*, e^*) constitutes an equilibrium if:

1. **Optimal Effort:** Given (γ^*, π^*), effort e^* satisfies the first-order condition:

$$\big\{(1-\epsilon)\pi^*(R_h-R_k)\alpha'(\tau^*)+(1-\pi^*)(R_l-R_k)\beta'(\tau^*)\big\}\kappa = \gamma^* e^* \tag{47}$$

   where $\tau^* = \kappa e^*$.

2. **Optimal Hiring:** Given π^*, partner type γ^* satisfies:

$$R_k'(\gamma^*)q^r(\tau^*) = \frac{1}{2}(e^*)^2 + u'(\gamma^*) \tag{48}$$

   where $q^r(\tau^*) = 1-(1-\epsilon)\pi^*\alpha(\tau^*)-(1-\pi^*)\beta(\tau^*)$ is the rejection probability.

3. **Entrepreneurial Entry:** The entry threshold η^l and quality threshold η^h satisfy:

$$\eta^l = \frac{c_l-\beta(\tau^*)b}{\lambda} \tag{49}$$

$$\eta^h = \frac{(c_h-c_l)-[\alpha(\tau^*)(\epsilon(R_h-R_k)+b)-\beta(\tau^*)b]}{1-\lambda} \tag{50}$$

   with corresponding project mass and quality fraction:

$$\pi^* = \frac{1-\eta^h}{1-\eta^l} \tag{51}$$

Theorem 1. *Under the model assumptions and parameter restrictions, an equilibrium* (π^*, γ^*, e^*) *exists.*

Proof. See Appendix E. $\square$

6.4 Interpreting stylized facts through the lens of the model

In this subsection we analyse the equilibrium and aim to interpret the stylized facts presented in the paper through the lens of the model. The main stylized facts that the paper documents are:

- Decline in financed novelty over time.
- Increase in specialization by VC firms over time.

I, show that both of these facts can be simultaneously explained by analysing how the equilibrium defined in the paper responds to c_l and c_h that is the entry costs for working on a high and low quality ventures.

6.4.1 One time increase in c_h

In this subsection we analyse what is the likely new equilibrium after a one time shock in exogenous c_h by tracing the propagation of the shock on equilibrium values. We will not prove the statements explicitly for now.

1. Step 1: direct effect on π. It is clear that:

$$\frac{\partial \eta^h}{\partial c_h} = \frac{1}{1-\lambda} > 0. \tag{52}$$

   since η^l does not explicitly depend on c_h it is clear that initially $\uparrow c_h \rightarrow \downarrow \pi$.

2. Effect on optimal effort. According to the corollary when π declines optimal effort e will also decline $\uparrow c_h \rightarrow \downarrow \pi \rightarrow \downarrow e$
3. Since signal informativeness declines, We have the true positive rate α going down and the false positive rate β going up $\uparrow c_h \rightarrow \downarrow \pi \rightarrow \downarrow e \rightarrow \downarrow \alpha(\tau), \uparrow \beta(\tau)$
4. Since β is going down this decreases η^l hence pushing π even further.
5. Now lower π pushes specialization up $\downarrow \pi \rightarrow \uparrow \gamma$
6. Now increase in γ increases the signal threshold for project acceptance which reduces α but also β with an overall effect on β positive through the decline in effort.

The following steps outline that the new equilibrium features a lower π a higher γ and a lower effort e. Intuitively, the higher the cost of working on good venture has a direct effect on the prior probability of a given project being high. This in turn reduces VCs screening incentives and increases the VCs value from the fallback option (a project is more likely to be rejected) which in turn decreases the incentives of entrepreneurs to produce good projects i.e. the new level of π is depressed even further than the direct effect of an increase in the cost of working on good ventures.

The feedback loop presented here provides one justification for the empirical findings of the paper which present a decline in average financed novelty π and an increase in VC specialization over time, so one simple way to rationalize the empirical findings through the lens of the model is to understand them in terms of a one time shift in cost of working on high novel ventures.

6.4.2 One time decrease in c_l

Now suppose we have a one time time decrease on the cost of producing a low type venture c_l. We again analyse what is the likely new equilibrium after a one time shock in exogenous c_l by tracing the propagation of the shock on equilibrium values. We will not prove the statements explicitly for now.

1. Step 1: direct effect on π. It is clear that:

$$\frac{\partial \eta^h}{\partial c_l} = \frac{-1}{1-\lambda} < 0. \tag{53}$$

   Similarly:

$$\frac{\partial \eta^l}{\partial c_l} = \frac{1}{\lambda} > 0. \tag{54}$$

   Therefore the direct effect of a one time decline is c_l is that the skill threshold for working on a good venture goes up and at the same time the skill threshold for working on a bad venture declines. Both of these effect push π down. Hence $\downarrow c_l \rightarrow \downarrow \pi$.

2. Effect on optimal effort. According to the corollary when π declines optimal effort e will also decline $\downarrow c_l \rightarrow \downarrow \pi \rightarrow \downarrow e$

3. Since signal informativeness declines, We have the true positive rate α going down and the false positive rate β going up $\downarrow c_l \rightarrow \downarrow \pi \rightarrow \downarrow e \rightarrow \downarrow \alpha(\tau), \uparrow \beta(\tau)$

4. Since β is going up this decreases η^l and α going down increases η^h hence pushing π even further.

5. Now lower π pushes specialization up $\downarrow \pi \rightarrow \uparrow \gamma$

6. Now increase in γ increases the signal threshold for project acceptance which reduces α but also β with an overall effect on β positive through the decline in effort.

Therefore a one time decrease in c_l in this model generates similar patterns for the new likely equilibrium as the one time increase in c_h.

7 Conclusion

This paper examines the role of venture capital (VC) partners' human capital breadth in investment selection, startup performance, and innovation outcomes. Empirically, I find that within VC firms, partners with broader backgrounds are more likely to lead investments in novel, high-risk startups. While these partners do not perform better on average average, their involvement in novel ventures significantly increases the likelihood of major success. These patterns are consistent with both selection—where broad-background partners excel at screening novel firms—and potential monitoring—where their engagement enhances firm performance. Exploiting plausibly exogenous variation in partner busyness as a shock to lead-partner assignment, I provide a plausibly causal evidence for these effects. These results highlight the critical role of human capital breadth in financing of novel business ventures and support the role for public policies fostering the development of broad human capital.

Figures

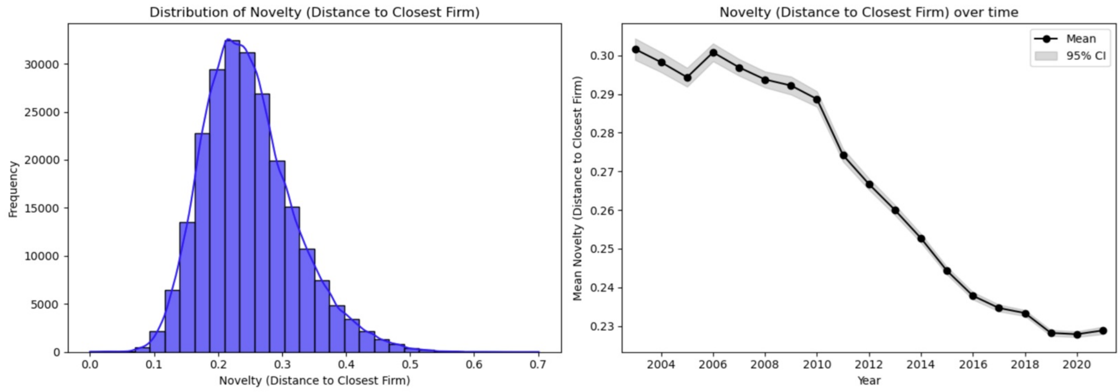

Figure 1: **Distribution of Novelty (Distance to Closest Firm) and time trend of Novelty (Distance to Closest Firm)** Left panel: This figure plots the distribution of the Novelty (Distance to Closest Firm) measure. Right Panel: Time trend of the mean of Novelty (Distance to Closest Firm) measure.

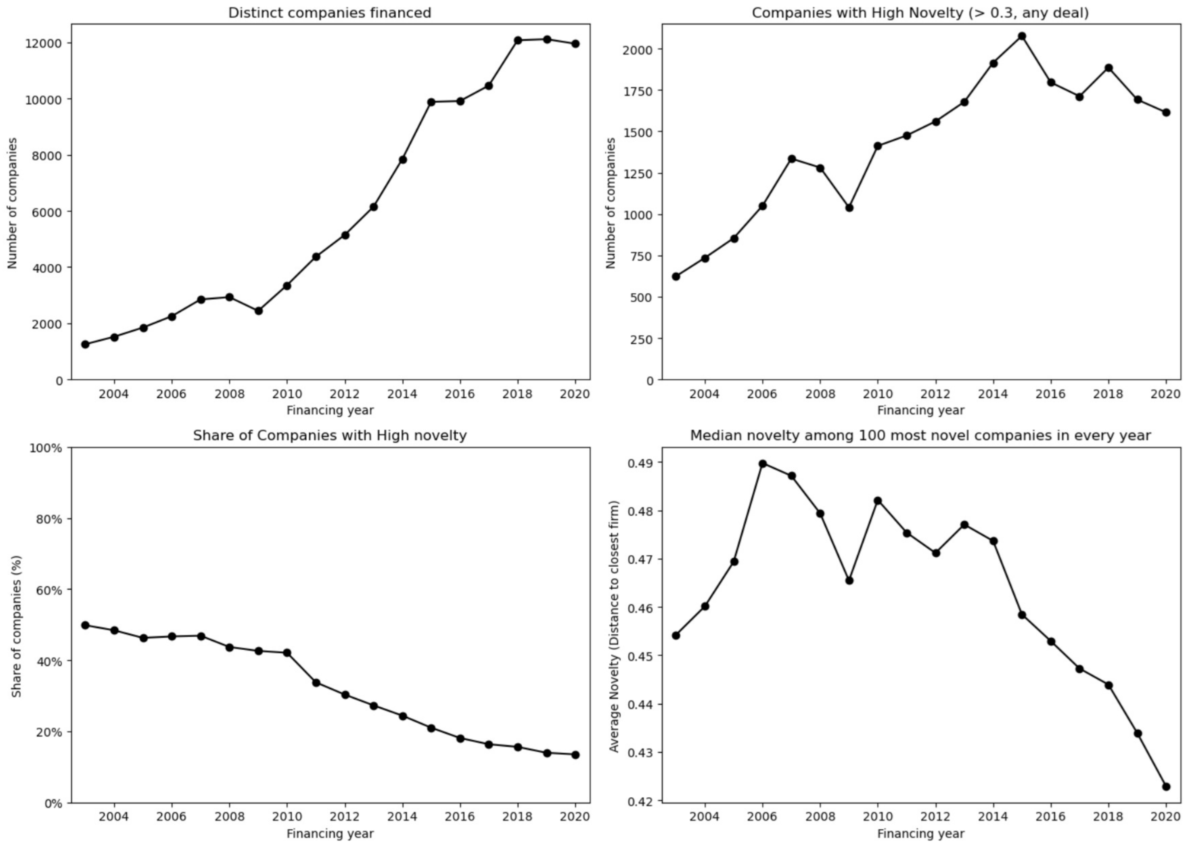

Figure 2: **Stylized facts about novelty of VC financed startups** Top left panel: Total number of newly VC financed; Top right panel: Total number of newly VC financed firms with novelty measure above 0.3 (top 25th percentile in novelty in the overall deal sample); Bottom left panel: Share of newly financed firms with novelty measure above 0.3 (top 25th percentile in novelty in the overall deal sample); Bottom right panel: Time evolution of median novelty among the top 100 most novel financed firms in each year.

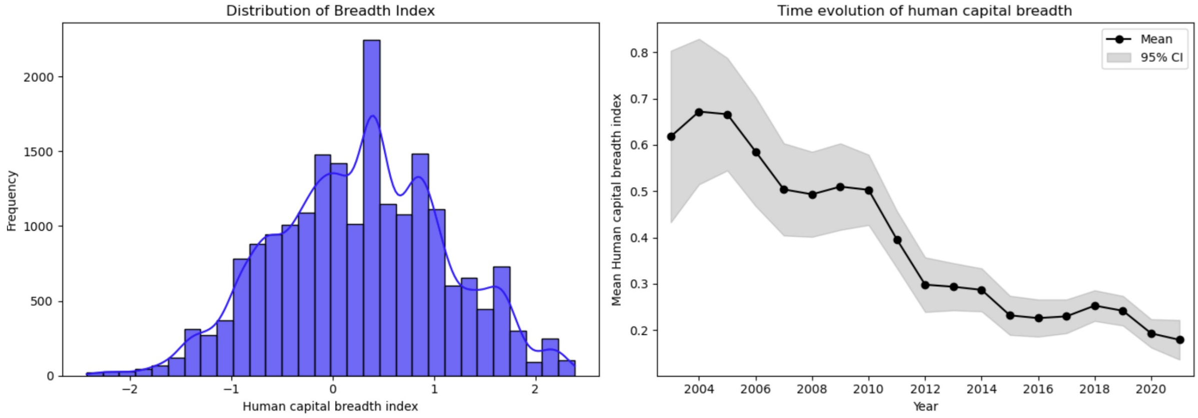

Figure 3: **Distribution of Breadth Index and time trend of Breadth Index** Left panel: This figure plots the distribution of the Breadth Index measure . Right Panel: Time trend of the mean of Breadth Index measure. Graph is done for partners for which we can observe at least 3 jobs prior to VC industry entry.

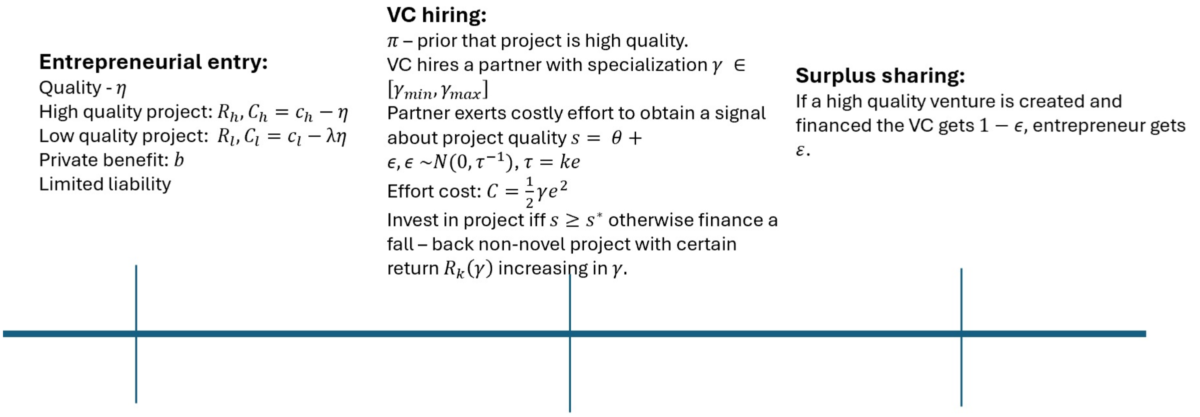

Figure 4: **Timeline of the model** This figure presents the timeline of the model

Tables

Variable	Obs	Mean	Std. Dev.	1%	5%	25%	50%	75%	95%	99%
Novelty (Distance to Closest Firm)	232,130	0.25	0.07	0.11	0.15	0.20	0.24	0.29	0.38	0.45
Novelty (Avg. Distance to Closest Firm)	232,130	0.28	0.07	0.14	0.18	0.23	0.27	0.32	0.41	0.48
IPO Exit	232,130	0.04	0.20	0.00	0.00	0.00	0.00	0.00	0.00	1.00
Major Success	232,130	0.07	0.26	0.00	0.00	0.00	0.00	0.00	1.00	1.00
Failure	232,130	0.35	0.48	0.00	0.00	0.00	0.00	1.00	1.00	1.00
Lead Investment	232,130	0.30	0.46	0.00	0.00	0.00	0.00	1.00	1.00	1.00
Number of Forward Patents	232,130	0.21	2.21	0.00	0.00	0.00	0.00	0.00	0.00	5.00
Number of Forward Citations	232,130	2.76	46.68	0.00	0.00	0.00	0.00	0.00	0.00	39.14
Breadth Index	34,959	-0.03	1.69	-3.14	-3.14	-0.76	0.34	1.21	2.19	2.29
Job categories ratio	28,520	0.59	0.28	0.14	0.20	0.33	0.50	1.00	1.00	1.00
Job roles ratio	28,520	0.83	0.21	0.25	0.43	0.67	1.00	1.00	1.00	1.00
Job industry ratio	28,520	0.71	0.27	0.00	0.25	0.50	0.71	1.00	1.00	1.00
Female	46,870	0.11	0.31	0.00	0.00	0.00	0.00	0.00	1.00	1.00
Partner has MBA	33,250	0.43	0.49	0.00	0.00	0.00	0.00	1.00	1.00	1.00
Partner has PhD	33,250	0.06	0.24	0.00	0.00	0.00	0.00	0.00	1.00	1.00
Partner STEM education	33,250	0.31	0.46	0.00	0.00	0.00	0.00	1.00	1.00	1.00
Partner Social science or Humanities education	33,250	0.63	0.48	0.00	0.00	0.00	1.00	1.00	1.00	1.00
Partner Attended Top School	33,250	0.50	0.50	0.00	0.00	0.00	1.00	1.00	1.00	1.00

Table 2: **Summary Statistics of Deal Level Sample** This table presents summary statistics for the deal level sample. Each observation is a deal. The summary statistics fro partner characteristics are at a deal level, i.e. a mean of 0.11 for the Female indicator means that over the sample period 11% of deals have a lead partner with a female gender.

Variable	Obs	Mean	Std. Dev.	1%	5%	25%	50%	75%	95%	99%
Breadth Index	6,763	0.06	1.51	-3.14	-3.14	-0.57	0.31	1.10	2.10	2.29
Job categories ratio	5,883	0.57	0.27	0.12	0.20	0.33	0.50	0.75	1.00	1.00
Job roles ratio	5,883	0.81	0.21	0.25	0.40	0.67	0.86	1.00	1.00	1.00
Job industry ratio	5,883	0.69	0.26	0.00	0.25	0.50	0.67	1.00	1.00	1.00
Female	9,644	0.13	0.34	0.00	0.00	0.00	0.00	0.00	1.00	1.00
Partner has MBA	6,406	0.37	0.48	0.00	0.00	0.00	0.00	1.00	1.00	1.00
Partner has PhD	6,406	0.06	0.24	0.00	0.00	0.00	0.00	0.00	1.00	1.00
Partner STEM education	6,406	0.28	0.45	0.00	0.00	0.00	0.00	1.00	1.00	1.00
Partner Social science or Humanities education	6,406	0.63	0.48	0.00	0.00	0.00	1.00	1.00	1.00	1.00
Partner Attended Top School	6,406	0.44	0.50	0.00	0.00	0.00	0.00	1.00	1.00	1.00

Table 3: **Summary Statistics for individual partners who have lead at least one investment** This table presents summary statistics for individual partners. Each observation is a unique partner for which the data is available. A mean of 0.13 for the Female indicator here means that 13% of partners who have led at least one deal are female.

Variable	Obs	Mean	Std. Dev.	1%	5%	25%	50%	75%	95%	99%
Novelty (Distance to Closest Firm)	164,762	0.24	0.07	0.11	0.14	0.19	0.24	0.28	0.38	0.45
Novelty (Avg. Distance to Closest Firm)	164,762	0.27	0.07	0.14	0.17	0.22	0.26	0.31	0.40	0.47
IPO Exit	164,762	0.05	0.22	0.00	0.00	0.00	0.00	0.00	1.00	1.00
Major Success	164,762	0.10	0.30	0.00	0.00	0.00	0.00	0.00	1.00	1.00
Failure	164,762	0.24	0.42	0.00	0.00	0.00	0.00	0.00	1.00	1.00
Number of Partners	164,762	12.02	9.28	1.00	2.00	5.00	9.00	18.00	30.00	41.00
Number of Available Partners	164,762	11.09	8.90	0.00	1.00	4.00	9.00	16.00	28.00	38.00
Partner Leads a Deal	164,762	0.21	0.41	0.00	0.00	0.00	0.00	0.00	1.00	1.00
Busy Partner	164,762	0.03	0.18	0.00	0.00	0.00	0.00	0.00	0.00	1.00
Breadth Index	164,762	-0.01	1.72	-3.14	-3.14	-0.75	0.37	1.29	2.19	2.29

Table 4: **Summary Statistics of Choice Model Sample** This table presents summary statistics for the choice model sample. A deal is included if at least 1 partner who could have been a lead partner on the focal deal has either job history or educational history available.

	(1) Failure	(2) Major Success	(3) Failure	(4) Major Success
Novelty (Distance to Closest Firm)	26.114***	64.686***	11.102***	64.555***
	(2.613)	(3.235)	(3.017)	(4.217)
Industry × Deal Year × Deal Type × Country FE	✓	✓		
Industry × Deal Year × Deal Type × Country × Investor FE			✓	✓
Observations	232108.00	232108.00	232108.00	232108.00
R^2	0.23	0.18	0.52	0.48

Table 5: **Association between startup novelty and likelihood of Failure and Major Success** This table reports the results of a deal - level regression of Failure and Major Success on the deal's novelty. The independent variable Novelty (Distance to Closest Firm) is a deal level measure of novelty defined as one - maximum of the cosine similarity of the textual description of the startup financed in the deal and all startups receiving venture capital financing within five years before the deal in the same deal stage. The dependent variable Major Success is an indicator variable taking a value of 1 if the firm exits via an IPO or via an Acquisition with an acquisition value at least five times greater than the total VC financing received by the firm. Failure is an indicator taking a value of 1 if the firm does not exit via an IPO, is not Acquired or does not receive any follow-up financing. Columns (1) and (2) include Industry × Deal Year × Deal Type × Country FE. Columns (3) and (4) include Industry × Deal Year × Deal Type × Country × Investor FE. Standard errors reported in parenthesis are double clustered at the investor and company level. * p<.10; ** p<.05; *** p<.01.

	(1) Failure	(2) Major Success	(3) Failure	(4) Major Success
Novelty Quartile (Distance to Closest Firm)=2	2.120***	-0.436*	2.050***	-0.242
	(0.423)	(0.261)	(0.499)	(0.315)
Novelty Quartile (Distance to Closest Firm)=3	4.201***	-0.265	2.816***	-0.102
	(0.439)	(0.281)	(0.524)	(0.341)
Novelty Quartile (Distance to Closest Firm)=4	5.713***	8.667***	2.948***	8.920***
	(0.493)	(0.509)	(0.575)	(0.658)
Industry × Deal Year × Deal Type × Country FE	✓	✓		
Industry × Deal Year × Deal Type × Country × Investor FE			✓	✓
Observations	232108.00	232108.00	232108.00	232108.00
R^2	0.23	0.17	0.52	0.47

Table 6: **Association between startup novelty quartile and likelihood of Failure and Major Success** This table reports the results of a deal - level regression of Failure and Major Success on the deal's novelty quartile. The independent variables are novelty quartile dummies indicating whether a startup belongs to the i the novelty quartile within a given year and deal stage based on the Novelty (Distance to Closest Firm) measure which is a deal level measure of novelty defined as one - maximum of the cosine similarity of the textual description of the startup financed in the deal and all startups receiving venture capital financing within five years before the deal in the same deal stage. The omitted category is Novelty Quartile (Distance to Closest Firm) = 1. Major Success is an indicator variable taking a value of 1 if the firm exits via an IPO or via an Acquisition with an acquisition value at least five times greater than the total VC financing received by the firm. Failure is an indicator taking a value of 1 if the firm does not exit via an IPO, is not Acquired or does not receive any follow-up financing. Columns (1) and (2) include Industry × Deal Year × Deal Type × Country FE. Columns (3) and (4) include Industry × Deal Year × Deal Type × Country × Investor FE. Standard errors reported in parenthesis are double clustered at the investor and company level. * p<.10; ** p<.05; *** p<.01.

	(1) Number of Forward Patents	(2) Number of Forward Citations	(3) Number of Forward Patents	(4) Number of Forward Citations
Novelty (Distance to Closest Firm)	1.717*	2.727**	1.037	3.292***
	(0.920)	(1.152)	(1.250)	(1.194)
Exit Type Controls	✓	✓	✓	✓
Industry × Deal Year × Deal Type × Country FE	✓	✓		
Industry × Deal Year × Deal Type × Country × Investor FE			✓	✓
Observations	232108.00	232108.00	232108.00	232108.00

Table 7: **Association between startup novelty and innovation outcomes - Poisson count model** This table reports the results of a deal - level regression of innovation outcomes on the deal's novelty. The independent variable Novelty (Distance to Closest Firm) is a deal level measure of novelty defined as one - maximum of the cosine similarity of the textual description of the startup financed in the deal and all startups receiving venture capital financing within five years before the deal in the same deal stage. The dependent variable in columns (1) and (3) is the Number of Forward Patents is the total number of patents granted to the firm after the deal date. The dependent variable in columns (2) and (4) Number of Forward Citations is the total number of adjusted citations (by grant year and NBER subcategory) that patents of the financed firm have received after the deal date. All columns include Exit Type controls which are separate controls specifying whether the startup goes public is acquired or receives follow-up financing. Columns (1) - (2) include Industry × Deal Year × Deal Type × Country FE. Columns (3) - (4) include Industry × Deal Year × Deal Type × Country × Investor FE. Standard errors reported in parenthesis are double clustered at the investor and company level. * p<.10; ** p<.05; *** p<.01.

	(1) Novelty (Distance to Closest Firm)	(2) Novelty (Distance to Closest Firm)	(3) Novelty (Distance to Closest Firm)	(4) Above Median Novelty	(5) Above Median Novelty	(6) Above Median Novelty
Breadth Index	0.162**	0.235*	0.660**	0.908	1.816**	4.027*
	(0.080)	(0.128)	(0.271)	(0.648)	(0.899)	(2.298)
VC Experience	0.032	-0.130	-0.109	0.518	-0.817	0.185
	(0.119)	(0.111)	(0.320)	(0.837)	(0.931)	(2.600)
Partner Industry Experience	-0.314**	0.099	0.346	-3.142**	0.912	5.044**
	(0.157)	(0.189)	(0.260)	(1.299)	(1.538)	(2.168)
Controls	✓	✓	✓	✓	✓	✓
Industry × Deal Year × Deal Type × Country FE	✓	✓	✓	✓	✓	✓
Investor FE × Deal Year FE		✓			✓	
Investor FE × Deal Year FE × Partner Entry Year FE			✓			✓
Observations	23531.00	23531.00	23531.00	23531.00	23531.00	23531.00
R^2	0.48	0.59	0.66	0.37	0.50	0.58

Table 8: **Association between lead partner's human capital breadth index and startup novelty** This table reports the results of an OLS regression of deal novelty and lead partner's human capital breadth. The dependent variable Novelty (Distance to Closest Firm) in columns (1)-(3) is a deal level measure of novelty defined as one minus the maximum of the cosine similarity of the textual description of the startup financed in the deal and all startups receiving venture capital financing within five years before the deal in the same deal stage. The independent variable in columns (4)-(6) is an indicator taking a value of 1 if the deal is a deal with above median novelty. The main independent variable Breadth Index is a measure of human capital breadth which is defined as the first principal component of a PCA from 4 individual human capital breadth proxies: 1) The ratio of distinct job categories to total employment spells 2) The ratio of distinct job roles to total employment spells 3) The ratio of distinct industries worked in to total employment spells 4) Educational breadth count. VC experience is a variable defined as the logarithm of one plus the number of deals financed by the lead partner prior to current deal. Partner Industry Experience is a dummy variable taking a value of 1 if the partner has had at least one job in the industry of the venture and 0 otherwise. i Columns (1) - (6) include Industry × Deal Year × Deal Type × Financed Company Country FE. Columns (2) and (5) also include Investor × Deal Year FE. Columns (3) and (6) include Investor × Deal Year × VC Partner Entry Year FE. All columns include individual level partner controls: age, sex and ethnicity. Standard errors reported in parenthesis are double clustered at the investor and company level. * p<.10; ** p<.05; *** p<.01.

	(1) Novelty (Distance to Closest Firm)	(2) Novelty (Distance to Closest Firm)	(3) Above Median Novelty	(4) Above Median Novelty	(5) Novelty (Distance to Closest Firm)	(6) Above Median Novelty
Breadth Index	0.509**	0.262	3.778*	0.985	0.157	1.018
	(0.235)	(0.182)	(2.140)	(1.240)	(0.141)	(0.973)
VC Experience	-0.473**	-0.078	-1.099	-0.395	-0.131	-0.818
	(0.204)	(0.174)	(1.737)	(1.546)	(0.110)	(0.923)
Partner Industry Experience	-0.108	0.471	2.258	0.920	0.097	0.887
	(0.433)	(0.301)	(3.700)	(2.375)	(0.189)	(1.536)
Lead Investment=1 × Breadth Index					0.192	1.941*
					(0.146)	(1.153)
Controls	✓	✓	✓	✓	✓	✓
Industry × Deal Year × Deal Type × Country FE	✓	✓	✓	✓	✓	✓
Investor FE × Deal Year FE	✓	✓	✓	✓	✓	✓
Observations	9519.00	14012.00	9519.00	14012.00	23531.00	23531.00
R^2	0.67	0.65	0.62	0.55	0.59	0.50

Table 9: **Association between lead partner's human capital breadth index and startup novelty: Lead vs. Non - Lead investments** This table reports the results of an OLS regression of deal novelty and lead partner's human capital breadth for lead and non-lead investments. The dependent variable Novelty (Distance to Closest Firm) in columns (1), (2) and (5) is a deal level measure of novelty defined as one minus the maximum of the cosine similarity of the textual description of the startup financed in the deal and all startups receiving venture capital financing within five years before the deal in the same deal stage. The independent variable in columns (3),(4) and (6) is an indicator taking a value of 1 if the deal is a deal with above median novelty. The main independent variable Breadth Index is a measure of human capital breadth which is defined as the first principal component of a PCA from 4 individual human capital breadth proxies: 1) The ratio of distinct job categories to total employment spells 2) The ratio of distinct job roles to total employment spells 3) The ratio of distinct industries worked in to total employment spells 4) Educational breadth count. Lead Investment is an indicator variable equal to 1 if the investment is led by the VC firm. In columns (1) and (3) the sample includes all lead investments by VC firms. In columns (2) and (4) the sample includes all non-lead investments by VC firms. VC experience is a variable defined as the logarithm of one plus the number of deals financed by the lead partner prior to current deal. Partner Industry Experience is a dummy variable taking a value of 1 if the partner has had at least one job in the industry of the venture and 0 otherwise. Columns (1) - (6) include Industry × Deal Year × Deal Type × Financed Company Country FE and Investor × Deal Year FE. All columns include individual level partner controls: age, sex and ethnicity. Standard errors reported in parenthesis are double clustered at the investor and company level. * p<.10; ** p<.05; *** p<.01.

	(1) Major Success	(2) Major Success	(3) Major Success
Novelty (Distance to Closest Firm)	0.409***	0.431***	0.337***
	(0.079)	(0.081)	(0.084)
Breadth Index	-0.024	-0.034**	-0.052***
	(0.016)	(0.016)	(0.020)
Novelty (Distance to Closest Firm) × Breadth Index	0.133*	0.154**	0.216***
	(0.071)	(0.069)	(0.076)
VC Experience	0.004	0.003	0.014
	(0.004)	(0.005)	(0.012)
Partner Industry Experience	0.014*	-0.007	0.006
	(0.007)	(0.011)	(0.012)
Controls	✓	✓	✓
Industry × Deal Year × Deal Type × Country FE	✓	✓	✓
Investor FE × Deal Year FE		✓	
Investor FE × Deal Year FE × Partner Entry Year FE			✓
Observations	23531.00	23531.00	23531.00
R^2	0.41	0.55	0.64

Table 10: **Association between the interaction of lead partner's human capital breadth and deal novelty and startup's success.** This table reports the results of an OLS regression of startup's likelihood of achieving a major exit on the interaction between deal's novelty and lead partner's human capital breadth. The independent variable Novelty (Distance to Closest Firm) is a deal level measure of novelty defined as one minus the maximum of the cosine similarity of the textual description of the startup financed in the deal and all startups receiving venture capital financing within five years before the deal in the same deal stage. The independent variable Breadth Index is a measure of human capital breadth which is defined as the first principal component of a PCA from 4 individual human capital breadth proxies: 1) The ratio of distinct job categories to total employment spells 2) The ratio of distinct job roles to total employment spells 3) The ratio of distinct industries worked in to total employment spells 4) Educational breadth count. Breadth Index × Novelty (Distance to Closest Firm) is the interaction between the deal's novelty and the lead partner's human capital breadth index. In columns (1)-(3) the dependent variable Major Success is an indicator that equals 1 if the startup goes public or is acquired at a valuation at least five times greater than the total VC invested capital. VC Experience is a variable defined as the logarithm of one plus the number of deals financed by the lead partner prior to current deal. Partner Industry Experience is a dummy variable taking a value of 1 if the partner has had at least one job in the industry of the venture and 0 otherwise. Columns (1) - (3) include Industry × Deal Year × Deal Type × Country FE. Column (2) includes Investor × Deal Year FE. Column (3) includes Investor × Deal Year × Partner Entry Year FE. Standard errors reported in parenthesis are double clustered at the investor and company level. * p<.10; ** p<.05; *** p<.01.

	(1) Partner Leads a Deal	(2) Partner Leads a Deal	(3) Partner Leads a Deal	(4) Partner Leads a Deal	(5) Partner Leads a Deal	(6) Partner Leads a Deal
Busy Partner	-1.730**	-2.814***	-1.399	-2.273**	-3.635***	-1.517
	(0.681)	(1.084)	(0.889)	(0.928)	(1.341)	(1.309)
VC Experience	7.463***	5.712***	8.524***	6.829***	5.182***	8.043***
	(0.117)	(0.196)	(0.147)	(0.157)	(0.246)	(0.207)
Partner Age	-0.094***	-0.096***	-0.094***	-0.079***	-0.043	-0.106***
	(0.014)	(0.023)	(0.018)	(0.018)	(0.028)	(0.025)
Partner Industry Experience	3.078***	2.869***	3.142***	3.125***	2.954***	3.173***
	(0.094)	(0.158)	(0.119)	(0.123)	(0.192)	(0.162)
Controls	✓	✓	✓	✓	✓	✓
Deal FE	✓	✓	✓	✓	✓	✓
Investor FE	✓	✓	✓	✓	✓	✓
Observations	242751.00	91232.00	151519.00	148916.00	62693.00	86223.00
R^2	0.32	0.31	0.33	0.33	0.31	0.34

Table 11: **Association between partner busyness and the likelihood of a partner leading a deal.** This table reports the results of an OLS regression of the likelihood of partner leading a deal on partner busyness. The dependent variable Partner Leads a Deal is an indicator equal to 1 if a partner leads a deal and 0 otherwise. The main independent variable Busy Partner is an indicator taking a value of 1 if the a partner is involved in exiting a deal via an IPO or a high value acquisition in a time period (-90, 90) around the focal deal date. VC Experience is a variable defined as the logarithm of one plus the number of deals financed by the lead partner prior to current deal. Partner Industry Experience is a dummy variable taking a value of 1 if the partner has had at least one job in the industry of the venture and 0 otherwise. In all columns we include controls for sex and ethnicity. In all columns we include Deal FE and Investor FE. Columns (1) reports the results for the full deal level sample. Columns (2) and (3) report the results for the full sample and split the coefficients for lead vs. non - lead investments. Column (4) reports the results for the main sample in the paper which is early stage novel investments. Columns (5) and (6) report the results for the main sample in the paper which is early stage novel investments and split the coefficients for lead vs. non - lead investments. Standard errors reported in parenthesis are clustered at the deal level. * p<.10; ** p<.05; *** p<.01.

	(1) Partner Leads a Deal	(2) Partner Leads a Deal	(3) Partner Leads a Deal
Novelty (Distance to Closest Firm) × Breadth Index	4.504***	5.011***	3.535**
	(1.146)	(1.751)	(1.541)
Busy Partner	-1.916**	-3.094**	-1.093
	(0.936)	(1.378)	(1.331)
Controls	✓	✓	✓
Deal FE	✓	✓	✓
Investor FE	✓	✓	✓
Partner FE	✓	✓	✓
Observations	148837.00	62666.00	86171.00
R^2	0.43	0.45	0.46

Table 12: **Interaction between Human Capital Breadth and Novelty and the likelihood of leading a deal** This table reports the results of an OLS regression of the likelihood of partner leading a deal on an interaction between deal novelty and the partner's human capital breadth. The dependent variable Partner Leads a Deal is an indicator equal to 1 if a partner leads a deal and 0 otherwise. The main independent variable Novelty (Distance to Closest Firm) × Breadth Index is an interaction between deal's novelty and partner's human capital breadth. Busy Partner is an indicator taking a value of 1 if the a partner is involved in exiting a deal via an IPO or a high value acquisition in a time period (-90, 90) around the focal deal date. VC Experience is a variable defined as the logarithm of one plus the number of deals financed by the lead partner prior to current deal. Partner Industry Experience is a dummy variable taking a value of 1 if the partner has had at least one job in the industry of the venture and 0 otherwise. In all columns we include controls for sex and ethnicity. In all columns we include Deal FE and Investor FE. Columns (1) reports the results for the full deal level sample. Columns (2) and (3) report the results for the full sample and split the coefficients for lead vs. non - lead investments. Column (4) reports the results for the main sample in the paper which is early stage novel investments. Columns (5) and (6) report the results for the main sample in the paper which is early stage novel investments and split the coefficients for lead vs. non - lead investments. Standard errors reported in parenthesis are clustered at the deal level. * p<.10; ** p<.05; *** p<.01.

	(1) Breadth Index	(2) Breadth Index × Novelty (Distance to Closest Firm)	(3) Major Success	(4) Major Success
Avg. Available Breadth	0.817***	-0.032**		
	(0.054)	(0.015)		
Avg. Available Breadth × Novelty (Distance to Closest Firm)	-0.577**	0.793***		
	(0.225)	(0.079)		
Breadth Index			-0.191***	-0.132***
			(0.063)	(0.046)
Breadth Index × Novelty (Distance to Closest Firm)			0.971***	0.722***
			(0.291)	(0.210)
Novelty (Distance to Closest Firm)			0.254	0.517
			(0.324)	(0.330)
Controls	✓	✓	✓	✓
Investor × Deal Year FE	✓	✓	✓	✓
Deal Stage × Industry × Year × Country FE	✓	✓	✓	✓
Observations	2233.00	2233.00	2233.00	2306.00
R^2	0.87	0.87	0.09	0.53
F-statistic of Instrument			100.01	

Table 13: **Effect of the interaction of lead partner's human capital breadth and deal novelty on startup outcomes.** This table presents the results of a instrumental variable regression of deal performance on the interaction between lead partner breadth and deal novelty. Column (1) presents the first stage regressions of the first instrumented variable Breadth Index on the two instruments Avg. Available Breadth and Avg. Available Breadth × Novelty, where Avg. Available Breadth is the average breadth index at a VC firm level across the firm's available partners constructed as the ratio of the sum of the total human capital breadth across all available partners (partners who are not busy around (-90, 90) days of the focal deal with a high value exit exit event). Column (2) presents the first stage regression of the second instrumented variable Breadth Index × Novelty on the two instruments Avg. Available Breadth and Avg. Available Breadth × Novelty. In columns (3) and (4) the dependent variable is Major success which is an indicator taking a value of 1 if the startup exits via an IPO or an acquisition of valued at least five times greater than the total VC capital raised by the company. Column (3) presents the IV estimates Column (4) presents the OLS estimates in the same sample. Columns (1) - (4) include Industry × Deal Year × Deal Type × Country FE and Investor FE. Standard errors reported in parenthesis are double clustered at the investor and company level. * p<.10; ** p<.05; *** p<.01.

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Appendix

A Stylized Facts Robustness

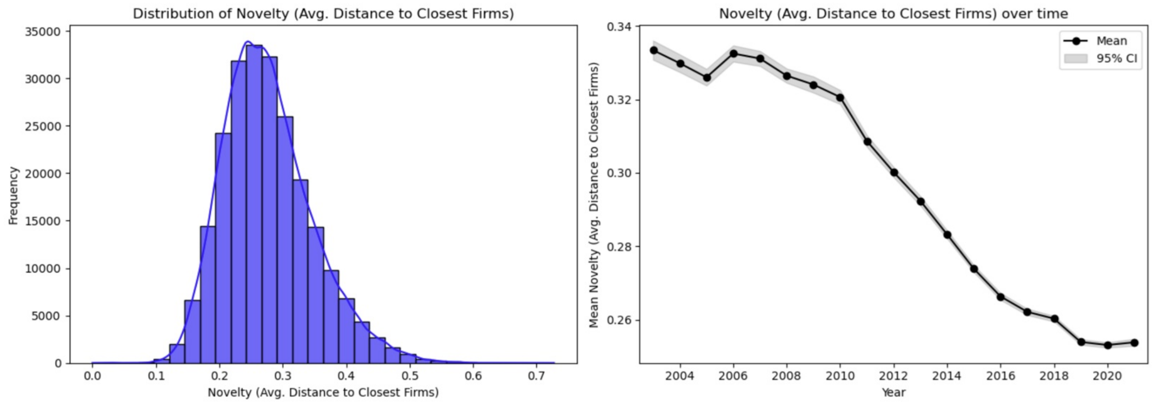

Figure A1: **Distribution of Novelty (Avg. Distance to Closest Firm) and time trend of Novelty (Avg. Distance to Closest Firm)** Left panel: This figure plots the distribution of the Novelty (Avg. Distance to Closest Firm) measure. Right Panel: Time trend of the mean of Novelty (Avg. Distance to Closest Firm) measure.

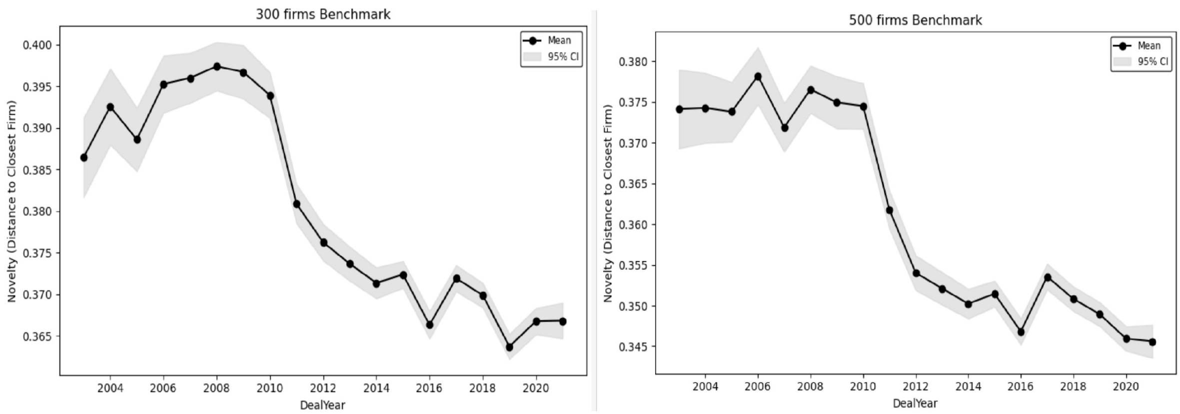

Figure A2: **Time trend of Novelty (Distance to Closest Firm)** Left panel: This panel plots the time trend of mean novelty across VC financed firms over time when novelty of a deal in each year is measured by comparing the deal in each year to a constant number of 300 random firms who have received financing over the last five years prior to the focal deal. Right panel: This panel plots the time trend of mean novelty across VC financed firms over time when novelty of a deal in each year is measured by comparing the deal in each year to a constant number of 500 random firms who have received financing over the last five years prior to the focal deal.

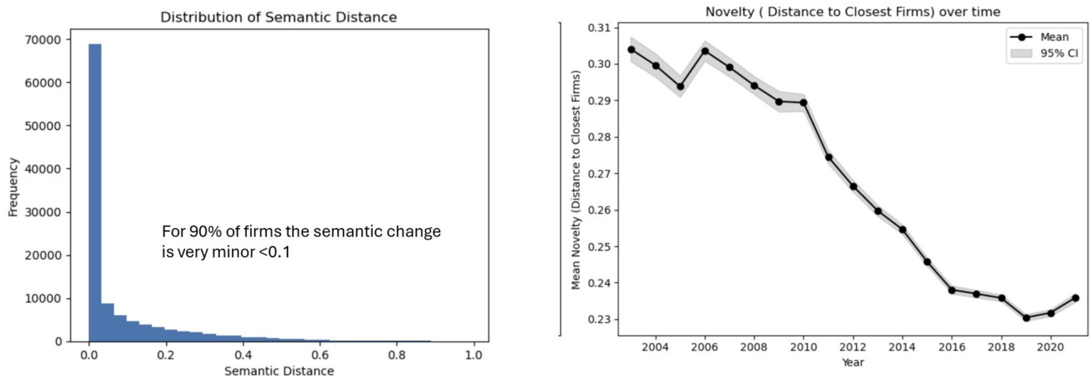

Figure A3: **Time trend of Novelty (Distance to Closest Firm)** Left panel: This panel plots the time trend of mean novelty across VC financed firms over time when novelty of a deal in each year is measured by comparing the deal in each year to a constant number of 300 random firms who have received financing over the last five years prior to the focal deal. Right panel: This panel plots the time trend of mean novelty across VC financed firms over time when novelty of a deal in each year is measured by comparing the deal in each year to a constant number of 500 random firms who have received financing over the last five years prior to the focal deal.

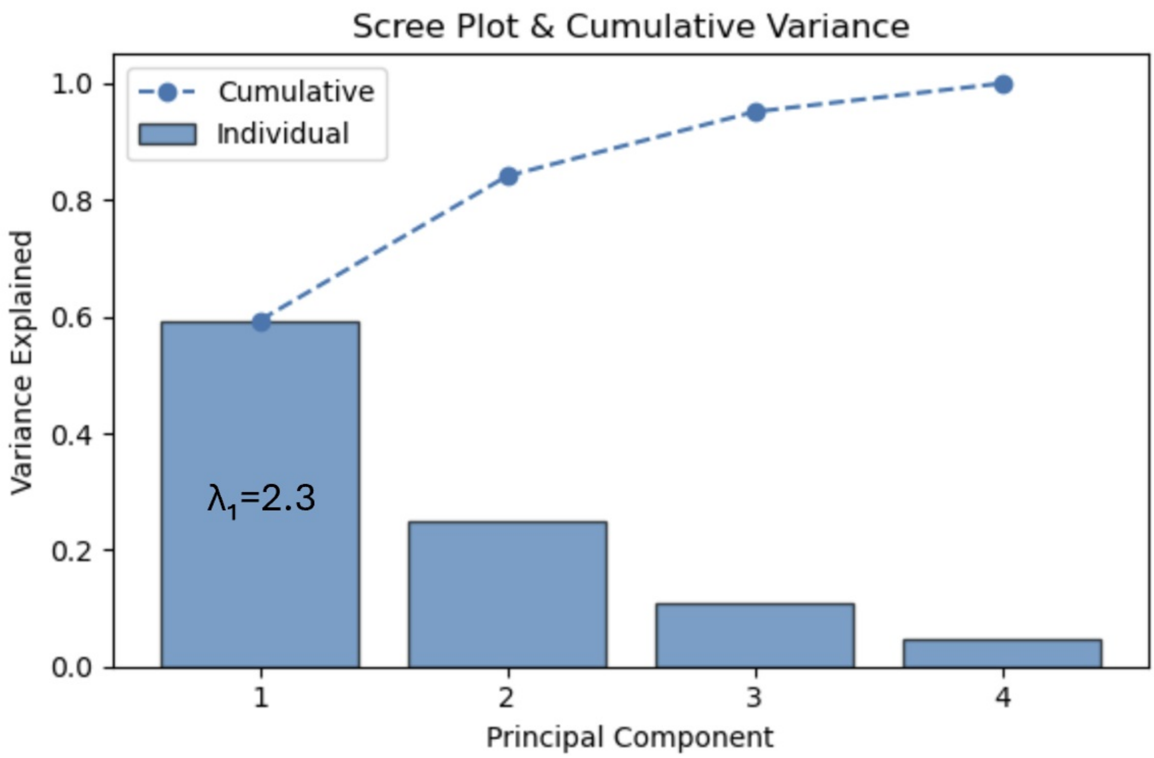

Figure A4: **Principal component analysis PCA scree plot** Scree plot of PCA

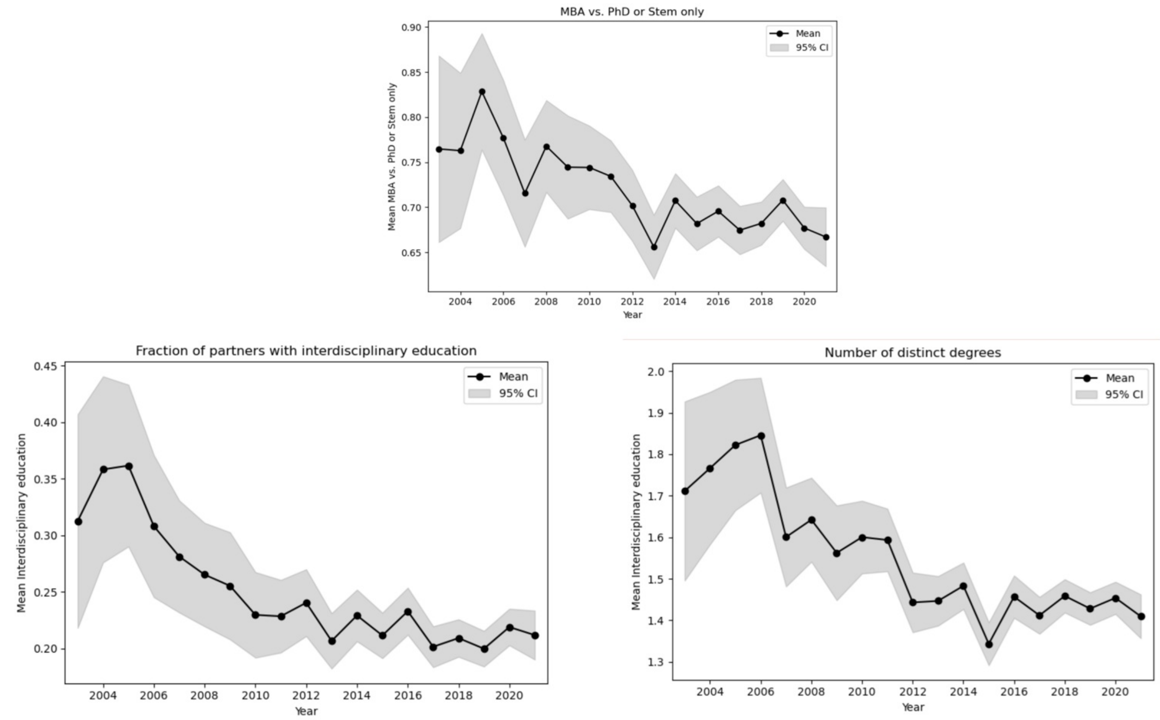

Figure A5: **Time trend of human capital breadth using educational variables to measure human capital breadth** Upper figure: This figure plots the time evolution of the fraction of partners with an MBA degree relative to the fraction of partners who hold either a PhD or are educated in a STEM field over time. Left figure: This figure plots the fraction of partners with an interdisciplinary education over time. Right figure: This figure plots the time evolution of the average number of distinct degrees per partner.

Startup	**Novelty Measure**	**Closest Startup**	**Novelty Percentile**
Tesla	0.52	Community Energy	99.9
Facebook	0.51	Mode Media	99.8
Square	0.48	Softgate Systems	99.5
SpaceX	0.48	Zero-G	99.5
Slack	0.48	Octopz	99.4
Airbnb	0.45	Dopplr	99.0
Skype	0.45	Arrival Communications	98.8
Dropbox	0.37	Omnidrive	94.2
Napster	0.27	Deezer	64.1
Revolut	0.19	Wise (Application)	22.9
Instagram	0.18	Pixable	18.8
Stripe	0.13	Moip	2.4

Table A1: **Example of novel and non-novel startups and previously VC funded startups closest to their business model.** This table presents the Novelty (Distance to Closest Firm) of well-known startups and the startup with closest business model them previously financed by the VC industry. Column (1) is the name of the startup. Column (2) is the raw novelty measure. Column (3) is the name of the closest startup and column (4) is a percentile ranking of novelty constructed using the full sample of firms.

B Robustness tables: Novelty stylized facts

	(1) Failure	(2) Major Success	(3) Failure	(4) Major Success
Novelty (Avg. Distance to Closest Firm)	32.309***	67.464***	14.550***	68.709***
	(2.807)	(3.418)	(3.172)	(4.505)
Industry × Deal Year × Deal Type × Country FE	✓	✓		
Industry × Deal Year × Deal Type × Country × Investor FE			✓	✓
Observations	232108.00	232108.00	232108.00	232108.00
R^2	0.23	0.18	0.52	0.48

Table A2: **Association between startup novelty and likelihood of Failure and Major Success - robustness to an alternative novelty measure** This table reports the results of a deal - level regression of Failure and Major Success on the deal's novelty. The independent variable Novelty (Avg. Distance to Closest Firm) is a deal level measure of novelty defined as one - average of the cosine similarity of the textual description of the startup financed in the deal and top five closest startups receiving venture capital financing within five years before the deal in the same deal stage. Major Success is an indicator variable taking a value of 1 if the firm exits via an IPO or is acquired at a valuation at least five times greater than the total financing received. Failure is an indicator taking a value of 1 if the firm does not exit via an IPO, is not Acquired or does not receive any follow-up financing. Columns (1) and (2) include Industry × Deal Year × Deal Type × Country FE. Columns (3) and (4) include Industry × Deal Year × Deal Type × Country × Investor FE. Standard errors reported in parenthesis are double clustered at an investor and company level. * p<.10; ** p<.05; *** p<.01.

	(1) Failure	(2) Major Success	(3) Failure	(4) Major Success
Novelty (Distance to Closest Firm)	44.764***	28.313***	25.285***	25.475***
	(4.918)	(3.350)	(6.223)	(3.953)
Industry × Deal Year × Deal Type × Country FE	✓	✓		
Industry × Deal Year × Deal Type × Country × Investor FE			✓	✓
Observations	92395.00	92395.00	92395.00	92395.00
R^2	0.20	0.11	0.51	0.48

Table A3: **Association between startup novelty quartile and likelihood of Failure and Major Success - robustness to including only firms with first financing rounds between 2018-2021** This table reports the results of a deal - level regression of Failure and Major Success on the deal's novelty. The independent variable Novelty (Distance to Closest Firm) is a deal level measure of novelty defined as one - maximum of the cosine similarity of the textual description of the startup financed in the deal and all startups receiving venture capital financing within five years before the deal in the same deal stage. Major Success is an indicator variable taking a value of 1 if the firm exits via an IPO or is acquired at a valuation at least five times greater than the total financing received. Failure is an indicator taking a value of 1 if the firm does not exit via an IPO, is not Acquired or does not receive any follow-up financing. Columns (1) and (2) include Industry × Deal Year × Deal Type × Country FE. Columns (3) and (4) include Industry × Deal Year × Deal Type × Country × Investor FE. Standard errors reported in parenthesis are double clustered at an investor and company level. * p<.10; ** p<.05; *** p<.01.

	(1) Failure	(2) IPO	(3) Failure	(4) IPO
Novelty (Distance to Closest Firm)	26.114*** (2.613)	72.290*** (3.202)	11.102*** (3.017)	72.889*** (4.403)
Industry × Deal Year × Deal Type × Country FE	✓	✓		
Industry × Deal Year × Deal Type × Country × Investor FE			✓	✓
Observations	232108.00	232108.00	232108.00	232108.00
R^2	0.23	0.23	0.52	0.53

Table A4: **Association between startup novelty and likelihood of Failure and IPO Exit** This table reports the results of a deal - level regression of Failure and IPO exit on the deal's novelty. The independent variable Novelty (Distance to Closest Firm) is a deal level measure of novelty defined as one - maximum of the cosine similarity of the textual description of the startup financed in the deal and all startups receiving venture capital financing within five years before the deal in the same deal stage. IPO is an indicator variable taking a value of 1 if the firm exits via an IPO. Failure is an indicator taking a value of 1 if the firm does not exit via an IPO, is not Acquired or does not receive any follow-up financing. Columns (1) and (2) include Industry × Deal Year × Deal Type × Country FE. Columns (3) and (4) include Industry × Deal Year × Deal Type × Country × Investor FE. Standard errors reported in parenthesis are double clustered at an investor and company level. * p<.10; ** p<.05; *** p<.01.

	(1) IPO Valuation	(2) IPO Multiple	(3) IPO Valuation	(4) IPO Multiple
Novelty (Distance to Closest Firm)	974.463*** (284.438)	654.215** (323.705)	1189.557*** (405.859)	632.906 (580.750)
Industry × Deal Year × Deal Type × Country FE	✓	✓		
Industry × Deal Year × Deal Type × Country × Investor FE			✓	✓
Observations	9086.00	7996.00	9086.00	7996.00
R^2	0.45	0.22	0.77	0.52

Table A5: **Association between startup novelty and IPO valuation for a subsample of deals with an IPO** This table reports the results of a deal - level regression of IPO valuation on the deal's novelty conditional on successful exit via an IPO. The independent variable Novelty (Distance to Closest Firm) is a deal level measure of novelty defined as one - maximum of the cosine similarity of the textual description of the startup financed in the deal and all startups receiving venture capital financing within five years before the deal in the same deal stage. The dependent variable in columns (1) and (3) is the valuation of the IPO. The dependent variable in column (2) and (4) is the IPO Multiple calculated as the ratio of the IPO Valuation divided by the Investment size of the VC firm. Columns (1) and (2) include Industry × Deal Year × Deal Type × Country FE. Columns (3) and (4) include Industry × Deal Year × Deal Type × Country × Investor FE. Standard errors reported in parenthesis are double clustered at an investor and company level. * p<.10; ** p<.05; *** p<.01.

	(1) Number of Forward Patents	(2) Number of Forward Citations	(3) Number of Forward Patents	(4) Number of Forward Citations
Novelty (Avg. Distance to Closest Firm)	2.212** (0.957)	3.220*** (1.191)	1.615 (1.371)	3.806*** (1.295)
Exit Type Controls	✓	✓	✓	✓
Industry × Deal Year × Deal Type × Country FE	✓	✓		
Industry × Deal Year × Deal Type × Country × Investor FE			✓	✓
Observations	232108.00	232108.00	232108.00	232108.00

Table A6: **Association between startup novelty and innovation outcomes - Poisson count model - robustness to an alternative novelty measure** This table reports the results of a deal - level regression of innovation outcomes on the deal's novelty. The independent variable Novelty (Avg. Distance to Closest Firm) is a deal level measure of novelty defined as one - average of the cosine similarity of the textual description of the startup financed in the deal and top five closest startups receiving venture capital financing within five years before the deal in the same deal stage. The dependent variable in columns (1) and (3) is the Number of Forward Patents is the total number of patents granted to the firm after the deal date. The dependent variable in columns (2) and (4) Number of Forward Citations is the total number of adjusted citations (by grant year and NBER subcategory) that patents of the financed firm have received after the deal date. All columns include Exit Type controls which are separate controls specifying whether the startup goes public is acquired or receives follow-up financing. Columns (1) - (2) include Industry × Deal Year × Deal Type × Country FE. Columns (3) - (4) include Industry × Deal Year × Deal Type × Country × Investor FE. Standard errors reported in parenthesis are double clustered at an investor and company level. * p<.10; ** p<.05; *** p<.01.

	(1) Log(1+Number of Forward Patents)	(2) Log(1+Number of Forward Citations)	(3) Log(1+Number of Forward Patents)	(4) Log(1+Number of Forward Citations)
Novelty (Distance to Closest Firm)	0.047*	0.071	0.048	0.084
	(0.026)	(0.047)	(0.032)	(0.059)
Exit Type Controls	✓	✓	✓	✓
Industry × Deal Year × Deal Type × Country FE	✓	✓		
Industry × Deal Year × Deal Type × Country × Investor FE			✓	✓
Observations	232108.00	232108.00	232108.00	232108.00
R^2	0.19	0.19	0.48	0.47

Table A7: **Association between startup novelty and innovation outcomes - log (1+) model** This table reports the results of a deal - level regression of innovation outcomes on the deal's novelty. The independent variable Novelty (Distance to Closest Firm) is a deal level measure of novelty defined as one - maximum of the cosine similarity of the textual description of the startup financed in the deal and all startups receiving venture capital financing within five years before the deal in the same deal stage. The dependent variable in columns (1) and (3) log(1+ Number of Forward Patents) where Number of Forward Patents is the total number of patents granted to the firm after the deal date. The dependent variable in columns (2) and (4) is log(1+ Number of Forward Citations) where Number of Forward Citations is the total number of adjusted citations (by grant year and NBER subcategory) that patents of the financed firm have received after the deal date. All columns include Exit Type controls which are separate controls specifying whether the startup goes public is acquired or receives follow-up financing. Columns (1) - (2) include Industry × Deal Year × Deal Type × Country FE. Columns (3) - (4) include Industry × Deal Year × Deal Type × Country × Investor FE. Standard errors reported in parenthesis are double clustered at an investor and company level. * p<.10; ** p<.05; *** p<.01.

	(1) Number of Forward Patents	(2) Number of Forward Citations	(3) Number of Forward Patents	(4) Number of Forward Citations
Novelty Quartile (Distance to Closest Firm)=2	0.145	0.410**	-0.063	0.316*
	(0.108)	(0.197)	(0.125)	(0.190)
Novelty Quartile (Distance to Closest Firm)=3	0.189	0.370*	0.068	0.315*
	(0.127)	(0.194)	(0.176)	(0.189)
Novelty Quartile (Distance to Closest Firm)=4	0.335**	0.675***	0.260	0.825***
	(0.163)	(0.232)	(0.227)	(0.251)
Exit Type Controls	✓	✓	✓	✓
Industry × Deal Year × Deal Type × Country FE	✓	✓		
Industry × Deal Year × Deal Type × Country × Investor FE			✓	✓
Observations	232108.00	232108.00	232108.00	232108.00

Table A8: **Association between startup novelty and innovation outcomes - Poisson count model quartile novelty measure** This table reports the results of a deal - level regression of innovation outcomes on the deal's novelty.The independent variables are novelty quartile dummies indicating whether a startup belongs to the i the novelty quartile within a given year and deal stage based on the Novelty (Distance to Closest Firm) measure which is a deal level measure of novelty defined as one - maximum of the cosine similarity of the textual description of the startup financed in the deal and all startups receiving venture capital financing within five years before the deal in the same deal stage. The dependent variable in columns (1) and (3) is the Number of Forward Patents is the total number of patents granted to the firm after the deal date. The dependent variable in columns (2) and (4) Number of Forward Citations is the total number of adjusted citations (by grant year and NBER subcategory) that patents of the financed firm have received after the deal date. All columns include Exit Type controls which are separate controls specifying whether the startup goes public is acquired or receives follow-up financing. Columns (1) - (2) include Industry × Deal Year × Deal Type × Country FE. Columns (3) - (4) include Industry × Deal Year × Deal Type × Country × Investor FE. Standard errors reported in parenthesis are double clustered at an investor and company level. * p<.10; ** p<.05; *** p<.01.

C Robustness tables: Human capital Breadth - Novelty Association

	(1) Novelty (Avg. Distance to Closest Firm)	(2) Novelty (Avg. Distance to Closest Firm)	(3) Novelty (Avg. Distance to Closest Firm)	(4) Above Median Novelty	(5) Above Median Novelty	(6) Above Median Novelty
Breadth Index	0.152** (0.076)	0.235** (0.115)	0.523* (0.278)	0.866 (0.650)	2.116** (0.926)	3.489 (2.633)
VC Experience	-0.027 (0.116)	-0.141 (0.103)	-0.214 (0.305)	-0.918 (0.846)	-1.522* (0.871)	-0.937 (2.319)
Partner Industry Experience	-0.352** (0.149)	0.059 (0.181)	0.351 (0.245)	-3.702*** (1.270)	1.059 (1.490)	4.738** (2.199)
Controls	✓	✓	✓	✓	✓	✓
Industry × Deal Year × Deal Type × Country FE	✓	✓	✓	✓	✓	✓
Investor FE × Deal Year FE		✓			✓	
Investor FE × Deal Year FE × Partner Entry Year FE			✓			✓
Observations	23531.00	23531.00	23531.00	23531.00	23531.00	23531.00
R^2	0.52	0.62	0.69	0.38	0.52	0.60

Table A9: **Association between lead partner's human capital breadth index and startup novelty - robustness to an alternative novelty measure** This table reports the results of an OLS regression of deal novelty and lead partner's human capital breadth. The dependent variable Novelty (Distance to Closest Firm) in columns (1)-(3) is a deal level measure of novelty defined as one minus average of cosine similarity between the top five closest firms based on the similarity of the textual description of the startup financed in the deal and all startups receiving venture capital financing within five years before the deal in the same deal stage. The dependent variable in columns (4)-(6) is an indicator taking a value of 1 if the deal is a deal with above median average novelty. The main independent variable Breadth Index is a measure of human capital breadth which is defined as the first principal component of a PCA from 4 individual human capital breadth proxies: 1) The ratio of distinct job categories to total employment spells 2) The ratio of distinct job roles to total employment spells 3) The ratio of distinct industries worked in to total employment spells 4) Educational breadth count. VC experience is a variable defined as the logarithm of one plus the number of deals financed by the lead partner prior to current deal. Partner Industry Experience is a dummy variable taking a value of 1 if the partner has had at least one job in the industry of the venture and 0 otherwise. Columns (1) - (6) include Industry × Deal Year × Deal Type × Financed Company Country FE. Columns (2) and (5) also include Investor × Deal Year FE. Columns (3) and (6) include Investor × Deal Year × VC Partner Entry Year FE. All columns include individual level partner controls: age, sex and ethnicity. Standard errors reported in parenthesis are double clustered at an Investor and Financed Company level. * p<.10; ** p<.05; *** p<.01.

	(1) Novelty (Distance to Closest Firm)	(2) Novelty (Distance to Closest Firm)	(3) Above Median Novelty	(4) Above Median Novelty
Breadth Index	0.428* (0.259)	0.167 (0.193)	3.285 (2.294)	0.217 (1.335)
VC Experience	-0.093 (0.233)	-0.064 (0.153)	-0.273 (1.977)	-0.299 (1.423)
Partner Industry Experience	0.356 (0.341)	0.203 (0.309)	1.006 (3.359)	0.701 (2.465)
Controls	✓	✓	✓	✓
Industry × Deal Year × Deal Type × Country FE	✓	✓	✓	✓
Investor FE × Deal Year FE	✓	✓	✓	✓
Observations	11963.00	11568.00	11963.00	11568.00
R^2	0.69	0.65	0.62	0.56

Table A10: **Association between lead partner's human capital breadth index and startup novelty - non syndicated vs. syndicated investments.** This table reports the results of an OLS regression of deal novelty and lead partner's human capital breadth for non-syndicated and syndicated investments. The dependent variable Novelty (Distance to Closest Firm) in columns (1) and (2) is a deal level measure of novelty defined as one minus the maximum of the cosine similarity of the textual description of the startup financed in the deal and all startups receiving venture capital financing within five years before the deal in the same deal stage. The dependent variable in columns (3) and (4) is an indicator taking a value of 1 if the deal is a deal with above median novelty. The main independent variable Breadth Index is a measure of human capital breadth which is defined as the first principal component of a PCA from 4 individual human capital breadth proxies: 1) The ratio of distinct job categories to total employment spells 2) The ratio of distinct job roles to total employment spells 3) The ratio of distinct industries worked in to total employment spells 4) Educational breadth count. Lead Investment is an indicator variable equal to 1 if the investment is led by the VC firm. In columns (1) and (3) the sample includes non-syndicated investments by VC firms (investments where the VC firm is a sole investor). In columns (2) and (4) the sample includes all syndicated investment by VC firms. VC experience is a variable defined as the logarithm of one plus the number of deals financed by the lead partner prior to current deal. Partner Industry Experience is a dummy variable taking a value of 1 if the partner has had at least one job in the industry of the venture and 0 otherwise. Columns (1) - (4) include Industry × Deal Year × Deal Type × Financed Company Country FE and Investor × Deal Year FE. All columns include individual level partner controls: age, sex and ethnicity. Standard errors reported in parenthesis are double clustered at an Investor and Financed Company level. * p<.10; ** p<.05; *** p<.01.

	(1) Novelty (Distance to Closest Firm)	(2) Novelty (Distance to Closest Firm)	(3) Novelty (Distance to Closest Firm)	(4) Novelty (Distance to Closest Firm)
Job Cat. Ratio	0.866** (0.343)			
Partner Industry Experience	0.089 (0.172)	0.022 (0.170)	0.004 (0.169)	0.005 (0.169)
Job Role. Ratio		0.437 (0.417)		
Job Ind Ratio.			0.594* (0.351)	
Educ. breadth				0.109 (0.091)
Controls	✓	✓	✓	✓
Industry × Deal Year × Deal Type × Country FE	✓	✓	✓	✓
Investor FE × Deal Year FE	✓	✓	✓	✓
Observations	23531.00	23531.00	23531.00	23531.00
R^2	0.62	0.62	0.62	0.62

Table A11: **Association between lead partner's human capital breadth index and startup novelty - robustness for individual human capital breadth measures** This table reports the results of an OLS regression of deal novelty and lead partner's human capital breadth. The dependent variable Novelty (Distance to Closest Firm) in columns (1)-(2) is a deal level measure of novelty defined as one minus the maximum of the cosine similarity of the textual description of the startup financed in the deal and all startups receiving venture capital financing within five years before the deal in the same deal stage. The dependent variable in columns (3) - (4) is am indicator variable taking a value of 1 if the startup has an above median deal novelty. The main independent variable Breadth Index is a measure of human capital breadth which is defined as the first principal component of a PCA from 4 individual human capital breadth proxies: 1) The ratio of distinct job categories to total employment spells 2) The ratio of distinct job roles to total employment spells 3) The ratio of distinct industries worked in to total employment spells 4) Educational breadth count. Columns (1) and (3) estimate the regression for early deals which are deals done within five years of VC partner VC industry entry. Columns (2) and (4) estimate the regression for later deals which are done at least five years after partner VC industry entry. VC experience is a variable defined as the logarithm of one plus the number of deals financed by the lead partner prior to current deal. Partner Industry Experience is a dummy variable taking a value of 1 if the partner has had at least one job in the industry of the venture and 0 otherwise. Columns (1) - (4) include Industry × Deal Year × Deal Type × Financed Company Country FE and Investor × Deal Year FE. All columns include individual level partner controls: age, sex and ethnicity. Standard errors reported in parenthesis are double clustered at an Investor and Financed Company level. * p<.10; ** p<.05; *** p<.01.

	(1) Novelty (Distance to Closest Firm)	(2) Novelty (Distance to Closest Firm)	(3) Novelty (Distance to Closest Firm)	(4) Novelty (Distance to Closest Firm)
Job Cat. Ratio	1.671** (0.743)			
Partner Industry Experience	0.059 (0.367)	-0.111 (0.360)	-0.114 (0.358)	-0.127 (0.358)
Job Role. Ratio		0.439 (0.948)		
Job Ind Ratio.			1.368* (0.735)	
Educ. breadth				0.024 (0.189)
Controls	✓	✓	✓	✓
Industry × Deal Year × Deal Type × Country FE	✓	✓	✓	✓
Investor FE × Deal Year FE		✓	✓	✓
Observations	9519.00	9519.00	9519.00	9519.00
R^2	0.70	0.69	0.70	0.69

Table A12: **Association between lead partner's human capital breadth index and startup novelty - robustness for individual human capital breadth measures only for deals where the VC firm is a lead investor.** This table reports the results of an OLS regression of deal novelty and lead partner's human capital breadth. The dependent variable Novelty (Distance to Closest Firm) in columns (1)-(4) is a deal level measure of novelty defined as one minus the maximum of the cosine similarity of the textual description of the startup financed in the deal and all startups receiving venture capital financing within five years before the deal in the same deal stage. The independent variable in column (1) is the ratio of distinct job categories to total employment spells The independent variable in column (2) is the ratio of distinct job roles to total employment spells. The independent variable in column (3)is the ratio of distinct industries worked in to total employment spells. The independent variable in column (4) is an educational breadth count. VC experience is a variable defined as the logarithm of one plus the number of deals financed by the lead partner prior to current deal. Partner Industry Experience is a dummy variable taking a value of 1 if the partner has had at least one job in the industry of the venture and 0 otherwise. Columns (1) - (4) include Industry × Deal Year × Deal Type × Financed Company Country FE and Investor × Deal Year FE. All columns include individual level partner controls: age, sex and ethnicity. Standard errors reported in parenthesis are double clustered at an Investor and Financed Company level. * p<.10; ** p<.05; *** p<.01.

	(1) Novelty (Distance to Closest Firm)	(2) Novelty (Distance to Closest Firm)	(3) Above Median Novelty	(4) Above Median Novelty
Breadth Index	0.547**	0.194	3.981**	0.187
	(0.240)	(0.243)	(1.704)	(2.104)
VC Experience	-0.015	-0.129	-0.361	2.500
	(0.199)	(0.249)	(1.545)	(2.522)
Partner Industry Experience	-0.111	0.060	-2.220	4.819
	(0.333)	(0.363)	(2.717)	(3.022)
Controls	✓	✓	✓	✓
Industry × Deal Year × Deal Type × Country FE	✓	✓	✓	✓
Investor FE × Deal Year FE	✓	✓	✓	✓
Observations	14702.00	8829.00	14702.00	8829.00
R^2	0.67	0.62	0.60	0.52

Table A13: **Association between lead partner's human capital breadth index and startup novelty - split by distance of partner year of entry and time of deal** This table reports the results of an OLS regression of deal novelty and lead partner's human capital breadth for deals done close and far away from partner VC industry entry year. The dependent variable Novelty (Distance to Closest Firm) in columns (1)-(4) is a deal level measure of novelty defined as one minus the maximum of the cosine similarity of the textual description of the startup financed in the deal and all startups receiving venture capital financing within five years before the deal in the same deal stage. The independent variable Breadth Index is a measure of human capital breadth which is defined as the first principal component of a PCA from 4 individual human capital breadth proxies: 1) The ratio of distinct job categories to total employment spells 2) The ratio of distinct job roles to total employment spells 3) The ratio of distinct industries worked in to total employment spells 4) Educational breadth count.VC experience is a variable defined as the logarithm of one plus the number of deals financed by the lead partner prior to current deal. Partner Industry Experience is a dummy variable taking a value of 1 if the partner has had at least one job in the industry of the venture and 0 otherwise. Columns (1) and (2) include Industry × Deal Year × Deal Type FE. Columns (2) and (4) include Industry × Deal Year × Deal Type × Investor FE. Columns (3) and (4) include additional partner level controls. Standard errors reported in parenthesis are clustered at an Investor level. * p<.10; ** p<.05; *** p<.01.

	(1) Major Success	(2) Major Success	(3) Major Success
Novelty (Avg. Distance to Closest Firm)	0.432***	0.452***	0.365***
	(0.081)	(0.082)	(0.086)
Breadth Index	-0.024	-0.041**	-0.062***
	(0.019)	(0.019)	(0.022)
Novelty (Avg. Distance to Closest Firm) × Breadth Index	0.120*	0.162**	0.232***
	(0.073)	(0.073)	(0.082)
VC Experience	0.004	0.003	0.015
	(0.004)	(0.005)	(0.012)
Partner Industry Experience	0.014*	-0.007	0.006
	(0.007)	(0.011)	(0.012)
Controls	✓	✓	✓
Industry × Deal Year × Deal Type × Country FE	✓	✓	✓
Investor FE × Deal Year FE		✓	
Investor FE × Deal Year FE × Partner Entry Year FE			✓
Observations	23531.00	23531.00	23531.00
R^2	0.41	0.55	0.64

Table A14: **Association between the interaction of lead partner's human capital breadth and deal novelty and startup's success likelihood - robustness to an alternative novelty measure.** This table reports the results of an OLS regression of startup's likelihood of achieving a major exit on the interaction between deal's novelty and lead partner's human capital breadth The independent variable Avg. Novelty (Distance to Closest Firm) is a deal level measure of novelty defined as one minus the average of the cosine similarity of the textual description of the startup financed in the deal and top five closest startups receiving venture capital financing within five years before the deal in the same deal stage. The independent variable Breadth Index is a measure of human capital breadth which is defined as the first principal component of a PCA from 4 individual human capital breadth proxies: 1) The ratio of distinct job categories to total employment spells 2) The ratio of distinct job roles to total employment spells 3) The ratio of distinct industries worked in to total employment spells 4) Educational breadth count. Breadth Index × Novelty (Distance to Closest Firm) is the interaction between the deal's novelty and the lead partner's human capital breadth index. In columns (1)-(3) the dependent variable Major Success is an indicator that equals 1 if the startup goes public or is acquired at a valuation at least five times greater than the total VC invested capital. VC Experience is a variable defined as the logarithm of one plus the number of deals financed by the lead partner prior to current deal. Partner Industry Experience is a dummy variable taking a value of 1 if the partner has had at least one job in the industry of the venture and 0 otherwise. Columns (1) - (3) include Industry × Deal Year × Deal Type × Country FE. Column (2) includes Investor × Deal Year FE. Column (3) includes Investor × Deal Year × Partner Entry Year FE. Standard errors reported in parenthesis are double clustered at an investor and company level. * p<.10; ** p<.05; *** p<.01.

	(1) Major Success	(2) Major Success
Novelty (Distance to Closest Firm)	0.278**	0.434***
	(0.139)	(0.121)
Breadth Index	-0.058*	-0.050**
	(0.030)	(0.025)
Novelty (Distance to Closest Firm) × Breadth Index	0.237*	0.223**
	(0.134)	(0.099)
VC Experience	-0.010	0.007
	(0.006)	(0.009)
Partner Industry Experience	-0.001	-0.009
	(0.020)	(0.020)
Controls	✓	✓
Industry × Deal Year × Deal Type × Country FE	✓	✓
Investor FE × Deal Year FE	✓	✓
Observations	9519.00	14012.00
R^2	0.64	0.61

Table A15: **Association between the interaction of lead partner's human capital breadth and deal novelty and startup's success likelihood - lead and non - lead investments** This table reports the results of an OLS regression of startup's likelihood of achieving a major exit on the interaction between deal's novelty and lead partner's human capital breadth for lead and non-lead investments. The independent variable Novelty (Distance to Closest Firm) is a deal level measure of novelty defined as one minus the maximum of the cosine similarity of the textual description of the startup financed in the deal and all startups receiving venture capital financing within five years before the deal in the same deal stage. The independent variable Breadth Index is a measure of human capital breadth which is defined as the first principal component of a PCA from 4 individual human capital breadth proxies: 1) The ratio of distinct job categories to total employment spells 2) The ratio of distinct job roles to total employment spells 3) The ratio of distinct industries worked in to total employment spells 4) Educational breadth count. Breadth Index × Novelty (Distance to Closest Firm) is the interaction between the deal's novelty and the lead partner's human capital breadth index. In columns (1) and (2) the dependent variable Major Success is an indicator that equals 1 if the startup goes public or is acquired at a valuation at least five times greater than the total VC invested capital. VC Experience is a variable defined as the logarithm of one plus the number of deals financed by the lead partner prior to current deal. Partner Industry Experience is a dummy variable taking a value of 1 if the partner has had at least one job in the industry of the venture and 0 otherwise. Column (1) reports the results for lead investments. Column (2) reports the results for non-lead investments. Columns (1) - (2) include Industry × Deal Year × Deal Type × Country FE. Column (2) includes Investor × Deal Year FE and Column (3) includes Investor × Deal Year FE. Standard errors reported in parenthesis are double clustered at an investor and company level. * p<.10; ** p<.05; *** p<.01.

	(1) Major Success	(2) Major Success	(3) Major Success	(4) Major Success
Job Cat. Ratio	-0.099*			
	(0.059)			
Novelty (Distance to Closest Firm) × Job Cat. Ratio	0.430*			
	(0.247)			
Partner Industry Experience	-0.008	-0.007	-0.008	-0.007
	(0.012)	(0.011)	(0.012)	(0.011)
Job Role. Ratio		-0.125		
		(0.077)		
Novelty (Distance to Closest Firm) × Job Role. Ratio		0.665**		
		(0.330)		
Job Ind Ratio.			-0.078	
			(0.061)	
Novelty (Distance to Closest Firm) × Job Ind Ratio.			0.294	
			(0.256)	
Educ. breadth				-0.038**
				(0.018)
Novelty (Distance to Closest Firm) × Educ. breadth				0.145*
				(0.078)
Controls	✓	✓	✓	✓
Industry × Deal Year × Deal Type × Country FE	✓	✓	✓	✓
Investor FE × Deal Year FE	✓	✓	✓	✓
Observations	23531.00	23531.00	23531.00	23531.00
R^2	0.55	0.55	0.55	0.55

Table A16: **Association between the interaction of lead partner's human capital breadth and deal novelty and startup's likelihood of success - individual human capital breadth measures.** This table reports the results of an OLS regression of startup's likelihood of achieving a major exit on the interaction between deal's novelty and lead partner's human capital breadth measured using individual human capital breadth measures. The independent variable Novelty (Distance to Closest Firm) is a deal level measure of novelty defined as one minus the maximum of the cosine similarity of the textual description of the startup financed in the deal and all startups receiving venture capital financing within five years before the deal in the same deal stage. The independent variable in column (1) is the ratio of distinct job categories to total employment spells. The independent variable in column (2) is the ratio of distinct job roles to total employment spells. The independent variable in column (3) is the ratio of distinct industries worked in to total employment spells. The independent variable in column (4) is educational breadth count. In columns (1)-(4) the dependent variable Major Success is an indicator that equals 1 if the startup goes public or is acquired at a valuation at least five times greater than the total VC invested capital. VC Experience is a variable defined as the logarithm of one plus the number of deals financed by the lead partner prior to current deal. Partner Industry Experience is a dummy variable taking a value of 1 if the partner has had at least one job in the industry of the venture and 0 otherwise. Columns (1) - (4) include Industry × Deal Year × Deal Type × Country FE and Investor × Deal Year FE. Standard errors reported in parenthesis are double clustered at an investor and company level. * p<.10; ** p<.05; *** p<.01.

	(1) Major Success	(2) Major Success	(3) Major Success
Breadth Index	0.007*	0.004	-0.007
	(0.004)	(0.005)	(0.014)
VC Experience	0.005	0.004	-0.004
	(0.005)	(0.004)	(0.014)
Partner Industry Experience	0.008	-0.009	-0.002
	(0.009)	(0.012)	(0.012)
Controls	✓	✓	✓
Industry × Deal Year × Deal Type × Country FE	✓	✓	✓
Investor FE × Deal Year FE		✓	
Investor FE × Deal Year FE × Partner Entry Year FE			✓
Observations	36459.00	36459.00	36459.00
R^2	0.37	0.46	0.55

Table A17: **The association between lead partner human capital breadth and startup performance.** This table reports the results of an OLS regression of startup outcome on the lead partner's breadth index. The independent variable Breadth Index is a measure of human capital breadth which is defined as the first principal component of a PCA from 4 individual human capital breadth proxies: 1) The ratio of distinct job categories to total employment spells 2) The ratio of distinct job roles to total employment spells 3) The ratio of distinct industries worked in to total employment spells 4) Educational breadth count. In columns (1)-(3) the dependent variable Major Success is an indicator that equals 1 if the startup goes public or is acquired at a valuation at least five times greater than the total VC invested capital. VC Experience is a variable defined as the logarithm of one plus the number of deals financed by the lead partner prior to current deal. Partner Industry Experience is a dummy variable taking a value of 1 if the partner has had at least one job in the industry of the venture and 0 otherwise. Columns (1) - (3) include Industry × Deal Year × Deal Type × Country FE. Column (2) includes Investor × Deal Year FE. Column (3) includes Investor × Deal Year × Partner Entry Year FE Standard errors reported in parenthesis are double clustered at an investor and company level. * p<.10; ** p<.05; *** p<.01.

	(1) IPO	(2) IPO	(3) IPO
Novelty (Distance to Closest Firm)	0.467***	0.543***	0.456***
	(0.062)	(0.065)	(0.064)
Breadth Index	-0.044***	-0.050***	-0.060***
	(0.014)	(0.016)	(0.019)
Novelty (Distance to Closest Firm) × Breadth Index	0.211***	0.229***	0.280***
	(0.064)	(0.072)	(0.082)
VC Experience	0.003	0.002	-0.003
	(0.003)	(0.003)	(0.009)
Partner Industry Experience	0.012***	-0.001	0.001
	(0.004)	(0.006)	(0.008)
Controls	✓	✓	✓
Industry × Deal Year × Deal Type × Country FE	✓	✓	✓
Investor FE × Deal Year FE		✓	
Investor FE × Deal Year FE × Partner Entry Year FE			✓
Observations	23531.00	23531.00	23531.00
R^2	0.52	0.61	0.70

Table A18: **Association between the interaction of lead partner's human capital breadth and deal novelty and startup's likelihood of success - only IPO as a success measure** This table reports the results of an OLS regression of startup's likelihood of achieving an IPO exit on the interaction between deal's novelty and lead partner's human capital breadth. The independent variable Novelty (Distance to Closest Firm) is a deal level measure of novelty defined as one minus the maximum of the cosine similarity of the textual description of the startup financed in the deal and all startups receiving venture capital financing within five years before the deal in the same deal stage. The independent variable Breadth Index is a measure of human capital breadth which is defined as the first principal component of a PCA from 4 individual human capital breadth proxies: 1) The ratio of distinct job categories to total employment spells 2) The ratio of distinct job roles to total employment spells 3) The ratio of distinct industries worked in to total employment spells 4) Educational breadth count. Breadth Index × Novelty (Distance to Closest Firm) is the interaction between the deal's novelty and the lead partner's human capital breadth index. In columns (1)-(3) the dependent variable Major Success is an indicator that equals 1 if the startup goes public or is acquired at a valuation at least five times greater than the total VC invested capital. VC Experience is a variable defined as the logarithm of one plus the number of deals financed by the lead partner prior to current deal. Partner Industry Experience is a dummy variable taking a value of 1 if the partner has had at least one job in the industry of the venture and 0 otherwise. Columns (1) - (3) include Industry × Deal Year × Deal Type × Country FE. Column (2) includes Investor × Deal Year FE. Column (3) includes Investor × Deal Year × Partner Entry Year FE. Standard errors reported in parenthesis are double clustered at an investor and company level. * p<.10; ** p<.05; *** p<.01.

	(1) Major Success (3x)	(2) Major Success (3x)	(3) Major Success (3x)
Novelty (Distance to Closest Firm)	0.381***	0.379***	0.289***
	(0.085)	(0.086)	(0.092)
Breadth Index	-0.021	-0.051***	-0.062***
	(0.018)	(0.018)	(0.022)
Novelty (Distance to Closest Firm) × Breadth Index	0.136*	0.220***	0.283***
	(0.076)	(0.076)	(0.086)
VC Experience	0.009*	0.005	0.014
	(0.005)	(0.005)	(0.012)
Partner Industry Experience	0.020**	-0.001	0.016
	(0.008)	(0.012)	(0.013)
Controls	✓	✓	✓
Industry × Deal Year × Deal Type × Country FE	✓	✓	✓
Investor FE × Deal Year FE		✓	
Investor FE × Deal Year FE × Partner Entry Year FE			✓
Observations	23531.00	23531.00	23531.00
R^2	0.40	0.54	0.64

Table A19: **Association between the interaction of lead partner's human capital breadth and deal novelty and startup's likelihood of success - robustness to different ways to measure successful outcome** This table reports the results of an OLS regression of startup's likelihood of achieving a successful exit on the interaction between deal's novelty and lead partner's human capital breadth. The independent variable Novelty (Distance to Closest Firm) is a deal level measure of novelty defined as one minus the maximum of the cosine similarity of the textual description of the startup financed in the deal and all startups receiving venture capital financing within five years before the deal in the same deal stage. The independent variable Breadth Index is a measure of human capital breadth which is defined as the first principal component of a PCA from 4 individual human capital breadth proxies: 1) The ratio of distinct job categories to total employment spells 2) The ratio of distinct job roles to total employment spells 3) The ratio of distinct industries worked in to total employment spells 4) Educational breadth count. Breadth Index × Novelty (Distance to Closest Firm) is the interaction between the deal's novelty and the lead partner's human capital breadth index. In columns (1)-(3) the dependent variable Major Success (3x) is an indicator that equals 1 if the startup goes public or is acquired at a valuation at least three times greater than the total VC invested capital. VC Experience is a variable defined as the logarithm of one plus the number of deals financed by the lead partner prior to current deal. Partner Industry Experience is a dummy variable taking a value of 1 if the partner has had at least one job in the industry of the venture and 0 otherwise. Columns (1) - (3) include Industry × Deal Year × Deal Type × Country FE. Column (2) includes Investor × Deal Year FE. Column (3) includes Investor × Deal Year × Partner Entry Year FE. Standard errors reported in parenthesis are double clustered at an investor and company level. * p<.10; ** p<.05; *** p<.01.

	(1) Major Success (1x)	(2) Major Success (1x)	(3) Major Success (1x)
Novelty (Distance to Closest Firm)	0.252***	0.248***	0.137
	(0.091)	(0.095)	(0.101)
Breadth Index	-0.035*	-0.058***	-0.069***
	(0.019)	(0.020)	(0.025)
Novelty (Distance to Closest Firm) × Breadth Index	0.186**	0.252***	0.311***
	(0.079)	(0.079)	(0.090)
VC Experience	0.011*	0.005	-0.001
	(0.006)	(0.006)	(0.015)
Partner Industry Experience	0.021**	0.009	0.022
	(0.009)	(0.013)	(0.015)
Controls	✓	✓	✓
Industry × Deal Year × Deal Type × Country FE	✓	✓	✓
Investor FE × Deal Year FE		✓	
Investor FE × Deal Year FE × Partner Entry Year FE			✓
Observations	23531.00	23531.00	23531.00
R^2	0.40	0.55	0.64

Table A20: **Association between the interaction of lead partner's human capital breadth and deal novelty and startup's likelihood of success - robustness to different ways to measure successful outcome** This table reports the results of an OLS regression of startup's likelihood of achieving a successful exit on the interaction between deal's novelty and lead partner's human capital breadth. The independent variable Novelty (Distance to Closest Firm) is a deal level measure of novelty defined as one minus the maximum of the cosine similarity of the textual description of the startup financed in the deal and all startups receiving venture capital financing within five years before the deal in the same deal stage. The independent variable Breadth Index is a measure of human capital breadth which is defined as the first principal component of a PCA from 4 individual human capital breadth proxies: 1) The ratio of distinct job categories to total employment spells 2) The ratio of distinct job roles to total employment spells 3) The ratio of distinct industries worked in to total employment spells 4) Educational breadth count. Breadth Index × Novelty (Distance to Closest Firm) is the interaction between the deal's novelty and the lead partner's human capital breadth index. In columns (1)-(3) the dependent variable Major Success (1x) is an indicator that equals 1 if the startup goes public or is acquired at a valuation at least greater than the total VC invested capital. VC Experience is a variable defined as the logarithm of one plus the number of deals financed by the lead partner prior to current deal. Partner Industry Experience is a dummy variable taking a value of 1 if the partner has had at least one job in the industry of the venture and 0 otherwise. Columns (1) - (3) include Industry × Deal Year × Deal Type × Country FE. Column (2) includes Investor × Deal Year FE. Column (3) includes Investor × Deal Year × Partner Entry Year FE. Standard errors reported in parenthesis are double clustered at an investor and company level. * p<.10; ** p<.05; *** p<.01.

D Robustness tables Identification

	(1) Partner Leads a Deal	(2) Partner Leads a Deal	(3) Partner Leads a Deal	(4) Partner Leads a Deal	(5) Partner Leads a Deal	(6) Partner Leads a Deal
Busy Partner (Placebo)	0.312	0.306	0.380	0.054	0.099	0.155
	(0.426)	(0.690)	(0.550)	(0.588)	(0.879)	(0.807)
VC Experience	7.404***	5.613***	8.477***	6.754***	5.055***	7.994***
	(0.114)	(0.191)	(0.144)	(0.154)	(0.240)	(0.203)
Partner Age	-0.094***	-0.096***	-0.094***	-0.078***	-0.043	-0.106***
	(0.014)	(0.023)	(0.018)	(0.018)	(0.028)	(0.025)
Partner Industry Experience	3.085***	2.881***	3.148***	3.133***	2.968***	3.179***
	(0.094)	(0.158)	(0.119)	(0.123)	(0.193)	(0.162)
Controls	✓	✓	✓	✓	✓	✓
Deal FE	✓	✓	✓	✓	✓	✓
Investor FE	✓	✓	✓	✓	✓	✓
Observations	242751.00	91232.00	151519.00	148916.00	62693.00	86223.00
R^2	0.32	0.31	0.33	0.33	0.31	0.34

Table A21: **Placebo test of the association between partner busyness and the likelihood of a partner leading a deal** This table reports the results of an OLS regression of the likelihood of partner leading a deal on a Busy Partner placebo. The dependent variable Partner Leads a Deal is an indicator equal to 1 if a partner leads a deal and 0 otherwise. The main independent variable Busy Partner (Placebo) is a placebo constructed by reshuffling the Busy Partner indicator within each deal while keeping the distribution of busy partners unchanged. VC Experience is a variable defined as the logarithm of one plus the number of deals financed by the lead partner prior to current deal. Partner Industry Experience is a dummy variable taking a value of 1 if the partner has had at least one job in the industry of the venture and 0 otherwise. In all columns we include controls for sex and ethnicity. In all columns we include Deal FE and Investor FE. Columns (1) reports the results for the full deal level sample. Columns (2) and (3) report the results for the full sample and split the coefficients for lead vs. non - lead investments. Column (4) reports the results for the main sample in the paper which is early stage novel investments. Columns (5) and (6) report the results for the main sample in the paper which is early stage novel investments and split the coefficients for lead vs. non - lead investments.Standard errors reported in parenthesis are clustered at a Deal level. * p<.10; ** p<.05; *** p<.01.

	(1) Partner Leads a Deal	(2) Partner Leads a Deal	(3) Partner Leads a Deal	(4) Partner Leads a Deal	(5) Partner Leads a Deal	(6) Partner Leads a Deal
Busy IPO Partner	-3.823***	-4.817***	-3.701***	-5.938***	-6.809***	-5.506***
	(0.850)	(1.326)	(1.116)	(1.132)	(1.614)	(1.599)
VC Experience	7.478***	5.713***	8.546***	6.863***	5.189***	8.091***
	(0.116)	(0.194)	(0.145)	(0.156)	(0.244)	(0.205)
Partner Age	-0.093***	-0.095***	-0.094***	-0.078***	-0.042	-0.105***
	(0.014)	(0.023)	(0.018)	(0.018)	(0.028)	(0.025)
Partner Industry Experience	3.080***	2.873***	3.144***	3.127***	2.960***	3.173***
	(0.094)	(0.158)	(0.119)	(0.123)	(0.193)	(0.162)
Controls	✓	✓	✓	✓	✓	✓
Deal FE	✓	✓	✓	✓	✓	✓
Investor FE	✓	✓	✓	✓	✓	✓
Observations	242751.00	91232.00	151519.00	148916.00	62693.00	86223.00
R^2	0.32	0.31	0.33	0.33	0.31	0.34

Table A22: **Association between partner busyness and the likelihood of a partner leading a deal - using only IPO events to measure busyness** This table reports the results of an OLS regression of the likelihood of partner leading a deal on partner busyness. The dependent variable Partner Leads a Deal is an indicator equal to 1 if a partner leads a deal and 0 otherwise. The main independent variable Busy IPO Partner is an indicator taking a value of 1 if the a partner is involved in exiting a deal via an IPO in a time period (-90, 90) around the focal deal date. VC Experience is a variable defined as the logarithm of one plus the number of deals financed by the lead partner prior to current deal. Partner Industry Experience is a dummy variable taking a value of 1 if the partner has had at least one job in the industry of the venture and 0 otherwise. In all columns we include controls for sex and ethnicity. In all columns we include Deal FE and Investor FE. Columns (1) reports the results for the full deal level sample. Columns (2) and (3) report the results for the full sample and split the coefficients for lead vs. non - lead investments. Column (4) reports the results for the main sample in the paper which is early stage novel investments. Columns (5) and (6) report the results for the main sample in the paper which is early stage novel investments and split the coefficients for lead vs. non - lead investments.Standard errors reported in parenthesis are clustered at a Deal level. * p<.10; ** p<.05; *** p<.01.

	(1) Partner Leads a Deal	(2) Partner Leads a Deal	(3) Partner Leads a Deal	(4) Partner Leads a Deal	(5) Partner Leads a Deal	(6) Partner Leads a Deal
Busy Partner	-1.385*	-2.829**	-0.883	-1.874*	-3.722**	-0.768
	(0.800)	(1.276)	(1.048)	(1.091)	(1.573)	(1.551)
VC Experience	7.438***	5.683***	8.498***	6.798***	5.146***	8.011***
	(0.116)	(0.194)	(0.146)	(0.156)	(0.245)	(0.206)
Partner Age	-0.094***	-0.096***	-0.094***	-0.079***	-0.043	-0.106***
	(0.014)	(0.023)	(0.018)	(0.018)	(0.028)	(0.025)
Partner Industry Experience	3.081***	2.873***	3.145***	3.128***	2.959***	3.176***
	(0.094)	(0.158)	(0.119)	(0.123)	(0.193)	(0.162)
Controls	✓	✓	✓	✓	✓	✓
Deal FE	✓	✓	✓	✓	✓	✓
Investor FE	✓	✓	✓	✓	✓	✓
Observations	242751.00	91232.00	151519.00	148916.00	62693.00	86223.00
R^2	0.32	0.31	0.33	0.33	0.31	0.34

Table A23: **Association between partner busyness and the likelihood of a partner leading a deal - robustness to alternative busyness time window** This table reports the results of an OLS regression of the likelihood of partner leading a deal on partner busyness. The dependent variable Partner Leads a Deal is an indicator equal to 1 if a partner leads a deal and 0 otherwise. The main independent variable Busy Partner is an indicator taking a value of 1 if the a partner is involved in exiting a deal via an IPO or a high value acquisition in a time period (-60, 60) around the focal deal date. VC Experience is a variable defined as the logarithm of one plus the number of deals financed by the lead partner prior to current deal. Partner Industry Experience is a dummy variable taking a value of 1 if the partner has had at least one job in the industry of the venture and 0 otherwise. In all columns we include controls for sex and ethnicity. In all columns we include Deal FE and Investor FE. Columns (1) reports the results for the full deal level sample. Columns (2) and (3) report the results for the full sample and split the coefficients for lead vs. non - lead investments. Column (4) reports the results for the main sample in the paper which is early stage novel investments. Columns (5) and (6) report the results for the main sample in the paper which is early stage novel investments and split the coefficients for lead vs. non - lead investments.Standard errors reported in parenthesis are clustered at a Deal level. * p<.10; ** p<.05; *** p<.01.

	(1) Partner Leads a Deal	(2) Partner Leads a Deal	(3) Partner Leads a Deal	(4) Partner Leads a Deal	(5) Partner Leads a Deal	(6) Partner Leads a Deal
Busy IPO Partner	-3.946***	-4.426***	-4.222***	-5.897***	-6.923***	-5.513***
	(1.003)	(1.568)	(1.321)	(1.326)	(1.853)	(1.910)
VC Experience	7.457***	5.674***	8.533***	6.828***	5.146***	8.062***
	(0.115)	(0.193)	(0.145)	(0.155)	(0.243)	(0.204)
Partner Age	-0.093***	-0.095***	-0.094***	-0.078***	-0.042	-0.106***
	(0.014)	(0.023)	(0.018)	(0.018)	(0.028)	(0.025)
Partner Industry Experience	3.081***	2.878***	3.144***	3.128***	2.966***	3.172***
	(0.094)	(0.158)	(0.119)	(0.123)	(0.193)	(0.162)
Controls	✓	✓	✓	✓	✓	✓
Deal FE	✓	✓	✓	✓	✓	✓
Investor FE	✓	✓	✓	✓	✓	✓
Observations	242751.00	91232.00	151519.00	148916.00	62693.00	86223.00
R^2	0.32	0.31	0.33	0.33	0.31	0.34

Table A24: **Association between partner busyness and the likelihood of a partner leading a deal - using only IPO events to measure busyness and alternative time window** This table reports the results of an OLS regression of the likelihood of partner leading a deal on partner busyness. The dependent variable Partner Leads a Deal is an indicator equal to 1 if a partner leads a deal and 0 otherwise. The main independent variable Busy IPO Partner is an indicator taking a value of 1 if the a partner is involved in exiting a deal via an IPO in a time period (-60, 60) around the focal deal date. VC Experience is a variable defined as the logarithm of one plus the number of deals financed by the lead partner prior to current deal. Partner Industry Experience is a dummy variable taking a value of 1 if the partner has had at least one job in the industry of the venture and 0 otherwise. In all columns we include controls for sex and ethnicity. In all columns we include Deal FE and Investor FE. Columns (1) reports the results for the full deal level sample. Columns (2) and (3) report the results for the full sample and split the coefficients for lead vs. non - lead investments. Column (4) reports the results for the main sample in the paper which is early stage novel investments. Columns (5) and (6) report the results for the main sample in the paper which is early stage novel investments and split the coefficients for lead vs. non - lead investments.Standard errors reported in parenthesis are clustered at a Deal level. * p<.10; ** p<.05; *** p<.01.

	(1) Partner Leads a Deal	(2) Partner Leads a Deal	(3) Partner Leads a Deal	(4) Partner Leads a Deal	(5) Partner Leads a Deal	(6) Partner Leads a Deal
Busy Partner	-1.461	-2.595*	-1.115	-1.756	-3.345*	-0.913
	(0.893)	(1.407)	(1.174)	(1.217)	(1.751)	(1.721)
VC Experience	7.431***	5.663***	8.497***	6.786***	5.119***	8.010***
	(0.116)	(0.194)	(0.145)	(0.156)	(0.244)	(0.205)
Partner Age	-0.094***	-0.096***	-0.094***	-0.078***	-0.043	-0.106***
	(0.014)	(0.023)	(0.018)	(0.018)	(0.028)	(0.025)
Partner Industry Experience	3.082***	2.876***	3.145***	3.130***	2.962***	3.177***
	(0.094)	(0.158)	(0.119)	(0.123)	(0.193)	(0.162)
Controls	✓	✓	✓	✓	✓	✓
Deal FE	✓	✓	✓	✓	✓	✓
Investor FE	✓	✓	✓	✓	✓	✓
Observations	242751.00	91232.00	151519.00	148916.00	62693.00	86223.00
R^2	0.32	0.31	0.33	0.33	0.31	0.34

Table A25: **Association between partner busyness and the likelihood of a partner leading a deal - robustness to alternative busyness time window** This table reports the results of an OLS regression of the likelihood of partner leading a deal on partner busyness. The dependent variable Partner Leads a Deal is an indicator equal to 1 if a partner leads a deal and 0 otherwise. The main independent variable Busy Partner is an indicator taking a value of 1 if the a partner is involved in exiting a deal via an IPO or a high value acquisition in a time period (-45, 45) around the focal deal date. VC Experience is a variable defined as the logarithm of one plus the number of deals financed by the lead partner prior to current deal. Partner Industry Experience is a dummy variable taking a value of 1 if the partner has had at least one job in the industry of the venture and 0 otherwise. In all columns we include controls for sex and ethnicity. In all columns we include Deal FE and Investor FE. Columns (1) reports the results for the full deal level sample. Columns (2) and (3) report the results for the full sample and split the coefficients for lead vs. non - lead investments. Column (4) reports the results for the main sample in the paper which is early stage novel investments. Columns (5) and (6) report the results for the main sample in the paper which is early stage novel investments and split the coefficients for lead vs. non - lead investments.Standard errors reported in parenthesis are clustered at a Deal level. * p<.10; ** p<.05; *** p<.01.

	(1) Partner Leads a Deal	(2) Partner Leads a Deal	(3) Partner Leads a Deal	(4) Partner Leads a Deal	(5) Partner Leads a Deal	(6) Partner Leads a Deal
Busy IPO Partner	-3.937***	-4.151**	-4.291***	-5.375***	-5.770***	-5.558***
	(1.117)	(1.721)	(1.472)	(1.487)	(2.107)	(2.101)
VC Experience	7.444***	5.657***	8.520***	6.806***	5.114***	8.047***
	(0.115)	(0.193)	(0.145)	(0.155)	(0.242)	(0.204)
Partner Age	-0.093***	-0.095***	-0.094***	-0.078***	-0.042	-0.106***
	(0.014)	(0.023)	(0.018)	(0.018)	(0.028)	(0.025)
Partner Industry Experience	3.083***	2.879***	3.145***	3.131***	2.968***	3.175***
	(0.094)	(0.158)	(0.119)	(0.123)	(0.193)	(0.162)
Controls	✓	✓	✓	✓	✓	✓
Deal FE	✓	✓	✓	✓	✓	✓
Investor FE	✓	✓	✓	✓	✓	✓
Observations	242751.00	91232.00	151519.00	148916.00	62693.00	86223.00
R^2	0.32	0.31	0.33	0.33	0.31	0.34

Table A26: **Association between partner busyness and the likelihood of a partner leading a deal - using only IPO events to measure busyness and alternative time window** This table reports the results of an OLS regression of the likelihood of partner leading a deal on partner busyness. The dependent variable Partner Leads a Deal is an indicator equal to 1 if a partner leads a deal and 0 otherwise. The main independent variable Busy IPO Partner is an indicator taking a value of 1 if the a partner is involved in exiting a deal via an IPO in a time period (-45, 45) around the focal deal date. VC Experience is a variable defined as the logarithm of one plus the number of deals financed by the lead partner prior to current deal. Partner Industry Experience is a dummy variable taking a value of 1 if the partner has had at least one job in the industry of the venture and 0 otherwise. In all columns we include controls for sex and ethnicity. In all columns we include Deal FE and Investor FE. Columns (1) reports the results for the full deal level sample. Columns (2) and (3) report the results for the full sample and split the coefficients for lead vs. non - lead investments. Column (4) reports the results for the main sample in the paper which is early stage novel investments. Columns (5) and (6) report the results for the main sample in the paper which is early stage novel investments and split the coefficients for lead vs. non - lead investments.Standard errors reported in parenthesis are clustered at a Deal level. * p<.10; ** p<.05; *** p<.01.

	(1) Breadth Index	(2) Breadth Index × Novelty (Distance to Closest Firm)	(3) IPO	(4) IPO
Avg. Available Breadth	0.817***	-0.032**		
	(0.054)	(0.015)		
Avg. Available Breadth × Novelty (Distance to Closest Firm)	-0.577**	0.793***		
	(0.225)	(0.079)		
Breadth Index			-0.171***	-0.160***
			(0.057)	(0.038)
Breadth Index × Novelty (Distance to Closest Firm)			0.829***	0.753***
			(0.260)	(0.164)
Novelty (Distance to Closest Firm)			0.425	0.511*
			(0.286)	(0.264)
Controls	✓	✓	✓	✓
Investor × Deal Year FE	✓	✓	✓	✓
Deal Stage × Industry × Year × Country FE	✓	✓	✓	✓
Observations	2233.00	2233.00	2233.00	2306.00
R^2	0.87	0.87	0.17	0.62
F-statistic of Instrument			100.01	

Table A27: **Effect of the interaction of lead partner's human capital breadth and deal novelty on startup outcomes - only IPO as a success proxy** This table presents the results of a instrumental variable regression of deal performance on the interaction between lead partner breadth and deal novelty. Column (1) presents the first stage regressions of the first instrumented variable Breadth Index on the two instruments Avg. Available Breadth and Avg. Available Breadth × Novelty, where Avg. Available Breadth is the average breadth index at a VC firm level across the firm's available partners constructed as the ratio of the sum of the total human capital breadth across all available partners (partners who are not busy around (-90, 90) days of the focal deal with a high value exit exit event). Column (2) presents the first stage regression of the second instrumented variable Breadth Index × Novelty on the two instruments Avg. Available Breadth and Avg. Available Breadth × Novelty. In columns (3) and (4) the dependent variable is IPO which is an indicator taking a value of 1 if the startup exits via an IPO. Column (3) presents the IV estimates Column (4) presents the OLS estimates in the same sample. Columns (1) - (4) include Industry × Deal Year × Deal Type × Country FE and Investor FE. Standard errors reported in parenthesis are double clustered at an investor and company level. * p<.10; ** p<.05; *** p<.01.

	(1) Breadth Index	(2) Breadth Index × Novelty (Distance to Closest Firm)	(3) Major Success	(4) Major Success
Avg. Available Breadth	0.920***	0.004		
	(0.086)	(0.027)		
Avg. Available Breadth × Novelty (Distance to Closest Firm)	-0.595**	0.728***		
	(0.262)	(0.096)		
Total Available Breadth	-0.004	-0.001	0.001	0.001
	(0.003)	(0.001)	(0.001)	(0.001)
Breadth Index			-0.185***	-0.124**
			(0.068)	(0.048)
Breadth Index × Novelty (Distance to Closest Firm)			0.779**	0.629***
			(0.331)	(0.189)
Novelty (Distance to Closest Firm)			0.387	0.506*
			(0.349)	(0.261)
Controls	✓	✓	✓	✓
Investor × Deal Year FE	✓	✓	✓	✓
Deal Stage × Industry × Year × Country FE	✓	✓	✓	✓
Observations	2222.00	2222.00	2222.00	2295.00
R^2	0.87	0.86	0.09	0.53
F-statistic of Instrument			87.19	

Table A28: **Effect of the interaction of lead partner's human capital breadth and deal novelty on startup outcomes - robustness to controlling for total available breadth** This table presents the results of a instrumental variable regression of deal performance on the interaction between lead partner breadth and deal novelty. Column (1) presents the first stage regressions of the first instrumented variable Breadth Index on the two instruments Avg. Available Breadth and Avg. Available Breadth × Novelty, where Avg. Available Breadth is the average breadth index at a VC firm level across the firm's available partners constructed as the ratio of the sum of the total human capital breadth across all available partners (partners who are not busy around (-90, 90) days of the focal deal with a high value exit exit event). Column (2) presents the first stage regression of the second instrumented variable Breadth Index × Novelty on the two instruments Avg. Available Breadth and Avg. Available Breadth × Novelty. In columns (3) and (4) the dependent variable is Major Success which is an indicator taking a value of 1 if the startup exits via an IPO or an Acquisition with a value of at least five times the invested amount. Column (3) presents the IV estimates Column (4) presents the OLS estimates in the same sample. Columns (1) - (4) include Industry × Deal Year × Deal Type × Country FE and Investor FE. Standard errors reported in parenthesis are double clustered at an investor and company level. * p<.10; ** p<.05; *** p<.01.

	(1) Breadth Index	(2) Breadth Index × Novelty (Distance to Closest Firm)	(3) Major Success	(4) Major Success
Avg. Available Breadth	0.865***	-0.005		
	(0.080)	(0.023)		
Avg. Available Breadth × Novelty (Distance to Closest Firm)	-0.573*	0.721***		
	(0.339)	(0.121)		
Breadth Index			-0.126	-0.109
			(0.119)	(0.072)
Breadth Index × Novelty (Distance to Closest Firm)			0.572	0.535*
			(0.550)	(0.295)
Novelty (Distance to Closest Firm)			0.455	0.433
			(0.517)	(0.324)
Controls	✓	✓	✓	✓
Investor × Deal Year FE	✓	✓	✓	✓
Deal Stage × Industry × Year × Country FE	✓	✓	✓	✓
Observations	1646.00	1646.00	1646.00	1694.00
R^2	0.88	0.87	0.08	0.55
F-statistic of Instrument			21.77	

Table A29: **Effect of the interaction of lead partner's human capital breadth and deal novelty on startup outcomes - alternative time interval for busyness proxy** This table presents the results of a instrumental variable regression of deal performance on the interaction between lead partner breadth and deal novelty. Column (1) presents the first stage regressions of the first instrumented variable Breadth Index on the two instruments Avg. Available Breadth and Avg. Available Breadth × Novelty, where Avg. Available Breadth is the average breadth index at a VC firm level across the firm's available partners constructed as the ratio of the sum of the total human capital breadth across all available partners (partners who are not busy around (-60, 60) days of the focal deal with a high value exit exit event). Column (2) presents the first stage regression of the second instrumented variable Breadth Index × Novelty on the two instruments Avg. Available Breadth and Avg. Available Breadth × Novelty. In columns (3) and (4) the dependent variable is Major success which is an indicator taking a value of 1 if the startup exits via an IPO or an acquisition of valued at least five times greater than the total VC capital raised by the company. Column (3) presents the IV estimates Column (4) presents the OLS estimates in the same sample. Columns (1) - (4) include Industry × Deal Year × Deal Type × Country FE and Investor FE. Standard errors reported in parenthesis are double clustered at an investor and company level. * p<.10; ** p<.05; *** p<.01.

	(1) Breadth Index	(2) Breadth Index × Novelty (Distance to Closest Firm)	(3) IPO	(4) IPO
Avg. Available Breadth	0.865***	-0.005		
	(0.080)	(0.023)		
Avg. Available Breadth × Novelty (Distance to Closest Firm)	-0.573*	0.721***		
	(0.339)	(0.121)		
Breadth Index			-0.143	-0.165***
			(0.090)	(0.045)
Breadth Index × Novelty (Distance to Closest Firm)			0.600	0.744***
			(0.420)	(0.201)
Novelty (Distance to Closest Firm)			0.634	0.475
			(0.466)	(0.296)
Controls	✓	✓	✓	✓
Investor × Deal Year FE	✓	✓	✓	✓
Deal Stage × Industry × Year × Country FE	✓	✓	✓	✓
Observations	1646.00	1646.00	1646.00	1694.00
R^2	0.88	0.87	0.19	0.63
F-statistic of Instrument			21.77	

Table A30: **Effect of the interaction of lead partner's human capital breadth and deal novelty on startup outcomes - alternative time interval for busyness proxy and only IPO as a success proxy** This table presents the results of a instrumental variable regression of deal performance on the interaction between lead partner breadth and deal novelty. Column (1) presents the first stage regressions of the first instrumented variable Breadth Index on the two instruments Avg. Available Breadth and Avg. Available Breadth × Novelty, where Avg. Available Breadth is the average breadth index at a VC firm level across the firm's available partners constructed as the ratio of the sum of the total human capital breadth across all available partners (partners who are not busy around (-60, 60) days of the focal deal with a high value exit exit event). Column (2) presents the first stage regression of the second instrumented variable Breadth Index × Novelty on the two instruments Avg. Available Breadth and Avg. Available Breadth × Novelty. In columns (3) and (4) the dependent variable is IPO which is an indicator taking a value of 1 if the startup exits via an IPO. Column (3) presents the IV estimates Column (4) presents the OLS estimates in the same sample. Columns (1) - (4) include Industry × Deal Year × Deal Type × Country FE and Investor FE. Standard errors reported in parenthesis are double clustered at an investor and company level. * p<.10; ** p<.05; *** p<.01.

	(1) Net Multiple	(2) Net Multiple	(3) Net Multiple	(4) Net Multiple	(5) Net Multiple	(6) Net Multiple
Fraction of IPO Exits	0.487 (0.334)			0.680* (0.373)		
Fraction of Major Success exits		0.717** (0.298)			0.899** (0.348)	
Fraction of Acquisition Exits			-0.037 (0.201)			-0.049 (0.236)
Fund Size	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
Industry Controls	✓	✓	✓	✓	✓	✓
Stage Controls	✓	✓	✓	✓	✓	✓
Investor FE	✓	✓	✓	✓	✓	✓
Vintage Year FE	✓	✓	✓			
Fund Type FE	✓	✓	✓			
Vintage Year × FundType FE				✓	✓	✓
Observations	1458.00	1458.00	1458.00	1458.00	1458.00	1458.00
R^2	0.52	0.52	0.52	0.53	0.53	0.53

Table A31: **Validation of Exit Measure Used: Pitchbook VC Funds with Performance Measure in Preqin** This table reports the results of a regression of realized fund performance on the Fraction of IPO, Major Success Exits and Acquisition Exits. The dependent variable in columns (1)-(6) is the Net Multiple of a fund defined as the total value of distributions and unrealized gains to investors relative to the total value invested. In columns (1) and (4) Fraction of IPO Exits is the fraction of IPO exited deals relative to the total number of deals made by the fund. In columns (2) and (5) Fraction of Major Success exits is the fraction of deals that are exited either via an IPO or an Acquisition at a valuation higher than at least five times of invested capital relative to the total number of deals made by the fund. In columns (3) and (6) Fraction of Acquisition Exits is the fraction of Acquisition exited deals relative to the total number of deals made by the fund. Fund Size is the size of the fund. First Fund is an indicator taking a value of 1 if the Fund is a First Fund raised by a given VC firm. In all columns we include Industry Controls, which are separate controls for the fund's industry composition, Stage Controls which are separate controls for the fund's stage of investment composition. In all columns we include Investor FE. In columns (1) - (3) we include Vintage Year FE and Fund Type FE. In columns (4)-(6) we include Vintage Year × Fund Type FE. Standard errors reported in parenthesis are clustered at an Investor level * p<.10; ** p<.05; *** p<.01.

E Proofs from main text

Proof of Lemma 1

Proof. We have $s \sim N(\theta, \frac{1}{\tau})$. Therefore:

$$f(s|\theta = d) = \sqrt{\frac{\tau}{2\pi}} \exp\bigg(-\frac{1}{2}\tau(s-d)^2 \bigg) \tag{55}$$

Next we explicitly calculate the likelihood ratio:

$$\frac{f(s|\theta = 1)}{f(s|\theta = 0)} = \exp\left(\frac{1}{2}\tau(2s-1)\right) \tag{56}$$

Applying Bayes rule:

$$P(\theta = 1|s) = \frac{f(s|\theta = 1)\pi}{f(s)} \tag{57}$$

Therefore:

$$\frac{P(\theta = 1|s)}{P(\theta = 0|s)} = \frac{\pi}{1-\pi} \exp\left(\frac{1}{2}\tau(2s-1)\right) \tag{58}$$

Partner invests in unknown project pool if and only if:

$$P(\theta = 1|s)R_h + P(\theta = 0|s)R_l \geq R_k \tag{59}$$

The last inequality can be rewritten as

$$P(\theta = 1|s)R_h + (1 - P(\theta = 0|s))R_l \geq R_k \tag{60}$$

The last equation is equivalent to:

$$P(\theta = 1|s) \geq \bar{p}, \tag{61}$$

where $\bar{p} := \frac{R_k - R_l}{R_h - R_l}$. Therefore the minimal threshold signal is defined by:

$$\frac{P(\theta = 1|s)}{P(\theta = 0|s)} = \frac{\pi}{1-\pi} \exp\left(\frac{1}{2}\tau(2s-1)\right) \geq \frac{\bar{p}}{1-\bar{p}} \tag{62}$$

We therefore have in log odds

$$ln(\frac{\pi}{1-\pi}) + \frac{1}{2}\tau(2s^* - 1) = ln(\frac{R_k - R_l}{R_h - R_k}) \tag{63}$$

Hence the cut-off signal is:

$$s^*(e) = \frac{1}{2} + \frac{\Lambda}{\tau} \tag{64}$$

where

$$\Lambda = ln\left(\frac{(R_k - R_l)(1-\pi)}{(R_h - R_k)\pi}\right) \tag{65}$$

□

Proof of Proposition 2 - Optimal Effort

Proof. By differentiating $U(e)$ with respect to e we obtain the FOC condition. We need to show that optimal effort e^* defined by (72) is indeed a maximum. Given the expressions for the true positive ((18)) and the false positive rate ((19)) we first define:

$$z_\alpha = (s^* - 1)\sqrt{\tau} = \frac{\Lambda}{\tau^{1/2}} - \frac{\tau^{1/2}}{2} \tag{66}$$

$$z_\beta = (s^*)\sqrt{\tau} = \frac{\Lambda}{\tau^{1/2}} + \frac{\tau^{1/2}}{2} \tag{67}$$

Then:

$$\alpha(\tau) = 1 - \Phi(z_\alpha) \tag{68}$$

$$\beta(\tau) = 1 - \Phi(z_\beta) \tag{69}$$

Then:

$$\alpha'(\tau) = -\phi(z_\alpha)\frac{\partial z_\alpha}{\partial \tau} = \phi(z_\alpha)\frac{2\Lambda + \tau}{4\tau^{3/2}} > 0 \tag{70}$$

$$\beta'(\tau) = -\phi(z_\beta)\frac{\partial z_\beta}{\partial \tau} = \phi(z_\beta)\frac{2\Lambda - \tau}{4\tau^{3/2}} < 0 \tag{71}$$

Intuitively the true positive rate is increasing and the false positive rate is decreasing with a rise in informativeness τ. For this to hold we must have in $\tau^* > 2\Lambda$ which must hold since for any e such that $\tau < 2\Lambda$ the signal threshold s^* rises above 1 and the true positive rate drops below half and this defines a local minimum.

Now we show that the second order condition is satisfied. We have to show that:

$$\left\{(1-\epsilon)\pi\left(R_h - R_k\right)\alpha''(\tau) + (1-\pi)\left(R_l - R_k\right)\beta''(\tau)\right\}\kappa^2 - \gamma \ \leq 0 \tag{72}$$

Define:

$$H(\tau) = (1-\epsilon)\pi\left(R_h - R_k\right)\alpha''(\tau) + (1-\pi)\left(R_l - R_k\right)\beta''(\tau) \tag{73}$$

We will show that $H(\tau)$ is negative. First from the expressions for $\alpha'(\tau)$ and $\beta'(\tau)$ we have:

$$\alpha''(\tau) = \phi(z_\alpha)\Big(A'(\tau) + z_\alpha A(\tau)^2\Big), \tag{74}$$

where

$$A(\tau) = -z'_\alpha \tag{75}$$

Calculating we obtain:

$$\alpha''(\tau) = \phi(z_\alpha)\frac{(2\Lambda+\tau)^2(2\lambda-\tau) - 4\tau(6\Lambda+\tau)}{32\tau^{7/2}}, \tag{76}$$

Now notice that since $\tau > 2\Lambda$ all of the terms in the numerator are negative hence the true positive rate is concave with respect to signal informativeness $\alpha(\tau)'' < 0$. A similar calculation for the false positive rate shows:

$$\beta''(\tau) = \phi(z_\beta)\frac{(2\Lambda+\tau)(2\lambda-\tau)^2 + 4\tau(6\Lambda+\tau)}{32\tau^{7/2}}, \tag{77}$$

Now notice:

$$\frac{|\alpha''(\tau)|}{|\beta''(\tau)|} = \frac{\phi(z_\alpha)}{\phi(z_\beta)}\frac{|2\Lambda+\tau)^2(2\lambda-\tau) - 4\tau(6\Lambda+\tau)|}{|(2\Lambda+\tau)(2\lambda-\tau)^2 + 4\tau(6\Lambda+\tau)|} = e^\Lambda\frac{|2\Lambda+\tau)^2(2\lambda-\tau) - 4\tau(6\Lambda+\tau)|}{|(2\Lambda+\tau)(2\lambda-\tau)^2 + 4\tau(6\Lambda+\tau)|} \tag{78}$$

Denote:

$$R(\tau^*,\Lambda) = \frac{|2\Lambda+\tau)^2(2\lambda-\tau) - 4\tau(6\Lambda+\tau)|}{|(2\Lambda+\tau)(2\lambda-\tau)^2 + 4\tau(6\Lambda+\tau)|} = \frac{2\Lambda+\tau)^2(\tau-2\lambda) + 4\tau(6\Lambda+\tau)}{(2\Lambda+\tau)(2\lambda-\tau)^2 + 4\tau(6\Lambda+\tau)} \tag{79}$$

Since both $\alpha''(\tau)$ and $\beta''(\tau)$ are negative, $H(\tau)$ is negative whenever:

$$(1-\epsilon)\pi\,(R_h - R_k)\,|\alpha''(\tau)| \geq (1-\pi)\,(R_k - R_h)\,|\beta''(\tau)| \tag{80}$$

, We note that from the last equality:

$$(1-\epsilon)\pi\,(R_h - R_k)\,|\alpha''(\tau)| = (1-\epsilon)\pi\,(R_h - R_k)e^\lambda|\beta''(\tau)|R(\tau^*,\Lambda) = (1-\epsilon)(1-\pi)\,(R_k - R_l)\,|\beta''(\tau)|R(\tau^*,\Lambda) \tag{81}$$

So a sufficient a necessary condition is:

$$R(\tau^*,\Lambda) \geq \frac{1}{1-\epsilon} \tag{82}$$

It is clear that $R(\tau^*,\Lambda) > 1$. Let ϵ^{tr} be a threshold on the bargaining power of the founder s.t.

$$R(\tau^*,\Lambda) = \frac{1}{1-\epsilon^{tr}} \tag{83}$$

, then for all $\epsilon < \epsilon^{tr}$ the inequality is satisfied and $H(\tau)$ is negative. Now since $H(\tau)$ is negative the second order condition is satisfied hence (72) indeed defines a maximum. □

Proof of Corollary 1 - Optimal Effort Comparative Statics

Proof. Define

$$F(\gamma, \pi, e^*) = \left\{(1-\epsilon)\pi\left(R_h - R_k\right)\alpha'(\tau) + (1-\pi)\left(R_l - R_k\right)\beta'(\tau)\right\}\kappa - \gamma\, e^\star = 0 \tag{84}$$

Implicitly differentiating we get:

$$\frac{\partial e^*}{\partial q} = -\frac{F_q}{F_e}, \tag{85}$$

where q is the parameter of the comparative statics and F_e and F_q denote the partial derivatives of F with respect to e and parameter q. Now from the second order condition we have $F_e < 0$ hence:

$$\text{sgn}(\frac{\partial e^*}{\partial q}) = \text{sgn}(F_q) \tag{86}$$

- Comparative statics of optimal effort with respect to γ.

  First by assumption $R_k(\gamma)' > 0$ We have:

$$\frac{\partial \Lambda}{\partial \gamma} = \frac{\partial \Lambda}{\partial R_k} R_k(\gamma)' = \frac{R_h - R_l}{(R_k - R_l)(R_h - R_k)} R_k(\gamma)' > 0 \tag{87}$$

  Denote:

$$Q(\tau, \lambda, \gamma) = \pi(R_h - R_k(\gamma))\alpha(\tau)' + (1-\pi)(R_l - R_k(\gamma))\beta(\tau)' \tag{88}$$

  Then applying the product rule:

$$\frac{\partial Q}{\partial \gamma} = -R_k(\gamma)' T(\tau) + M(\tau, \gamma), \tag{89}$$

  where:

$$T(\tau) = (1-\epsilon)\pi\alpha(\tau)' + (1-\pi)\beta(\tau)' \tag{90}$$

  and

$$M(\tau, \gamma) = (1-\epsilon)\pi(R_h - R_k)\alpha(\tau)'_\Lambda \frac{\partial \Lambda}{\partial \gamma} + (1-\pi)(R_l - R_k)\beta(\tau)'_\Lambda \frac{\partial \Lambda}{\partial \gamma} \tag{91}$$

  First we show that $M(\tau, \gamma) < 0$. Explicitly calculating:

$$\alpha(\tau)'_\Lambda = \phi(z_\alpha)\frac{4\tau - 4\Lambda^2 + \tau^2}{8\tau^{3/2}} \tag{92}$$

Similarly:

$$\beta(\tau)'_\Lambda = \phi(z_\beta)\frac{4\tau - 4\Lambda^2 + \tau^2}{8\tau^{3/2}} \tag{93}$$

So we obtain:

$$\alpha(\tau)'_\Lambda = \beta(\tau)'_\lambda e^\Lambda = \beta(\tau)_\lambda \frac{(1-\pi)(R_k - R_l)}{\pi(R_h - R_k)} \tag{94}$$

Plugging in the last equality in the expression for M we obtain:

$$M(\tau,\gamma) = -\frac{\partial\Lambda}{\partial\gamma}\beta'(\tau)_\Lambda(1-\pi)(R_k - R_l)\epsilon < 0 \tag{95}$$

. Hence:

$$F_\gamma = -R_k(\gamma)'T(\tau) + M(\tau,\gamma) - e^*, \tag{96}$$

Not clearly a sufficient (not necessary condition) for a negative F_γ is:

$$T(\tau) > 0 \tag{97}$$

One can show that a sufficient condition for this to be satisfied is:

$$R_k(2-\epsilon) \geq R_h + (1-\epsilon)R_l. \tag{98}$$

- Comparative statics of optimal effort with respect to π.

  We have:

$$F_\pi = (1-\epsilon)(R_h - R_k)\alpha(\tau)' + (R_l - R_k)\beta(\tau)' + \frac{\partial\Lambda}{\partial\pi}\left((1-\epsilon)\pi(R_h - R_k)\alpha(\tau)'_\Lambda + (1-\pi)(R_l - R_k)\beta(\tau)'_\Lambda\right) \tag{99}$$

  Now we have shown in proof of the comparative statics of optimal effort with respect to γ that:

$$\pi(R_h - R_k)\alpha(\tau)'_\Lambda + (1-\pi)(R_l - R_k)\beta(\tau)'_\Lambda < 0 \tag{100}$$

  Hence the second term is positive since $\frac{\partial\Lambda}{\partial\pi} < 0$. Now since:

$$(1-\epsilon)(R_h - R_k)\alpha(\tau)' + (R_l - R_k)\beta(\tau)' > 0 \tag{101}$$

  since both terms are positive ($R_l - R_k < 0$ and $\beta(\tau)' < 0$)

□

Proof of Proposition 3 - The likelihood of financing a novel project decreases with specialization

Proof. Explicitly calculating:

$$\frac{\partial L_N(e^*(\gamma))}{\partial \gamma} = \frac{\partial}{\partial \gamma}(\pi\alpha(\tau) + (1-\pi)\beta(\tau)) \tag{102}$$

Notice that $\alpha(\tau)$ and $\beta(\tau)$ depend on γ directly through optimal effort and through Λ which is a function of R_k. Computing the derivative we obtain:

$$\frac{\partial L_N(e^*(\gamma))}{\partial \gamma} = \frac{k}{N}\frac{\partial e^*}{\partial \gamma}(\pi\alpha(\tau)' + (1-\pi)\beta(\tau)') + \frac{\partial \Lambda}{\partial \gamma}(\pi\alpha_\Lambda(\tau) + (1-\pi)\beta_\Lambda(\tau)) \tag{103}$$

Now the second term is clearly negative since $\frac{\partial \Lambda}{\partial \gamma} > 0$ and both $\alpha_\Lambda(\tau) < 0$, $\beta_\Lambda(\tau) < 0$. Hence a sufficient condition (not necessary condition) for negative derivative is:

$$\pi\alpha(\tau)' + (1-\pi)\beta(\tau)' > 0 \tag{104}$$

which is certainly satisfied when:

$$R_k \geq \frac{R_h + R_l}{2} \tag{105}$$

□

Proof of Proposition 4 - The expected return in the novel sector decreases with specialization

Proof. We explicitly calculate:

$$\frac{\partial E_N}{\partial \gamma} = \frac{\partial}{\partial \gamma}(\alpha(\tau^*)R_h + \beta(\tau^*)R_l) \tag{106}$$

We have:

$$\frac{\partial E_N}{\partial \gamma} = \frac{\partial e^*}{\partial \gamma}(\pi\alpha(\tau)'R_h + (1-\pi)\beta(\tau)'R_l) + \frac{\partial \Lambda}{\partial \gamma}(\pi\alpha_\Lambda(\tau)R_h + (1-\pi)\beta_\Lambda(\tau)R_l) \tag{107}$$

since by the previous corollary $\frac{\partial e^*}{\partial \gamma} < 0$ and $\beta(\tau)' < 0$, $R_l < 0$ the first term is clearly negative. A sufficient condition fo the second term to be negative is $R_h \geq |R_l|$ which is easily shown. Similarly:

$$\frac{\partial E_K}{\partial \gamma} = \frac{\partial}{\partial \gamma}(R_k(\gamma)q^r) = R_k'(\gamma)q^r - R_k(\gamma)\frac{\partial e^*}{\partial \gamma}\frac{k}{N}(\pi\alpha(\tau)' + (1-\pi)\beta(\tau)') - R_k(\gamma)\frac{\partial \Lambda}{\partial \gamma}(\pi\alpha_\Lambda(\tau) + (1-\pi)\beta_\Lambda(\tau)) > \tag{108}$$

since $R_k(\gamma)' > 0$ by assumption and $\frac{\partial e^*}{\partial \gamma} < 0$, $\pi\alpha(\tau)' + (1-\pi)\beta(\tau)' > 0$, since the last term is positive. □

Proof of Proposition 5 - Optimal Hiring rule

Proof. We have:

$$\frac{dV}{d\gamma} = \frac{\partial V}{\partial e}(e^*(\gamma), \gamma)\frac{de^*}{d\gamma} + \frac{\partial V}{\partial \gamma}(e^*(\gamma), \gamma) \tag{109}$$

By the envelope theorem and since the outside option of the partner does not depend on optimal effort we have $\frac{\partial V}{\partial e}(e^*(\gamma), \gamma) = 0$

Hence the first order condition reads:

$$\frac{\partial \Pi}{\partial \gamma} = \frac{1}{2}e^2 - u(\gamma)' \tag{110}$$

Now for the FOC to define a local maximum we must have:

$$\frac{\partial}{\partial \gamma}\left(\frac{\partial \Pi}{\partial \gamma} - \frac{1}{2}e^2 - u(\gamma)'\right) < 0 \tag{111}$$

Finally we have the FOC for optimal γ:

$$R_k(\gamma^*)'q^r = \frac{1}{2}e(\gamma^*)^2 + u'(\gamma) \tag{112}$$

$$\frac{\partial}{\partial \gamma}\left(R_k(\gamma^*)'q^r - \frac{1}{2}e(\gamma^*)^2 - u'(\gamma)\right) < 0 \tag{113}$$

This is equivalent to:

$$R_k''(\gamma)q^r - e^*\frac{\partial e^*}{\partial \gamma} - u''(\gamma) < 0 \tag{114}$$

If the outside option of the partners is such that $u''(\gamma) == 0$ γ defines a maximum iff:

$$|R_k''(\gamma)|q^r > e^*|\frac{\partial e^*}{\partial \gamma}| \tag{115}$$

□

Proof of Corollary 2 - Comparative statics of optimal specialization

Proof. Define:

$$J(N, \gamma^*, \pi, e^*) = R_k(\gamma^*)' q^r - \frac{1}{2}(e^*)^2 - u'(\gamma) = 0 \tag{116}$$

Then implicit differentiation again gives:

$$\frac{\partial \gamma}{\partial q} = -\frac{J_q}{J_\gamma} \tag{117}$$

From second order condition for a maximum $J_\gamma < 0$ hence:

$$\mathrm{sgn}(\frac{\partial \gamma}{\partial q}) = \mathrm{sgn}(J_q) \tag{118}$$

- Comparative statics of optimal specialization with respect to π. We have:

$$J_\pi = R_k(\gamma)' \frac{\partial q^r}{\partial \pi} - e^* \frac{\partial e^*}{\partial \pi} \tag{119}$$

, where

$$\frac{\partial q^r}{\partial \pi} = -(1-\epsilon)\alpha(\tau) + \beta(\tau) - \frac{\partial \Lambda}{\partial \pi}\Big((1-\epsilon)\pi\alpha(\tau)_\Lambda + (1-\pi)\beta(\tau)_\Lambda\Big) \tag{120}$$

We have:

$$\frac{\partial \Lambda}{\partial \pi} = -\frac{1}{\pi(1-\pi)} \tag{121}$$

$$\alpha(\tau)_\Lambda = -\frac{\phi(z_\alpha)}{\tau^{1/2}} \tag{122}$$

$$\beta(\tau)_\Lambda = -\frac{\phi(z_\beta)}{\tau^{1/2}} \tag{123}$$

Hence the claim follows since $\frac{\partial q^r}{\partial \pi} < 0$

□

Proof of Theorem I - Existence of equilibrium

Proof. We prove existence via Brouwer's fixed-point theorem. Define the domain $\mathcal{D} \subset R^3$ as:

$$\mathcal{D}[\underline{\pi}, \overline{\pi}] \times [\gamma_{\min}, \gamma_{\max}] \times [0, e_{\max}] \tag{124}$$

where:

- $\pi \in [\underline{\pi}, \overline{\pi}] \subset (0, 1)$ (bounded away from 0 and 1)
- $\gamma \in [\gamma_{\min}, \gamma_{\max}]$ (specialization bounds)
- $e \in [0, e_{\max}]$ (effort bounded by cost)

$\mathcal{D}$ is **compact** and **convex** as a Cartesian product of compact convex intervals.

Define the mapping $T : \mathcal{D} \to \mathcal{D}$ by $T(\pi, \gamma, e) = (\pi', \gamma', e')$ where:

$$e' \arg\max_{e \geq 0} \left[R_k(\gamma) + (1 - \epsilon)\pi\alpha(\tau)(R_h - R_k(\gamma)) + (1 - \pi)\beta(\tau)(R_l - R_k(\gamma)) - \frac{\gamma e^2}{2} \right] \tag{Optimal Effort}$$

$$\gamma' \arg\max_{\gamma \geq 0} \left[\Pi(e', \gamma) - \frac{1}{2}\gamma(e')^2 - u(\gamma) \right] \tag{Optimal Hiring}$$

$$\pi' \frac{1 - \eta^h}{1 - \eta^l} \quad \text{with} \quad \tau' = \kappa e' \tag{Entry Update}$$

where η^l and η^h are computed using (γ', e').

Step 1: Continuity of T

- e' is continuous in (π, γ) by the Implicit Function Theorem applied to the FOC in Proposition 2, since the objective is strictly concave in e.
- γ' is continuous in (π, e') by the Implicit Function Theorem applied to the FOC in Proposition 5, given $R_k(\gamma)$ concave and $u(\gamma)$ differentiable.
- π' is continuous in (γ', e') because:
  - $\alpha(\tau)$ and $\beta(\tau)$ are smooth (normal CDF)
  - $R_k(\gamma)$ is differentiable
  - Entrepreneurial thresholds are rational functions

Thus, T is continuous on $\mathcal{D}$.

Step 2: Self-Mapping $T(\mathcal{D}) \subseteq \mathcal{D}$

- **Effort:** $e' \in [0, e_{\max}]$ since effort cost $\frac{1}{2}\gamma e^2 \to \infty$ as $e \to \infty$, and $e_{\max}$ bounds the solution.
- **Specialization:** $\gamma' \in [\gamma_{\min}, \gamma_{\max}]$ by partner market constraints.
- **Project Quality:** $\pi' \in [\underline{\pi}, \overline{\pi}]$ because:
  - $\eta^l \geq 0$ by $c_l \geq \beta(\tau)b$ (Condition 1)

- $\eta^h \leq 1$ by $c_h \leq 1 - \lambda + c_l - \beta(\tau)b + \alpha(\tau)(\epsilon(R_h - R_k) + b)$ (Condition 2)
- $\eta^h \geq \eta^l$ (Condition 3)

Step 3: Fixed Point Exists Since $\mathcal{D}$ is compact and convex, and $T : \mathcal{D} \to \mathcal{D}$ is continuous, by Brouwer's Fixed-Point Theorem, there exists $(\pi^*, \gamma^*, e^*) \in \mathcal{D}$ such that:

$$T(\pi^*, \gamma^*, e^*) = (\pi^*, \gamma^*, e^*)$$

This fixed point satisfies all equilibrium conditions by construction.

Parameter Restrictions:

1. $c_l \geq \beta(\tau)b$ (ensures $\eta^l \geq 0$)
2. $c_h \in \left[\frac{c_l - \beta(\tau)b}{\lambda} + \alpha(\tau)(\epsilon(R_h - R_k) + b), 1 - \lambda + c_l - \beta(\tau)b + \alpha(\tau)(\epsilon(R_h - R_k) + b)\right]$ (ensures $\eta^h \in [\eta^l, 1]$)
3. $R_k > \frac{R_h + R_l}{2}$ (for Proposition 3)
4. $R_h \geq |R_l|$ (for Proposition 4)
5. $(2 - \epsilon)R_k \geq R_h + (1 - \epsilon)R_l$ (for Corollary 1 and 2)

$\square$

F Data Construction

F.1 Matching Pitchbook-Revelio Labs

To construct the link between PitchBook investors and Revelio Labs firms, I implement a structured multi-step matching procedure designed to maximize accuracy while minimizing false positives. The procedure begins with a systematic harmonization of identifiers. Specifically, I standardize organization names (PitchBook: InvestorName; Revelio: company) by removing legal suffixes such as Inc., Ltd., or GmbH, stripping bracketed numeric tags, collapsing multiple whitespaces, and converting all characters to lowercase. I also parse website information (PitchBook: Website; Revelio: url) by extracting the registrable domain (e.g., example.com) to reduce noise from URL extensions, and I harmonize location data (PitchBook: HQCountry; Revelio: `country_code`).[30]

Once identifiers are standardized, I carry out a sequence of exact-match passes that proceed in descending order of specificity. In the first pass, I match firms on the joint pair of (cleaned name, website domain), which provides the highest likelihood of uniquely identifying the same entity across datasets. In the second pass, I consider the remaining unmatched records and implement exact matches on the pair (cleaned name, country), conditional on non-missing location data. In the third pass, I restrict attention to unmatched firms with non-missing website information and implement exact matches on the pair (website domain, country). Finally, in the fourth pass, I allow exact matches on cleaned firm name alone. After each pass, I remove all successfully matched PitchBook records from the pool of candidates in order to avoid duplicate links. In cases where multiple potential matches arise, I retain only one-to-one links. The overall sample with non-missing partner IDs from Pitchbook contains 6346 distinct investors (distinct InvestorID). Out of these following this procedure I am able to match 4667 investors to a unique Revelio identifier (unique rcid) resulting in an overall one-to-one match rate of around 74%. For the one - to many matches (i.e., cases where one InvestorID from Pitchbook is matched to multiple rcid identifiers in Revelio) I do a manual check, based on detailed location data and keep only the correct matches. This results in the matching of additional 306 investors bringing the overall match rate to 78%. For the cases where one InvestorID is correctly matched to multiple rcids (e.g., Austin Ventures with an investor ID 10146-16 matched to Austin Ventures LLC and Austin Ventures LP with rcids 20152010 and 22143640 respectively) I keep both rcids as a correct match.

[30]Revelio Labs academic access does not provide the company's headquarters. I use the employment dataset and construct a proxy for headquarters based on the country where the majority of employees are based.

Next, I use the matched Revelio rcids and I collect the full history of employees for the matched rcids. To link individual partners in PitchBook to employees in Revelio Labs, I implement a name-based exact matching procedure conditional on the firm-level match established in the previous step. I begin by harmonizing all person names to ensure comparability across sources. Specifically, I normalize text encoding, split full names into first and last names using a structured parser, and then clean each component by removing legal suffixes, bracketed numeric identifiers, and other suffixes and prefixes (e.g., Pitchbook names often contain a title such as PhD, MD or JD). I apply the same cleaning procedure symmetrically to both PitchBook partner names and Revelio employee names. I then merge the two datasets by requiring an exact match on three keys: the firm identifier carried over from the firm-level match (the Revelio rcid), the cleaned first name, and the cleaned last name. This conservative design ensures that a partner is linked to a Revelio record only if the firm affiliation and both name components match exactly. After the merge, I remove duplicates to retain a one-to-one mapping.

F.2 Industry Match Revelio - Pitcbhook

Because PitchBook and Revelio use different taxonomies, I align PitchBook's Industry Group labels to Revelio's RICS taxonomy using embedding-based cosine similarity. For each PitchBook group, I compute its cosine similarity to each of the 50 Revelio RICS categories and select the two categories with the highest scores as the mapped matches for that group. Table A32 shows the mapping along with the raw cosine similarity scores.

PB industry group	RICS (top match)	Sim. (top)	RICS (second)	Sim. (second)
Other Financial Services	Financial Services	0.876	Business Services	0.639
Retail	Apparel Retail	0.823	Retail and Consumer Goods	0.804
Media	Media and Entertainment	0.810	Culture and Entertainment	0.550
Pharmaceuticals and Biotechnology	Pharmaceuticals	0.803	Biotech and Healthcare Services	0.713
Transportation	Logistics and Transportation	0.803	Automotive Services	0.479
Healthcare Services	Healthcare and Wellness Services	0.786	Business Services	0.687
Agriculture	Agricultural Services	0.776	Environmental Services	0.407
Apparel and Accessories	Apparel Retail	0.769	Retail and Consumer Goods	0.536
Commercial Services	Business Services	0.761	Marketing and Advertising Services	0.703
IT Services	Information Technology Services	0.760	IT Consulting Services	0.737
Containers and Packaging	Packaging Services	0.750	Logistics and Transportation	0.430
Other Business Products and Services	Business Services	0.744	Digital Commerce Services	0.593
Commercial Transportation	Logistics and Transportation	0.734	Commercial Aviation	0.595
Services (Non-Financial)	Financial Services	0.732	Business Services	0.662
Restaurants, Hotels and Leisure	Food and Hospitality Services	0.714	Hospitality and Tourism Management	0.662
Other Consumer Products and Services	Retail and Consumer Goods	0.690	Consumer Technology Distribution	0.652
Other Energy	Energy and Resources	0.684	Food and Beverage	0.299
Other Information Technology	Information Technology Services	0.664	IT Consulting Services	0.459
Energy Services	Environmental Services	0.643	Energy and Resources	0.592
Other Healthcare	Healthcare and Wellness Services	0.637	Biotech and Healthcare Services	0.484
Commercial Banks	Financial Services	0.617	Business Services	0.454
Consumer Durables	Retail and Consumer Goods	0.604	Consumer Technology Distribution	0.557
Other Materials	Materials Manufacturing	0.604	Miscellaneous	0.417
Energy Equipment	Energy and Resources	0.601	Electronics Manufacturing	0.390
Commercial Products	Retail and Consumer Goods	0.594	Marketing and Advertising Services	0.590
Healthcare Technology Systems	Biotech and Healthcare Services	0.585	Healthcare and Wellness Services	0.573
Computer Hardware	Electronics Manufacturing	0.577	Industrial Manufacturing	0.447
Consumer Non-Durables	Retail and Consumer Goods	0.572	Consumer Technology Distribution	0.541
Textiles	Materials Manufacturing	0.556	Apparel Retail	0.542
Communications and Networking	Telecommunications Services	0.530	Media and Entertainment	0.406
Healthcare Devices and Supplies	Healthcare and Wellness Services	0.523	Wellness Products	0.479
Semiconductors	Electronics Manufacturing	0.493	Materials Manufacturing	0.351
Construction (Non-Wood)	Engineering and Construction Services	0.491	Materials Manufacturing	0.397
Metals, Minerals and Mining	Energy and Resources	0.477	Materials Manufacturing	0.472
Software	Automation Solutions	0.475	Information Technology Services	0.438
Utilities	Energy and Resources	0.446	Environmental Services	0.437
Insurance	Financial Services	0.434	Legal Services	0.398
Capital Markets/Institutions	Financial Services	0.432	Professional and Trade Associations	0.412
Forestry	Agricultural Services	0.416	Environmental Services	0.403
Exploration, Production and Refining	Energy and Resources	0.404	Industrial Manufacturing	0.403
Chemicals and Gases	Pharmaceuticals	0.378	Environmental Services	0.307

Table A32: Mapping of PitchBook industry groups to closest RICS categories with cosine similarity scores.

G Additional Results

G.1 Individual or team?

The results in the previous subsection highlighted the importance of individual VC partners' human capital breadth in financing novel ventures. In this subsection, I shift the focus to the team level and investigate whether diversity among partners at the fund level is associated with the financing of more novel ventures and with the successful exit of such ventures.

To conduct this analysis, I aggregate individual-level data to the fund level and construct several diversity indices, following a similar methodology to the construction of the human capital breadth index. These fund-level diversity measures capture heterogeneity in partners' prior professional experiences, education and gender composition. Specifically to capture heterogeneity in prior professional experience, I define three proxies: (i) job category diversity, which reflects variation in the functional roles held by partners; (ii) job industry diversity, which captures the range of industries in which partners have previously worked; and (iii) job role diversity, which measures variation in the specific roles held across employment spells. Each index is computed at the fund level. For example, the job role diversity index is defined as:

$$D_f = \frac{\text{Number of distinct roles}_f}{\text{Number of total employment spells}_f} \tag{125}$$

the numerator simply counts the total number of distinct roles held by all partners in the past and the denominator scales this measure by the number of total past employment spells of partners involved in the funds' deals.[31]

I also construct educational and gender diversity categories at a fund level, defined as follows:

$$D_f \;=\; \exp\left(-\sum_{i=1}^{K} \frac{n_{f,i}}{N_f} \ln\left(\frac{n_{f,i}}{N_f}\right)\right), \tag{126}$$

where N_f is the total number of distinct partners in the fund, $n_{f,i}$ is the number of partners in category i and K is the number of categories. For example, in constructing gender diversity $K = 2$ for Male and Female partners. Intuitively, (126) captures converts an entropy diversity measure into effective categories. The measure ranges between 1 and the number of categories, for example if the fund consists only of partners of the female gender the measure is 1 and if the fund is perfectly balanced i.e., 50% of partners are male and 50% of partners are female the effective gender diversity is 2.[32]

[31] This is a fund level analogue to the individual partner human capital breadth.

[32] To construct the effective educational diversity measure I use the following degree types: STEM

Analogously, to the individual level tests, I first test whether fund level diversity is associated with financing more novel ventures. Specifically, I estimate,

$$\text{Frac. Novel}_f = \alpha + \beta D_f + X_f + \rho_{t\times c} + \epsilon_f, \tag{127}$$

where Frac. Novel_f is the fraction of top quartile novelty firms financed by fund f, D_f is a diversity measure, X_f are fund level controls which include fund size, a dummy for first fund equal to 1 if it is the first fund raised by a given GP as well as controls for industry and stage allocation and $\rho_{t\times c}$ are vintage year $\times$ fund category fixed effects.

Table A33 about here.

The results are presented in Table A33. I do not find any economically nor statistically significant relationship between fund level diversity and the fraction of novel firms financed. Next, along similar lines I test whether fund level human capital diversity is associated with performance. I estimate the following specification:

$$\text{Frac. Successfull Exits}_f = \alpha+\beta_1 D_f+\beta_2\text{Frac. Novel}_f+\beta_3 D_f\times\text{Frac. Novel}_f+X_f+\rho_{t\times c}+\epsilon_f, \tag{128}$$

where Frac. $\text{Successfull Exits}_f$ is the fraction of investments exited via an IPO or high value acquisition. The coefficients of interest are β_1, β_2 and β_3.

Table A34 about here.

The results are presented in Table A34. Analogous to the individual exit regressions, I find that the fraction of financed novel firms (β_2 estimate) are correlated with the fraction of successful exits, however, I do not find robust evidence that fund level diversity is associated with performance for both funds with a high and low fraction of financed novel firms.

In Appendix Tables A35 and A36, I use PCA to reduce dimensionality and construct summary measures to capture fund-level diversity from the individual measures. I do not find robust evidence that fund-level diversity is associated with financing a higher fraction of novel projects, nor do I find evidence that it is associated with stronger performance for novel firms.

degree, Social Science or Humanities degree, MBA degree, PhD degree, Medical Doctor degree.

G.2 The role of human capital breadth over time

In this subsection, I examine how the relationship between human capital breadth and novelty has evolved over time. The stylized facts point to a gradual decline in both average startup novelty - driven by a lower fraction of high novelty firms financed by the venture capital industry and human capital breadth.

To examine this trend, I re-estimate specification (5) by progressively excluding earlier cohorts of VC-backed deals, thereby focusing on more recent years.

Figure A6 about here.

Figure A6 presents the estimated coefficients on human capital breadth. Each point reflects the coefficient from specification (5), estimated on a sample restricted to deals financed after year t. The results indicate a gradual weakening in the relationship between human capital breadth and novelty over time, particularly beginning around 2015.

Next, I examine how the relationship between human capital breadth, novelty, and performance has changed by estimating specification (6) over time, again excluding earlier deals.

Figure A7 about here.

Figure A7 shows the estimated coefficients on the interaction between human capital breadth and novelty. As before, each point reflects the estimate from a sample restricted to deals completed after year t. Unlike the previous result, the interaction effect appears stable over time.

G.3 The role of on the job VC experience on financing novelty

Here, I examine the role of experience of partners acquired on the job i.e., experience acquired through investments made post VC industry entry on financing of novel startups. In particular, I examine the role of (i) Industry specialization post VC industry entry (ii) Deal diversity post VC industry entry. To do so, I construct a Herfindahl-Hirschmann industry specialization measure following Gompers et al. (2009) based on the industry sector of past deals financed by VC partners:

$$HHI_{p,t} = \sum_{j} \left(\frac{n_{p,j,t}}{N_{p,t}}\right)^2, \tag{129}$$

where p denotes parter, t time, $n_{p,j,t}$ is the number of investments partner p has made from VC industry entry to time t in industry j and $N_{p,t}$ is the total number of investments made by partner p. Similarly, I construct an average deal diversity index defined as:

$$\text{Deal Diversity}_{p,t} = \frac{\sum_{k,j,k\neq j}(1 - CosSim(j,k))}{K_{p,t}}, \tag{130}$$

where k, j denote companies financed by partner p before time t, $CosSim(j,k)$ is the cosine similarity between business model of company j and company k and $K_{p,t}$ is the number of distinct companies financed before year t. I next test whether, partner industry specialization and past deal diversity are correlated with the novelty of the financed focal deal. I estimate:

$$N_{j,k,p,t} = \alpha + \beta_1 HHI_{p,t} + \beta_2 \text{Deal Diversity}_{p,t} + X_{t,p} + \eta_{i\times t\times s\times c} + \rho_{t\times j} + \epsilon_{j,k,p,t}, \tag{131}$$

where the coefficients of interests are β_1 and β_2. Model (131) is estimated on the full set of partners available in Pitchbook data i.e., in this specification I do not require partners to have a matched to Revelio data. Furthermore since for each partner I need to measure past deal diversity, I require partners to have made at least 2 past investments in distinct companies.

Table A37 about here.

The results are reported in Table A37. Columns (1) and (2) estimate equation (131) using the full sample, while columns (3) and (4) restrict the analysis to the subsample of investments where the VC firm acts as the lead investor. In columns (1) and (3), I find that both greater industry specialization by the partner after entering the VC industry and greater diversity in previously financed deals are positively associated with the novelty of the focal investment. However, once VC firm fixed effects are included, both the economic magnitude and statistical significance of these relationships decline. This suggests that much of the observed variation is driven by cross-firm differences in investment novelty and specialization, and that the within-firm variation in these characteristics has a more limited association with deal novelty.

Table A38 about here.

In Table A38, I re-estimate (5) by including industry specialization post VC entry as well as deal diversity of past financed deals and I show that (i) the baseline effect of human capital breadth remains robust and (ii) post VC entry industry specialization plays a role in selecting most novel firms, highlighting the role of post VC entry industry specialization (Gompers et al., 2009).

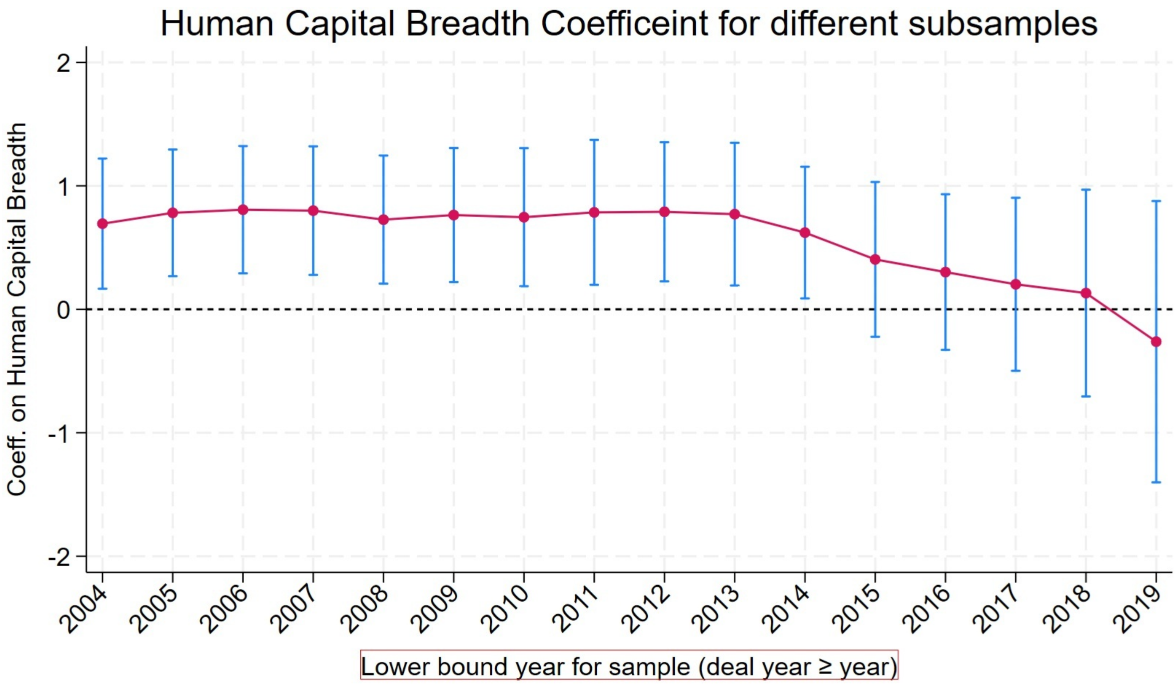

Figure A6: **Association between Lead Partner Human Capital Breadth and Novelty over time** This figure presents the coefficient β of the association between human capital breadth and novelty estimated via $N_{j,k,p,t} = \alpha + \beta B_p + X_{t,p} + \eta_{i\times t\times s\times c} + \rho_{t\times j} + \epsilon_{j,k,p,t}$ by progressively excluding cohorts of earlier financed VC-deals. For example, the coefficient estimate plotted in year 2010, is the estimated β in the regression excluding deals done before 2010.

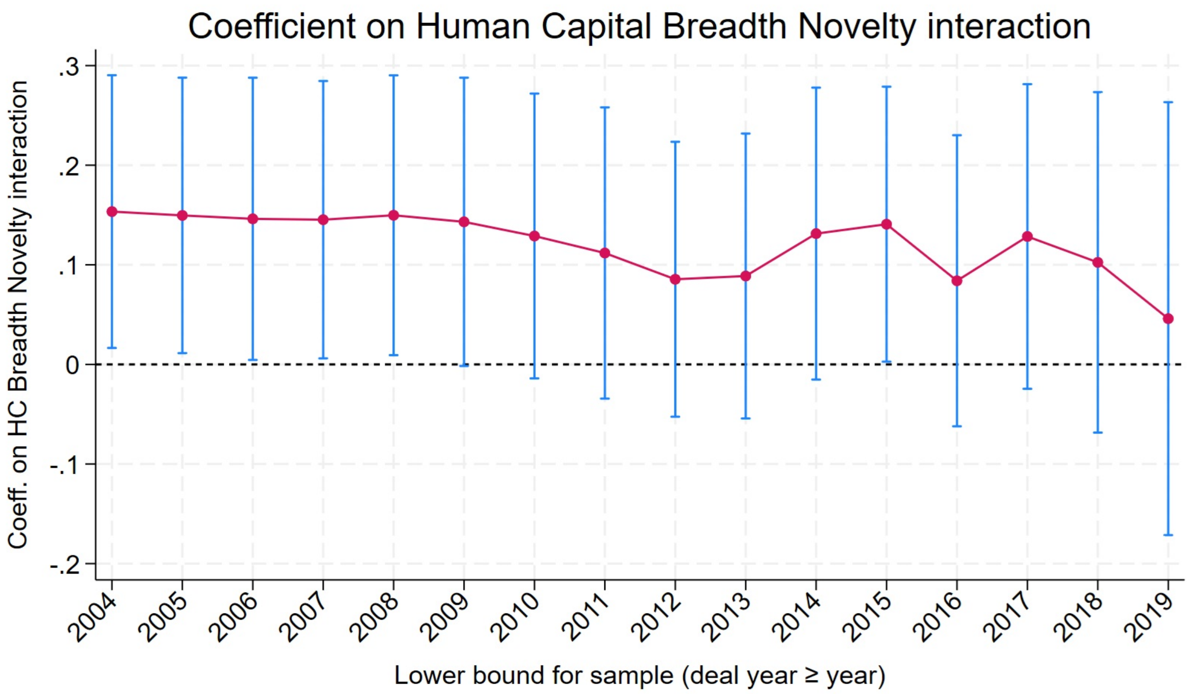

Figure A7: **Interaction between Lead Partner Human Capital Breadth, Novelty and Investment Performance over time** This figure presents the coefficient δ of the association between the interaction between lead partner breadth and deal novelty and deal performance estimated via $P_{j,k,p,t} = \alpha + \beta B_p + \gamma N_{j,k,p,t} + \delta B_p \times N_{j,k,p,t} + X_{t,p} + \eta_{i\times t\times s\times c} + \rho_{t\times j} + \epsilon_{j,k,p,t}$ by progressively excluding cohorts of earlier financed VC-deals. For example, the coefficient estimate plotted in year 2010, is the estimated δ in the regression excluding deals done before 2010.

	(1) Frac. Top Quartile Novelty	(2) Frac. Top Quartile Novelty	(3) Frac. Top Quartile Novelty	(4) Frac. Top Quartile Novelty	(5) Frac. Top Quartile Novelty
Job Cateogory ratio	0.009 (0.019)				
Job Industry ratio		0.000 (0.022)			
Job Role ratio			-0.005 (0.023)		
Educational diversity index				-0.004 (0.004)	
Gender diversity index					0.001 (0.010)
Fund Size	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
First Fund	-0.013 (0.009)	-0.013 (0.009)	-0.013 (0.009)	-0.018* (0.009)	-0.013 (0.009)
Industry Controls	✓	✓	✓	✓	✓
Stage Controls	✓	✓	✓	✓	✓
Vintage Year × FundType FE	✓	✓	✓	✓	✓
Observations	2036.00	2036.00	2036.00	2009.00	2031.00
R^2	0.12	0.12	0.12	0.13	0.12

Table A33: **Fund level Diversity and Novelty** This table presents of an OLS regression of fund level diversity measures on the fraction of investments in top quartile novelty firms. The dependent variable Frac. Top Quartile Novelty is the fraction of investments in top quartile novelty firms. The independent variable in column (1) Job Category ratio is the ratio between distinct job categories held by all partners in the fund and the total number of past employment spells of all partners in the fund. The independent variable in column (2) Job industry ratio is the ratio between distinct industries worked in by all partners in the fund and the total number of past employment spells of all partners in the fund. The independent variable in column (3) Job Role ratio is the ratio between distinct job roles held by all partners in the fund and the total number of past employment spells by all partners in the fund. The independent variable in column (4) is an educational diversity index at a fund level, which is the exponential of the Shannon entropy computed using the fraction of partners with a given educational degree (STEM education, Social Science or Humanities Education, MBA degree, PhD degree or Medical degree). The independent variable in column (t) is an gender diversity index at a fund level, which is the exponential of the Shannon entropy computed using the fraction of partners with a given gender (Male or Female). Fund Size is the AUM of the fund. First Fund is an indicator variable taking a value of 1 if this is the first fund raised by a VC firm. All columns include Industry Controls, which are separate controls for the fraction of investments made by the fund in each industry sector. All columns include Stage Controls, which are separate controls for the fraction of investments made by the fund in each investment Stage. All columns include Vintage Year × Fund Category fixed effects. Standard errors reported in parenthesis are clustered at the investor level * p<.10; ** p<.05; *** p<.01. Sample constrained on at least 2 partners observable for each fund

	(1) Fraction of Successful Exits	(2) Fraction of Successful Exits	(3) Fraction of Successful Exits	(4) Fraction of Successful Exits	(5) Fraction of Successful Exits
Frac. Top Quartile Novelty	0.265*** (0.074)	0.396*** (0.110)	0.459*** (0.155)	0.119 (0.085)	0.324*** (0.102)
Job Cateogory ratio	0.008 (0.024)				
Frac. Top Quartile Novelty × Job Cateogory ratio	-0.085 (0.137)				
Job Industry ratio		0.042 (0.027)			
Frac. Top Quartile Novelty × Job Industry ratio		-0.257* (0.150)			
Job Role ratio			0.039 (0.033)		
Frac. Top Quartile Novelty × Job Role ratio			-0.313 (0.195)		
Educational diversity index				-0.005 (0.004)	
Frac. Top Quartile Novelty × Educational diversity index				0.039 (0.028)	
Gender diversity index					0.011 (0.014)
Frac. Top Quartile Novelty × Gender diversity index					-0.075 (0.075)
Industry Controls	✓	✓	✓	✓	✓
Stage Controls	✓	✓	✓	✓	✓
Vintage Year × FundType FE	✓	✓	✓	✓	✓
Observations	2036.00	2036.00	2036.00	2009.00	2031.00
R^2	0.33	0.33	0.33	0.33	0.33

Table A34: **Fund level Diversity, Novelty and Performance.** This table presents of an OLS regression of fund level diversity measures, the fraction of investments in top quartile novelty firms and fund performance. The dependent variable Fraction of Successful Exits is the fraction of deals that have achieved an exit via IPO or high value acquisition (an acquisition with a value of at least five times greater than the total VC amount invested in the company). The independent variable Frac. Top Quartile Novelty is the fraction of investments in top quartile novelty firms. The independent variable in column (1) Job Category ratio is the ratio between distinct job categories held by all partners in the fund and the total number of past employment spells of all partners in the fund. The independent variable in column (2) Job industry ratio is the ratio between distinct industries worked in by all partners in the fund and the total number of past employment spells of all partners in the fund. The independent variable in column (3) Job Role ratio is the ratio between distinct job roles held by all partners in the fund and the total number of past employment spells by all partners in the fund. The independent variable in column (4) is an educational diversity index at a fund level, which is the exponential of the Shannon entropy computed using the fraction of partners with a given educational degree (STEM education, Social Science or Humanities Education, MBA degree, PhD degree or Medical degree). The independent variable in column (t) is an gender diversity index at a fund level, which is the exponential of the Shannon entropy computed using the fraction of partners with a given gender (Male or Female). All columns also include controls of for fund size and first fund. Fund Size is the AUM of the fund. First Fund is an indicator variable taking a value of 1 if this is the first fund raised by a VC firm. All columns include Industry Controls, which are separate controls for the fraction of investments made by the fund in each industry sector. All columns include Stage Controls, which are separate controls for the fraction of investments made by the fund in each investment Stage. All columns include Vintage Year × Fund Category fixed effects. Standard errors reported in parenthesis are clustered at the investor level * p<.10; ** p<.05; *** p<.01. Sample constrained on at least 2 partners observable for each fund

	(1) Frac. Top Quartile Novelty	(2) Frac. Top Quartile Novelty	(3) Frac. Top Quartile Novelty	(4) Frac. Top Quartile Novelty	(5) Frac. Top Quartile Novelty	(6) Frac. Top Quartile Novelty
Fund level breadth index PC 1	0.001 (0.003)		0.001 (0.003)	0.003 (0.005)		0.003 (0.005)
Fund level breadth index PC 2		-0.004 (0.004)	-0.003 (0.004)		-0.005 (0.006)	-0.004 (0.006)
Fund Size	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
Industry Controls	✓	✓	✓	✓	✓	✓
Stage Controls	✓	✓	✓	✓	✓	✓
Investor FE				✓	✓	✓
Vintage Year × FundType FE	✓	✓	✓	✓	✓	✓
Observations	2264.00	2264.00	2264.00	2264.00	2264.00	2264.00
R^2	0.12	0.12	0.12	0.53	0.53	0.53

Table A35: **Fund level Diversity and Novelty: Diversity measures using Principal Component Analysis** This table presents of an OLS regression of fund level diversity measures on the fraction of investments in top quartile novelty firms. The dependent variable Frac. Top Quartile Novelty is the fraction of investments in top quartile novelty firms. The independent variables Fund level breadth index PC 1, Fund level breadth index PC 2 are the first and second principal component respectively of a fund level breadth index constructed using (1) Job Category ratio: the ratio between distinct job categories held by all partners in the fund and the total number of past employment spells of all partners in the fund, (2) Job industry ratio: ratio between distinct industries worked in by all partners in the fund and the total number of past employment spells of all partners in the fund, (3) Job Role ratio: ratio between distinct job roles held by all partners in the fund and the total number of past employment spells by all partners in the fund, (4) Educational diversity index at a fund level: which is the exponential of the Shannon entropy computed using the fraction of partners with a given educational degree (STEM education, Social Science or Humanities Education, MBA degree, PhD degree or Medical degree), (5) Gender diversity index at a fund level, which is the exponential of the Shannon entropy computed using the fraction of partners with a given gender (Male or Female). Fund Size is the AUM of the fund. All columns include Industry Controls, which are separate controls for the fraction of investments made by the fund in each industry sector. All columns include Stage Controls, which are separate controls for the fraction of investments made by the fund in each investment Stage. All columns include Vintage Year × Fund Category fixed effects. Standard errors reported in parenthesis are clustered at an Investor level * p<.10; ** p<.05; *** p<.01. Sample constrained on at least 2 partners observable for each fund

	(1) Fraction of Major Success exits	(2) Fraction of Major Success exits	(3) Fraction of Major Success exits
Frac. Top Quartile Novelty	0.121** (0.049)	0.142*** (0.046)	0.128*** (0.049)
Fund level breadth index PC 1	0.015* (0.008)		0.015* (0.008)
Frac. Top Quartile Novelty × Fund level breadth index PC 1	-0.032 (0.033)		-0.032 (0.034)
Fund level breadth index PC 2		0.007 (0.008)	0.009 (0.008)
Frac. Top Quartile Novelty × Fund level breadth index PC 2		-0.036 (0.035)	-0.037 (0.036)
Frac. Top Quartile Novelty			0.000 (.)
Industry Controls	✓	✓	✓
Stage Controls	✓	✓	✓
Investor FE	✓	✓	✓
Vintage Year × FundType FE	✓	✓	✓
Observations	2264.00	2264.00	2264.00
R^2	0.60	0.60	0.60

Table A36: **Fund level Diversity, Novelty and Performance: Diversity measures using Principal Component Analysis** This table presents of an OLS regression of fund level diversity measures computed using principal component analysis. The dependent variable Fraction of Successful Exits is the fraction of deals that have achieved an exit via IPO or high value acquisition (an acquisition with a value of at least five times greater than the total VC amount invested in the company). The independent variable Frac. Top Quartile Novelty is the fraction of investments in top quartile novelty firms. The independent variables Fund level breadth index PC 1, Fund level breadth index PC 2 are the first and second principal component respectively of a fund level breadth index constructed using (1) Job Category ratio: the ratio between distinct job categories held by all partners in the fund and the total number of past employment spells of all partners in the fund, (2) Job industry ratio: ratio between distinct industries worked in by all partners in the fund and the total number of past employment spells of all partners in the fund, (3) Job Role ratio: ratio between distinct job roles held by all partners in the fund and the total number of past employment spells by all partners in the fund, (4) Educational diversity index at a fund level: which is the exponential of the Shannon entropy computed using the fraction of partners with a given educational degree (STEM education, Social Science or Humanities Education, MBA degree, PhD degree or Medical degree), (5) Gender diversity index at a fund level, which is the exponential of the Shannon entropy computed using the fraction of partners with a given gender (Male or Female). Fund Size is the AUM of the fund. All columns include Industry Controls, which are separate controls for the fraction of investments made by the fund in each industry sector. All columns include Stage Controls, which are separate controls for the fraction of investments made by the fund in each investment Stage. All columns include Vintage Year × Fund Category fixed effects. Standard errors reported in parenthesis are clustered at an Investor level * p<.10; ** p<.05; *** p<.01. Sample constrained on at least 2 partners observable for each fund

	(1) Novelty (Distance to Closest Firm)	(2) Novelty (Distance to Closest Firm)	(3) Novelty (Distance to Closest Firm)	(4) Novelty (Distance to Closest Firm)
HHI (Past Investments)	0.457**	0.414	0.645*	1.031
	(0.228)	(0.399)	(0.377)	(1.112)
Deal Diversity (Past Investments)	4.116***	1.382	3.551**	2.199
	(0.788)	(1.650)	(1.406)	(4.533)
VC Experience	0.036	-0.110	0.251**	-0.154
	(0.063)	(0.131)	(0.108)	(0.293)
Industry × Deal Year × Deal Type × Country FE	✓	✓	✓	✓
Investor FE × Deal Year FE		✓		✓
Observations	20083.00	20083.00	7607.00	7607.00
R^2	0.40	0.61	0.36	0.67

Table A37: **Association between lead partner's experience acquired from past deals financed and focal startup novelty** This table reports the results of an OLS regression of deal novelty and measures of lead partner's experience acquired through past financed deals. The dependent variable Novelty (Distance to Closest Firm) in columns (1)-(4) is a deal level measure of novelty defined as one minus the maximum of the cosine similarity of the textual description of the startup financed in the deal and all startups receiving venture capital financing within five years before the deal in the same deal stage. The independent variable HHI (Past Investments) is a Herfindahl-Hirschmann industry specialization measure based on the lead partner's past investments. The independent variables Deal Diversity (Past Investments) is a measure of diversity of past deals financed computed as the average cosine distance between ventures financed by the partner before the focal deal. VC experience is a variable defined as the logarithm of one plus the number of deals financed by the lead partner prior to current deal. Columns (1) - (4) include Industry × Deal Year × Deal Type × Financed Company Country FE. Columns (2) and (4) also include Investor × Deal Year FE. Standard errors reported in parenthesis are double clustered at an Investor and Financed Company level. * p<.10; ** p<.05; *** p<.01.

	(1) Novelty (Distance to Closest Firm)	(2) Novelty (Distance to Closest Firm)
Breadth Index	0.356*	1.434**
	(0.209)	(0.706)
HHI (Past Investments)	0.447	2.614*
	(0.640)	(1.522)
Deal Diversity (Past Investments)	-2.116	-8.991
	(2.597)	(10.418)
VC Experience	0.122	0.456
	(0.309)	(1.038)
Partner Industry Experience	0.018	0.805
	(0.388)	(0.675)
Controls	✓	✓
Industry × Deal Year × Deal Type × Country FE	✓	✓
Investor FE × Deal Year FE × Partner Entry Year FE		✓
Observations	5909.00	5909.00
R^2	0.59	0.75

Table A38: **Association between lead partner's human capital breadth index and startup novelty controlling for on the VC job experience** This table reports the results of an OLS regression of deal novelty and lead partner's human capital breadth with additional controls related to on the VC job acquired experience. The dependent variable Novelty (Distance to Closest Firm) in columns (1)-(2) is a deal level measure of novelty defined as one minus the maximum of the cosine similarity of the textual description of the startup financed in the deal and all startups receiving venture capital financing within five years before the deal in the same deal stage. The main independent variable Breadth Index is a measure of human capital breadth which is defined as the first principal component of a PCA from 4 individual human capital breadth proxies: 1) The ratio of distinct job categories to total employment spells 2) The ratio of distinct job roles to total employment spells 3) The ratio of distinct industries worked in to total employment spells 4) Educational breadth count. The independent variable HHI (Past Investments) is a Herfindahl-Hirschmann industry specialization measure based on the lead partner's past investments. The independent variables Deal Diversity (Past Investments) is a measure of diversity of past deals financed computed as the average cosine distance between ventures financed by the partner before the focal deal. VC experience is a variable defined as the logarithm of one plus the number of deals financed by the lead partner prior to current deal. Columns (1) include Industry × Deal Year × Deal Type × Financed Company Country FE. Column (2) includes Investor × Deal Year × VC Partner Entry Year FE. All columns include individual level partner controls: age, sex and ethnicity. Standard errors reported in parenthesis are double clustered at an Investor and Financed Company level. * p<.10; ** p<.05; *** p<.01.