The Broader Impact of Venture Capital on innovation:

Reducing information frictions through due-diligence[1]

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Most research on venture capital (VC) focuses on VCs' value-add to their portfolio companies. We explore VCs' broader value-add on the companies they do not fund, specifically as a by-product of their due diligence. We use novel data from a seed Fund that assigns applicants to due diligence based on the scores of quasi-randomly assigned reviewers. We find that assignment to due diligence leads to higher growth, but also increased closure, even among applicants rejected for investment. The results suggest that VC due diligence helps entrepreneurs reduce their information frictions, possibly by enabling entrepreneurs to learn about their business.

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Over the last seven decades venture capital (VC) has spread globally, especially in innovation clusters around the world, including London, Shanghai, Silicon Valley, and Tel Aviv (Mallaby, 2022; Klingler-Vidra, 2018). Like the phenomenon it studies, research on how VCs contribute to innovation has also expanded during this period. The main thrust of the research has focused on the relationship between VCs and their portfolio companies—the companies in which they invest (Lerner and Nanda, 2020). Existing work shows that VCs provide "smart money" to companies that might otherwise have difficulty attracting financing, for example, by providing support[2], connections[3] and certification[4] that enable company growth.

In this paper, we pursue a new line of inquiry on the impact that VCs have on non-portfolio companies, that is, the wider ecosystem of companies they do not fund. We are motivated by the observation that modern VCs spend significant resources closely interacting with companies outside of their investment portfolios, specifically while conducting due diligence. Due diligence comprises the multi-stage process that VCs use to assess companies for potential investment; it includes the "evaluating and selecting" activities performed after the initial screening for fit with the fund's mandate, as described by Gompers, Gornall, Kaplan, and Strebulaev (2020).[5] Extensive due diligence is now key as VC has evolved from a cottage industry into a highly competitive asset class using sophisticated due-diligence approaches to allocate capital, rather than relying on personal connections and "hunches." (Chernenko et al., 2020; Mallaby, 2022). To be sure, for every company in which they invest, VCs nowadays typically consider 100 applicants and conduct due diligence on approximately 30 (Gompers et al., 2020).

While prior research has shown the importance of due diligence as a driver of VC returns (e.g., Cumming and Zambelli, 2016), our novel premise is that due diligence can also add value to companies, even those they ultimately reject for investment. As VCs conduct due diligence to screen out low return projects, they ask questions, listen to pitches, and engage in discussion to learn more about the "horse" and the "jockey", that is, the business and the entrepreneurs (Kaplan, Sensoy, and Stromberg, 2009). As a by-product, due-diligence can help entrepreneurs reduce their information frictions that constrain project growth. For example, due diligence can provide high-stake learning opportunities for entrepreneurs to acquire information about their business (e.g., project's return—in a similar sense as in the learning models of Jovanovic (1982) and Bergemann and Hege (1998)). Due diligence can also

[2] See the work on how VCs provide support to portfolio-companies through advice and monitoring: Lerner, 1995; Casamatta, 2003; Dessi, 2010; Bernstein et al., (2016).

[3] The papers showing that VCs provide entrepreneurs with access to professional networks include: Gorman and Sahlman, 1989; Sahlman, 1990; Hellmann and Puri, 2002; Hochberg, Ljungqvist and Lu, 2007; Lindsey, 2007; Gonzalez-Uribe, 2020.

[4] The work arguing that VCs' decision to start and continue financing a company acts as a credible signal of company's prospects to uninformed market players like investors and clients include: Megginson and Weiss, 1991 and Li, Liao, Wang and Xiang, 2020.

[5] This definition of due diligence reflects the understanding that industry analysts such as PitchBook use to describe the numerous interactions between ventures and external sources to assess potential businesses for investment. See https://pitchbook.com/blog/due-diligence-checklist-for-vc-pe-and-ma-investors.

reduce information frictions by connecting entrepreneurs with VCs' networks and certifying the company's quality to other potential investors.

However, in practice it is not a given that VCs' due-diligence should add-value by reducing information frictions, or increase efficiency. Due diligence could actually increase rather than decrease information frictions if entrepreneurs learn how to "window-dress" (e.g., manipulations to suggest improved performance) rather than make substantive business changes, potentially leading to capital misallocation (Clingingsmith and Shane, 2018; Cusolito, Dautovic and McKenzie, 2021; Lyonnet and Stern, 2022). Moreover, entrepreneurs (especially those that are rejected for investment) may not take advantage of due-diligence to learn, because they are (or become) "overconfident" (e.g., they have an overly precise prior about their own quality and therefore are not responsive to informative signals; Bergemann and Hege, 2005; De Meza, Dawson, Henely and Arabsheibani, 2019; Landier and Thesmar, 2009). Finally, in the absence of information frictions, due diligence should add no value to companies, as entrepreneurs would already know about their projects' returns and effectively convey this information to the market.

Empirically determining whether VC due diligence affects the growth of non-portfolio companies is challenging. Observing the companies that engage in due diligence but do not ultimately obtain investment is rare as there are no public records of the companies applying for VC (see, for example, Kaplan and Lerner, 2016). Moreover, tracking venture growth is difficult, as many companies that attempt to obtain VC funding never manage to raise financing or have publicly available production records. Finally, selection for due diligence is endogenous, since VCs decide to conduct due diligence based on several observable and unobservable factors. Comparing the growth of companies selected for VC due diligence with those that are not may yield biased estimates of due diligence effects if VCs select the companies with the highest growth prospects.

To overcome these empirical challenges, we partnered with a VC seed fund in the United Kingdom (hereafter "the Fund") focusing on software. The Fund is representative of other seed funds that are increasingly prevalent in innovation ecosystems (Lerner and Nanda, 2020). Our data comprises nearly 2,000 ventures applying for seed investment from the Fund. To measure and track venture growth, we draw on administrative UK balance sheet data, which we combine with data from web sources. For identification, we exploit the Fund's process of screening applicants for due diligence. This process features the quasi-random assignment of each application to three reviewers who can vary in how generously they score applicants.

Through this empirical strategy, we find evidence that VC due diligence can be a positive driver of venture growth even for non-portfolio companies. We find that assignment to due diligence leads to significant increases in venture growth within two years of application even after we exclude portfolio companies. We measure venture growth through several intensive-margin proxies, including fundraising, employment, asset growth, and the number of technologies used to build and test products (e.g., the "tech stack"). In terms of economic magnitude, our most conservative estimates imply that assignment to due diligence increases venture growth within two years of application by an average of 22% across growth proxies. Notably, we find the opposite result at the extensive margin growth: due diligence assignment reduces the chances of business continuation by 11% among non-portfolio companies, a 12% decrease relative to the average continuation in the sample. Collectively, the results suggest that assignment to due diligence, in its own right, impacts venture performance. Results are robust to different specifications and multiple robustness checks.

Taken together, the findings are more supportive of the hypothesis that VCs' due diligence helps mitigate the information frictions that impede ventures' growth, possibly by enabling entrepreneurs to learn about their business. Learning is consistent with the results on closure (Howell, 2021), and the changes in tech-stack—a strong indication that the Fund's due diligence led to changes in the operations of the startup—which we show are not explained by fundraising. Additionally consistent with learning, we show that results are weaker when the Fund has a less precise understanding of the business as measured by the degree of disagreement across the venture's reviewers. Other complementary findings are also less consistent with the alternative explanations that (i) due diligence reduces information frictions by connecting and certifying companies, (ii) due diligence increases (rather than decrease) information frictions by leading to window-dressing, and, (iii) due diligence has no effect on information frictions because founders are (or become) overconfident. Therefore, while the lack of micro-data limits our ability to fully rule out alternative channels, the empirical patterns seem most consistent with VC due diligence reducing information frictions by enabling entrepreneurs to learn about their business.

The main implication of the results is that VCs have a broader impact on innovation than previously acknowledged. In addition to the value-add they provide to their portfolio companies; they also impact the wider pool of entrepreneurs they interact with during the due diligence process. A back-of-the-envelope calculation (based on our findings) points to the first-order nature of this broader impact: the size of the Fund's due diligence assignment effects on non-portfolio companies amount to roughly 40% percent (average across intensive-growth proxies) the size of the Fund's total investment effects on portfolio companies.

Although our setting allows us to mitigate challenges in estimating the value-add of VC due diligence, one important limitation is that our reliance on the quasi-experiment of the Fund potentially trades off external for internal validity for several reasons. The identification strategy measures the effect of due-diligence assignment for marginal Fund applicants, and it is possible that potential impacts are different differ for applicants who are not on the margin. However, we find little evidence of treatment heterogeneity using marginal treatment effects (Heckman and Vytlacil, 2005). Moreover, while our analysis provides rigorous evidence that VC due diligence *can* add value to non-portfolio companies, it has little to say about how systematic this value-add is across VC firms. Yet, our setting is representative of the seed-stage investment activity by blue-chip VC firms and new market players that, according to Crunchbase, increased by a factor of seven in the decade following the Global Financial Crisis, especially for non-deep-tech (e.g., software) businesses (Teare, 2021). Our results are therefore most likely to be applicable to other funds that, like the Fund, specialize in seed-stage investments, are recently established (so they have incentives to build reputations as value-add investors to attract higher quality deal flow) and do not specialize in deep-tech (which requires more specialized expertise).

Our findings contribute primarily to the literature exploring the information frictions that impede venture growth and the early-stage intermediaries who can help mitigate those frictions (Lerner and Nanda, 2020). González-Uribe and Leatherbee (2017) and González-Uribe and Reyes (2020) show evidence that entrepreneurs in developing countries have capabilities gaps and that business accelerators can help close them. In a series of papers, Howell shows that business plan competitions can help entrepreneurs mitigate information frictions by certifying winners (Howell, 2020) and by providing entrepreneurs with information on their relative performance vis-a-vis other participants (Howell, 2021). We contribute to this literature by showing how seed VCs provide entrepreneurs with high-stake opportunities to learn and improve their businesses, thus producing a positive externality for innovation ecosystems, by helping non-portfolio companies to mitigate their information frictions.

Our work also contributes to the literature on the VC industry. While this literature has focused on understanding the structure of investment agreements and post-deal activities, the process before the investment is much less understood. Ours is the first paper to investigate the broader effects of VC due diligence, an activity that takes place before investment and beyond portfolio companies. Our findings have important implications about understanding VC's role in the economy. They show that ventures' inability to interact with VCs through due-diligence have profound implications for growth, as such interactions can positively affect venture performance even when there is no investment. They complement the literature on the value-add of VCs to their portfolio companies (Lerner and Nanda, 2020) and their disproportionate contribution to the economy (Kortum and Lerner, 2000; Opp, 2019; González-Uribe, 2020; Gornall and Strebulaev, 2021). Our results also contribute to recent work articulating the potential costs of the increasingly popular "spray-and-pray" investment strategy at the seed stage, in which VCs spend more resources learning about the potential of many companies through due diligence at the cost of decreased monitoring post-investment (Ewens, Nanda, and Rhodes-Kropf, 2018). We put forward a potential silver lining: VC due diligence has a positive growth externality by boosting the performance of the larger pool of early-stage businesses going through this process.

Understanding the potential trade-off between VCs' value-add inside their portfolios and their value-add outside them appears to be a promising area for future research.

The remainder of this paper proceeds as follows. In Section 1, we describe two important trends in the VC industry: the rise of systematic assessment and the increasingly prevalent seed investment activity. In Section 2, we describe the context and data. We detail the empirical strategy and present the results in Sections 3 and 4, respectively. We discuss the interpretation of the results in Section 5, and the external validity of the findings and the implications in Section 6. We present robustness checks in Section 7 and offer concluding remarks in Section 8.

1. The VC industry in the 21st century and the due-diligence process

The VC industry has seen profound changes since its inception in the post-World War II era. Two important shifts have been the increase in investments in early-stage companies through seed funds dedicated to pre-Series A financing, and the concomitant systematization of portfolio selection based on scorecards and highly interactive due-diligence processes.

Venture capital has grown from a cottage industry in the 1960s to a global and highly competitive craft. Whereas traditional Silicon Valley funds such as Kleiner Perkins Caufield & Byers (KPCB), Accel, Index, and Sequoia used to rely on personal networks and their ability to assess successful founders based on their instinct, today's crowded market requires sophisticated approaches to capital allocation decisions that can reach a wider universe of founders. By using technology (e.g., AI) (Bonelli, 2022), systems (e.g., a scorecard), and interactive due diligence, VCs strive to mitigate the information frictions of investing in early-stage startups with little or no revenue, and even no product. Scorecards involve multiple team members rating companies for potential investment, which helps the VCs to identify the most promising companies for investment.[6]

In many ways, the transition of the VC industry since the 1960s has followed a similar trajectory to that of other sectors within the alternative investment space. The hedge fund industry, for instance, initially relied on naturally talented "stock pickers" and progressively expanded across asset types (from equities to debt, commodities, and currencies) while deploying more systematic and technologically fueled approaches (e.g., algorithmic trading). Like hedge funds, VCs face ever-greater competition (Chernenko, Lerner, and Zeng, 2020) to gain access to deals and secure equity stakes at more attractive valuations. In response, VCs have increased their investment in seed rounds to gain access (in the form of a "pro rata") to more and better-priced deals (Klingler-Vidra, 2016). According to Crunchbase, seed-stage deals increased by a factor of seven in the decade following the Global Financial Crisis (Teare,

[6] See, for example, this scorecard from Speedinvest, an early-stage VC fund: https://medium.com/speedinvest/why-we-have-created-a-scorecard-317355d1c046.

2021). Blue-chip investors like KPCB and Sequoia, who used to invest exclusively in the A and B rounds, when startups have already demonstrated product-market fit, have now launched funds aimed at investing in the seed, and even pre-seed, stage.[7]

In addition to traditional VC firms intervening earlier in the startup lifecycle, there has been a proliferation of seed funds by new investors focusing on this early and relatively more affordable stage. This reflects advances in technology, particularly the introduction of cloud computing, which has dramatically reduced the cost and time involved in creating businesses based on information and communications technology (ICT), and has led to increasingly inexperienced founders seeking VC financing (Ewens, Nanda, and Rhodes-Kropf, 2018). Other new intermediaries have emerged in early-stage entrepreneurial finance markets, including super angels and business accelerators, all seeking to sort through the noise of ventures looking for early-stage equity investment and gain early investment access to the most promising candidates.

The combination of these forces—advances in technology that lowered the costs of starting a business and the deluge of new global entrants to entrepreneurial finance—has meant that VCs are increasingly active at the seed stage. Moreover, given the increased competition, to raise funds from limited partners (LPs), VCs now need to demonstrate that their deal filtering approach is systematic and replicable. To do this, they pitch the systems they have built to manage their deal pipeline, including deal sourcing, screening, and rigorous evaluation, to prospective LPs. This includes customer relationship management (CRM) technology to track founders and web-scraping to identify potential startups, as well as proprietary scorecards to systematically evaluate startups' numerous attributes.

Once a company is selected for due diligence, VCs begin an intense and highly interactive process in which they ask tough questions of founders, propose alternative theses, and "kick the tires" of the technology. The due-diligence process is typically guided by a platform or spreadsheet that underpins the questions they ask of each startup (see Appendix 5). In asking these questions across a series of meetings with the founders, the VCs seek to overcome information frictions in two main areas: the "horse" and the "jockey", that is, the business and the entrepreneurs (Kaplan, Sensoy, and Stromberg, 2009). In terms of the business, VCs need to assess the potential for startups to successfully serve a large market and execute the scaling of their product. They also ask questions to learn more about the entrepreneurs, including their education, work experience, and co-founders' complementarity. Seed-stage investors are said to invest in the team, not the product, because of the high likelihood of a change in the business model (e.g., a "pivot") (Bernstein, Korteweg, and Laws, 2017).

[7] The following are links to Techcrunch articles on recent seed fund launches by traditional VCs: Accel; Andreesen Horowitz; Index; KPCB.

Entrepreneurs are not passive bystanders in the due-diligence process: organizing business materials for presentations can set in motion learning-by-doing processes. Responding to tough questions can force useful introspection, alternative theses can lead to pivots, technology testing by informed investors can reveal flaws as well as opportunities and interacting with VCs can lead to expanded connections and visibility. Therefore, our hypothesis is that a by-product of VCs due-diligence process is the mitigation of *entrepreneurs'* information frictions that constraint their growth. However, in practice it is not obvious that a VC's due diligence process should add value to entrepreneurs by reducing information frictions. For one, due diligence could actually increase information frictions. For example, if low quality entrepreneurs learn how to "window-dress" their businesses (like presenting it better, or outward lying about what VCs want to hear about), rather than undergoing substantive operational change. Selection for due diligence could also lead founders to become "overconfident" and underweight other more informative signals. Finally, in the absence of information frictions, there should be no due-diligence effects on venture growth. Therefore, whether due diligence helps entrepreneurs reduce information frictions is an empirical question, and one that we tackle in this paper by focusing on the novel setting we now describe.

2. Empirical setting

2.1. The Fund

The Fund is a seed fund managed by a UK-based VC firm established in November 2016; it began to invest in portfolio companies in March 2017.[8] The Fund's investment check size is on average between $500K and $1.5M, which attracts early-stage businesses seeking to raise seed capital.[9] The Fund specializes in investing in the software sector, broadly defined. It is business-model agnostic within that sector, predominantly covering sales engine and platform businesses and, to a lesser extent, deep technology.

As is increasingly common among VC funds investing at the seed stage, the Fund does online deal sourcing, relying on an online platform to receive applications. This, the Fund contends, helps to democratize access to VC financing by offering an open platform for application rather than entrepreneurs having to rely on social networks to obtain an introduction. By November 2019, the Fund had received nearly 2,000 online applications as it reached the end of the period in which it was making new investments. We have all application data for this entire period in which new investments were made. While we cannot provide specific details of applicants to the Fund, examples include companies

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[8] The Fund shared their data with us under a non-disclosure agreement which prevents us from sharing more specific details about the setting.
[9] The average seed-stage investment in Europe was $1.9M in 2021, and the average seed-stage investment in the UK was £0.57M in 2019. See reports by the British Venture Capital Association.

seeking to advance the use of biometric data in security measures and to enable desk management in collaborative workplaces.

Like other seed funds, the Fund uses a systematic approach—explained in more detail below—to screen applicants for due diligence. Figure 1 shows the Fund's selection funnel. By November 2019, roughly 30% of applicants had been assigned to due diligence, but only 0.6% had secured funding from the Fund. The contours of this funnel are broadly consistent with those of other VCs: for every 100 companies seeking investment, 30 advance to due diligence, and only one ultimately receives funding (Zider, 1998; Gompers et al., 2020).

2.2. Application data

The Fund provided us with all the application data, including reviewer assessments and the final selection decisions for each applicant. Our sample consists of all the 1,953 applicants seeking capital from the Fund between March 2017 and November 2019. Figure 2 shows the number of applications made per month, which peaked at 140.

Based on the applications, we constructed several variables to use as controls in our empirical strategy: applicant's location, age of the company at the time of application (relative to incorporation date), target amount to raise, funding stage (pre-seed, seed, or post-seed), business type (sales engine, platform, deep technology), and founders' personal characteristics, including gender and education. Table 1 reports summary statistics for the main variables in the application forms. On average, applicants had been incorporated for 2.61 years at the time of application and aimed to raise £1.69M. In terms of gender, 13% of applicant businesses had at least one female founder. Figure 3 shows the location, stage, and business type breakdown: 44.14% were in London, 44.29% were at the seed stage, and roughly half were categorized as sales engine businesses and half as platform businesses, with only a small proportion of applicants in deep technology. The average number of founders per company was 1.94.[10]

Although self-selection of companies applying for funding online could suggest a degree of sophistication of the ventures in our sample, which could possibly lead to positive subsequent development, other factors may lead to a negative self-selection bias. For example, companies with founders with prior VC fundraising and exit experience are less likely to apply for funding through an online platform because they can reach out to networks of previous investors. Consistent with this idea, we show that applicants to the Fund are comparable to the average company securing seed financing in the UK but appear smaller at the median. We collect data from Crunchbase and Preqin on all companies in the ICT sector that raised seed funding in the UK in 2019, and look for information on their asset

[10] This information is sourced from Crunchbase. We found 1,178 ventures and 2,286 founders, so the average number of founders per startup is 1.94 (=2,286/1,178).

size in the UK's business registry, Companies House (CH).[11] We retrieved the CH data about UK companies' detailed information from FAME of BvD (Bureau van Dijk). The average asset size for companies securing seed financing in the UK is £492K, which is slightly smaller than the average in our sample of £641K. However, at the median, our applicants look much smaller, with £23K in assets, relative to an asset size of £184K for the median company that secured seed funding in the UK in 2019.

2.3. Outcome data

We use two complementary strategies to collect outcome data for the Funds' applicants. First, we collect administrative data for applicants incorporated in the UK, which captures the great majority (80%) of ventures applying to the Fund. Access to administrative data on a venture-specific basis represents a significant advantage relative to most other work in the VC literature (Kaplan and Lerner, 2016). These data come from CH and include information on survival, annual equity issuance and assets. The registry includes this information because UK ventures submit mandatory annual abridged financial accounts. Using these data, we track annual outcomes for each applicant after their application to the Fund, which covers the very earliest applications (2017) to the time of data collection (2020). Because the midpoint of the application dates is in 2018, and the latest administrative records were extracted in 2020, all outcomes measure growth within an average of 1.93 years since application.

We construct the following outcome variables from CH filings: log equity issuance, log growth in assets and company survival. Survival is an indicator variable that equals 1 if the company did not file for liquidation, closure, or dormancy after application by 2020. We have no data on profits, revenue or employment, as smaller companies, like those in our sample, are exempt from reporting more detailed financial information.

Our second strategy for collecting growth data follows the standard practice in the VC literature of using web sources like Crunchbase and LinkedIn, as these sites' coverage is likely to be better for seed-stage companies with no institutional investors relative to later-stage data vendors like Preqin or VentureSource (González-Uribe and Reyes, 2020). We construct the following outcome variables: funding, number of employees, number of funding rounds, and number of investors after the application. We can cover all applicants using this method, rather than UK businesses only as in the first method, since the latter only relied on company data reported to the UK government. Notably, we also extract more novel web-based data on startups' technology adoptions and "A/B testing" (of a web application) from BuiltWith, an analysis platform for web technologies (see Koning, Hasan, and

[11] According to Crunchbase and Preqin, a total of 257 companies in the information and technology sector raised seed funding in the UK during 2019. We matched 169 of them by name and location to companies that reported total assets to CH in 2018.

Chatterji (2019)).[12] The information on A/B testing is limited to platform companies, explaining the reduced number of observations.[13]

We also collect founders' educational backgrounds and previous work experience from their LinkedIn profiles whenever available and triangulate this information with details of co-founders' work experience on their Crunchbase webpages.[14] Based on literature on the role of university-derived social networks in entrepreneurial growth and VC fundraising (Klofsten et al., 2019), we code whether founders have completed tertiary education (e.g., a bachelor's degree) at an elite university. Because most of the applicants in our sample are UK companies, we operationalize elite university according to the Russell Group (e.g., top 20 UK universities) and the "Golden Triangle" (Oxford, Cambridge, UCL, LSE, and Imperial). We also code and group universities according to 2020 global rankings, including Times Higher Education (THE) and Academic Ranking of World Universities (ARWN).

Taken together, our collected data comprise information on funding from both administrative (CH) and web (Crunchbase and LinkedIn) sources for applicants in the UK. However, we note that the two sets of variables are not directly comparable for several reasons. The administrative data include equity sources other than specialized financing, for example, equity capital from family and friends. In contrast, the Crunchbase data mainly include investments made by specialized financiers like angels, VCs, and private equity, as well as exit events (e.g., IPOs or acquisitions). Furthermore, any rounds involving the use of convertible instruments are not recorded as equity issuance (until conversion) in CH but rather as debt (see González-Uribe and Paravisini, 2018). Information from the two sources also possibly capture different periods post-application. While Crunchbase data are updated continuously, companies file yearly administrative data asynchronously, implying that for some applicants we have only one filing post-application.

Table 1 reports summary statistics of the outcome variables. The average (median) value of assets post-application is £1,066K (£86K). The average survival rate and average number of investors post-application are 0.81 and 1.02, respectively. After application, the average (median) total funding and equity issuance are £1,330K (£0) and £770K (£0), respectively. The average number of employees is

[12] 1,526 (1,284) out of 1,953 applicants adopted new technologies after (within 12 months of) the application date. In unreported analysis, we also collected information from Product Hunt, but we find no evidence of any effects. The vast majority of our companies do not launch products through a website (114 of them do; 26 launched at least one product within 12 months of the application date).

[13] Following Koning, Hasan, and Chatterji (2019), our final set of A/B testing technologies includes the following tools: AB Tasty, Adobe Target Standard, Experiment.ly, Google Optimize, Google Website Optimizer, Omniture Adobe Test and Target, Optimizely, Optimost, Split Optimizer, and Visual Website Optimizer.

[14] We extract higher education backgrounds for 1,981 founders who provide their education information on LinkedIn webpages. We then combine 1,801 founders' working experience from LinkedIn pages and 2,092 founding team members' work experience from their Crunchbase personal webpages.

6.09, and the average number of (before fundraising post-application) technology adoptions and A/B testing is 15.83 (13.81) and 0.80 (0.67).

As is common among early-stage ventures, outcome variables are highly skewed. Therefore, for most of the analysis we rely on logarithmic transformations of the variables (after adding 1) to implement the regressions. As we discuss in Section 6 on robustness checks, results are generally robust to using Poisson models based on untransformed variables (see Cohn, Liu, and Wardlaw, 2022).

2.4. Due-diligence assignment

The Fund uses a two-step process to classify applicants into three categories. The first category comprises applicants assigned to due diligence; 31.5% fall into this group. The second category (64.5%) are applicants the Fund will not consider for investment but still invites to an informal meeting. The final category (4%) are applicants the Fund does not consider venture-backable and are therefore not invited to meet, even informally. We now explain the process used by the Fund to classify applicants into these categories.

2.4.1. Reviewer assignment

The first step in the due-diligence process is the assignment of three reviewers to each applicant. Reviewers are internal to the Fund and may be managing partners (4 out of 12), partners (4 out of 12), or associates (4 out of 12).[15] There are 12 reviewers in the data, including three women. The average (median) number of applicants assessed by a single reviewer is 488 (553), and the minimum (maximum) is 29 (795). Therefore, the data can be characterized as having relatively few reviewers, with each reviewer evaluating a relatively large number of applications. Appendix 1 details the distribution of applications across reviewers and reviewer trios.

The assignment of applications to reviewers is done using proprietary software developed by the Fund for collaborating and managing spreadsheet-like inputs.[16] The software assigns case numbers to applications and classifies them according to the location of the business. There are 16 regions in total, following the delineation of countries (England, Wales, Scotland and Northern Ireland), the nine regions

[15] The compensation of the Fund's staff is not directly tied to their reviews. In addition, prior to our work, the Fund had not conducted any internal analysis of their selection process. All investors have "carry" (carried interest, or a share in the profits), with the managing partners (who form the Investment Committee) having a greater share of carry. The carry structure suggests that staff are unlikely to disregard reviewer duties. Moreover, the three-reviewer system provides incentives for judicious assessment: as explained in more detail in this section, one reviewer acts as the Investment Lead and collates the scores, meaning that each reviewer's scoring of a given applicant is seen by at least one other member of the Fund (if the reviewer is not the Investment Lead). We exclude scores provided by trainees and temps, which do not count toward the Fund's selection decisions.

[16] Initially, the Fund used Zapier to manage reviewer allocations, but eventually developed a proprietary software application for this task.

comprising England[17], plus the Fund's determination of a further breakdown to best reflect local entrepreneurship clusters and non-UK applicants. The software automatically assigns three reviewers to each applicant based on location and reviewers' workload (staff can be taken off the review assignment temporarily if they go on holiday or are busy with other tasks, like completing other funding deals). In addition, the system prioritizes allocations to reviewers that have a regional focus relevant to the applicant's location; 6 of the 12 reviewers have a regional focus and act as Investment Leads for specific regions, which can vary from single cities (e.g., Cambridge) to larger areas (e.g., Southwest of England). Most regions (10 out of 16) have at least one designated Investment Lead. However, a "regional focus match" between applicants and reviewers is neither sufficient nor necessary for an assignment. See Appendix 1 for more details.

The software also determines who among the three assigned reviewers will be the Investment Lead. The Investment Lead oversees the work of the other two reviewers and ensures that they complete their reviews within the Fund's 24-hour turnaround goal. The Investment Lead then collates the reviewers' assessments and communicates the initial screening decision to the applicant, as we explain in more detail in Section 2.4.3. The software prioritizes assignment of the Investment Lead role in line with the company's region, but due to availability constraints, this regional match is not always possible.

The other two reviewers in the trio cannot see their co-reviewers' assessments via the review software, though it is possible that they learn about it through other means; we discuss how to address this possibility in Section 3 on methodology. From a practical perspective, it is worth noting that the reviewers do not share office space, which lowers the probability of coordinating reviews, as the Fund chose early on not to have a permanent office. Instead, their intention is to "be on trains" around the country so they can have a consistent presence and network outside London, and their organizational model involves a combination of working from home and hot-desking in various co-working spaces.

The automated reviewer assignment system means that the Fund does not assign applicants to reviewers based on any application characteristics other than location (on which we can condition). The Fund aims to balance the potential selection advantages of reviewer specialization, in terms of regional focus, with the potential bias reductions of arbitrary and multiple assessments. One key conclusion from this institutional context is that random assignment of applications to reviewers conditional on location is plausible. Consistent with this, we show in Appendix 1 that conditional on location, the sample of applicants is balanced across reviewers, meaning that they are well-distributed among reviewers after accounting for regional focus.

[17] North East, North West, Yorkshire and The Humber, East Midlands, West Midlands, East of England, London, South East, South West.

2.4.2. Reviewers' scores and heterogeneity in scoring generosity

Each reviewer evaluates the application and provides a score and optional screening comments using the Fund's software. Scores are discrete numbers ranging from 1 to 4, where 4 is best. Scores are not shared with applicants, but they are a crucial input for due-diligence assignment, as we explain below. There is substantial scoring heterogeneity across reviewers. Below we summarize the results from our methodology to showcase this heterogeneity. Full details are presented in Appendix 2.

We construct a dataset with reviewer scores as the unit of observation (three observations per applicant) and regress the scores against applicant and reviewer fixed effects with controls for location. We refer to the estimated applicant fixed effects as adjusted scores throughout. They proxy for the applicants' potential is perceived by reviewers at the time of application (see González-Uribe and Reyes, 2021).

Appendix 2 shows that we strongly reject the hypothesis that the reviewer fixed effects are the same (p-value<0.01). This result is consistent with the heterogeneity across reviewers in what we refer to as their "scoring generosity". In terms of economic magnitude, more generous reviewers are twice as likely to provide a score of 3 or 4 relative to stricter reviewers (as measured in terms of positive and negative reviewer fixed effects, respectively). We run several checks to make sure that the heterogeneity tests are not spurious, using the methodology from Fee, Hadlock, and Pierce (2013).

Appendix 2 also shows two important characteristics of reviewers' scoring generosity. First, it is unrelated to applicants' observable pre-application characteristics, as is consistent with the quasi-random assignment of reviewers. Second, it is also unrelated to reviewers' skill in selecting applicants. We rank each reviewer's applications according to their scores and separately according to subsequent growth. We measure skill as the correlation between these two ranks. The relation between generosity and skill is nil (–0.039; p-value=0.642) across reviewers, albeit with the caveat that the correlation is estimated with only 12 observations corresponding to the reviewers in the sample.[18] In unreported analysis, we establish that the scoring generosity is also unrelated to reviewer characteristics like gender, geographical focus, or seniority (as measured by job designation: founding/managing partner, partner, or associate).

2.4.3. Aggregation of scores: Selection rules

The second step in the selection process is the aggregation of the reviewers' scores according to predetermined selection rules that vary with time and location. Before May 2018, the Fund used the same selection rule for applicants headquartered in any location. During their first annual review, however, the Fund changed the selection rule in response to internal discussions regarding its

[18] This is not to say that reviewers are not skilled at discerning applicants' potential; see Section 4.1.

investment mandate. Senior partners perceived a need to treat entrepreneurs located outside London differently, to improve their chances of making it to due diligence and ultimately to investment. The partners' perception was that UK VC money chases too few deals outside of London, given the inconvenience involved in scrutinizing potential deals in other cities. Therefore, talented entrepreneurs outside the capital remain underserved, which echoes the well-known local preference of VC investors (Lerner, 1995; Bernstein, Giroud and Townsend, 2016). Beginning in May 2018, therefore, applicants from London faced a stricter selection rule than others.

Figure 4 shows the selection rules for all the potential combinations of scores for the three distinct selection regimes: (1) pre-May 2018, (2) post-May 2018–London, and (3) post-May 2018–Outside London. To illustrate the workings of a selection rule, consider the post-May 2018–London scenario (a startup based in London applying for funding after May 2018). The selection rule in that regime is the so-called "Champion Model" (Malenko et al., 2021), where the Fund only assigns to due diligence those applicants who received a score of 4 from at least one reviewer. Any other combination of scores does not lead to due-diligence assignment, even for score combinations with equal average scores but without a 4. For example, a score combination of {1 2 4} has the same average score (2.33) as the combinations {1 3 3} and {2 2 3}, yet neither alternative score combination leads to due-diligence assignment under the post-May 2018–London regime. We note too that the only combination of scores that leads to no meeting is {1 1 1}. The Fund considers companies with such a score combination as not venture-backable. Reasons for this include the smallness of the target market, the insufficient sophistication of the business, and/or the lack of technological talent (e.g., outsourcing the chief technology officer function).

Figure 5 shows the distribution of score combinations across distinct selection rule regimes. There are two main takeaways from the figure. First, specific scores are popular regardless of the regime—for example, {2 2 2} is always the most popular score across regimes. Second, the distributions of score combinations in the three regimes are similar, even though the selection outcome (due diligence, informal meeting, or no meeting) for specific scores varies across regimes. The pattern in the plot thus suggests that the scoring behavior of reviewers is independent of the selection rule. Kolmogorov–Smirnov tests show that there is no significant difference in the scores' distributions between applications before and after the change in selection rules, nor between London and non-London applications (see notes to Figure 5). We note that this pattern is not mechanical, as reviewers are aware of the selection rules. Rather, the pattern is likely a manifestation of the persistence of the underlying heterogeneity in scoring across reviewers, which is discussed in Section 2.4.3.

The Fund is strict on rule compliance: no informal meeting ever led to due diligence. The informal meeting is considered a gesture of good will, and not a path to investment. The Fund does accept reapplications, but they are rare: only 129 companies (6.6% of the sample) applied again. We only keep the first application in our sample and can confirm that all those who received "no meeting" or "informal meeting" in their first application did not later move to "due diligence" in their second application.

2.4.4. Communication with applicants

After aggregating the reviewers' scores, the Investment Lead communicates the screening result to applicants via email, follows up, and, if applicable, holds the first meeting with the founders. The Fund uses three standardized email templates; see Appendix 4 for full transcripts. The wording used in the emails is precise about the application's result, whether the founders get to meet the Investment Lead, and the expectations for that meeting. No email includes individual or average scores, or the names of the reviewers. While the Investment Lead signs the email, the applicants are unaware that the signer is part of the reviewing team. No email template includes any details on the selection rules (which are also not available online or shared outside the Fund). Finally, all templates include all the reviewers' screening comments. As the Fund explained to us, the Investment Lead uses one of the templates to compile a "top-and-tail" message to the founder(s) that contains standard text above and below the three reviewers' screening comments, which are included in the body of the message without being edited.

2.4.5. Reviewers' screening comments

Reviewers' screening comments play no independent role in due-diligence assignment—only reviewers' scores determine whether an applicant is selected for due diligence or not (see Section 2.4.4). Not all application responses have comments (159 have none), yet the majority have comments from all three reviewers (88% or 1,727/1,953).[19] Eleven of the 12 reviewers wrote screening comments for at least one application. On average, each reviewer wrote comments for 88.72% of the applications he/she was assigned. Screening comments are usually short, with a mean length of 55 words (roughly two sentences), and a maximum length of 130 words.

Given that comments are recorded for the purpose of screening, they usually focus on assessments of the company's fit with the Fund's investment mandate, rather than of the startup's quality. Examples include: "*This looks like a wonderful initiative. I fear that the market size for the venture and revenues in 5 years just make it hard to VC fund. It can be a very good small business. I don't see a large enough demand for this to make it a big market. This looks way too small for us*." Many comments relay a popular refrain in early-stage VC investing, namely, that the investment opportunity is "too early for us"—a polite way of saying that the Fund is not interested without saying much about the startup.

[19] In unreported robustness checks, we show that results are similar if we restrict the sample to applicants with comments from all three reviewers.

Two important questions pertain to reviewers' screening comments. First, do more generous reviewers provide different types of screening comments? If so, generosity may not only affect growth through its effect on due-diligence assignment but also possibly through comments' effects. However, we detect no significant difference in the types of screening comments across reviewers who demonstrate different levels of generosity, as we explain in detail in Appendix 3. We use natural language processing (NLP) tools to characterize screening comments in terms of their tone—positive, negative, or neutral—and whether they offer practical advice on financing opportunities, employment decisions, product improvement, or market strategy. More generous reviewers, relative to less generous reviewers, have homogenously-toned comments, although they are on average slightly shorter—a one standard deviation increase in generosity is associated with 6.5 fewer words (relative to a mean of 55 words).[20]

Second, do screening comments have independent effects on venture growth, beyond potential due-diligence assignment impacts? Conceptually, there may exist interactions between due-diligence assignment and reviewers' screening comments that could affect the interpretation of results. For example, applicants may be more likely to accept a due-diligence invitation, and engage more actively, if it includes incisive comments and suggestions. If so, any venture growth effects we find with our empirical strategy cannot be attributed exclusively to the due-diligence assignment, but rather to the bundled treatment of due-diligence assignment and reviewers' screening comments. However, several pieces of evidence from unreported regressions suggest that reviewers' screening comments appear to have little practical consequence in our setting. First, the results are similar when we cut the sample between applicants with different reviewers' screening comments (i.e., positive versus negative sentiment). If screening comments significantly modified entrepreneurs' attitude to and engagement with due diligence, we expect to see stronger effects in applicants with more positively toned and informative comments. Second, our results are robust to controlling for the content of reviewers' comments. If screening comments played a primary role in our setting, we would expect to see stronger growth effects for entrepreneurs who received positive feedback from the reviewers. We find no significant correlation between comment content and startup growth for the sample of applicants who are not assigned to due diligence.

Overall, the above evidence points to a limited role for screening comments in influencing entrepreneurs in our setting. At first glance, these results may appear inconsistent with related studies on how individuals respond to feedback in competitive settings. For example, Howell (2021) shows that entrepreneurs participating in business plan competitions in the US are more likely to abandon their ventures if they are told by the competition that judges ranked them low relative to other contestants.

[20] This is not to say that reviewers exhibit no heterogeneity in their commenting style. Appendix 3 shows joint significance of reviewer fixed effects in specifications regressing comment characteristics against reviewer and company fixed effects. However, this heterogeneity is uncorrelated to scoring heterogeneity across reviewers.

However, in contrast to the context studied by Howell (2021), the Fund shares with the applicants the screening comments only, whereas neither scores nor rankings are shared. These comments do not inform entrepreneurs about the quality of their ventures compared to other applicants, nor do they provide them with numerical anchors that are easier to interpret and process as an assessment of their overall quality (Eil and Rao, 2011; Gross, 2017). Moreover, as stated by the Fund, the comments are mostly observations about the companies' fit with the Fund's investment mandate rather than thorough assessments of a given applicant's standalone quality.

2.4.6. What happens during due diligence?

As in other seed funds, the first planned step for companies that are assigned to due diligence is to formally meet with the Investment Lead. This meeting can also include other members of the Fund's team; it typically takes place in person and lasts for 45 to 60 minutes. It involves talking through the application, and the VC asking questions about unit economics, the scalability of the business, the revenue model, and key performance indicators (see Appendix 5). This first meeting marks the beginning of what the Fund calls the "discovery" phase of the due-diligence process.

The second stage of due diligence typically involves three to five meetings between the founder(s), the Investment Lead, and other team members, to further probe the investment opportunity. The members of the Fund ask questions and the founders collate information, give responses, and grant access to their "data room." Appendix 5 details the questions asked by the Fund, which are guided using a spreadsheet that the Lead fills out with the entrepreneur throughout the due-diligence process. The discovery process also brings in external experts from relevant markets, sectors, or skill areas to meet with the founders. The external experts assess the strength of the technology, the candidate company's market assumptions, and evidence of growth and opportunity.

If the discovery phase concludes satisfactorily, the final stage of due diligence involves the Investment Lead preparing the company to meet with the Investment Committee (IC), marking the start of the "opportunity assessment" part of the process. To prepare for the IC, the Investment Lead completes the opportunity assessment form shown in Appendix 5 (Opportunity Assessment [pre-IC]). This form scores companies into 10 categories. Questions include "Is this a crowded market?" and "Is the business model proven?" The opportunity assessment form is then reviewed by each IC member before the IC meeting. They individually score the company on a scale of 1 to 10 in each category, 10 being the highest score.

The IC meeting represents an opportunity for companies to formally present to the Fund's leadership. It begins with the company delivering a 20-minute pitch, which is followed by a 40-minute discussion with the IC. There is then a 30-minute discussion among the members of the IC, without any startup founders present, to review and discuss the opportunity assessment scores that they each gave ahead of the meeting. After the meeting, the IC members again revert to individually assessing the company. They make their investment recommendations, voting on whether the Fund should offer a term sheet. The IC vote requires a two-thirds majority for a term sheet to be offered. Further proposals may be made (different terms, including investment amount and equity proposed) and conditions may be set (e.g., discussion of key hires, other investors' participation in the round, and types of support) to guide the terms of the investment offer. The Investment Lead shares the IC meeting outcome with the founder(s) by phone or in person. If the result is rejection, feedback is given about areas that raised concerns and what adjustments could be made to the business model, product, team, and so forth. If the IC votes to offer a term sheet, then the rationale for the terms is communicated and a negotiation ensues.

We note that the Fund keeps no systematic records of what occurs between the initial screening assessment and the opportunity assessment conducted ahead of the IC meeting. That is, for any given applicant selected for due diligence, we have no information on how many due-diligence meetings occurred or what was discussed. The only exception is IC participation, for which we have information on the ratings recorded in the opportunity assessment form as well as the outcome of the IC. We use this information in auxiliary analysis in Section 4. As we explain in greater depth in the next section, this absence of micro-data about what occurs during due-diligence does not undermine our empirical strategy, which is geared towards estimating the effects of due-diligence *assignment*, rather than actual due diligence, an endogenous outcome. The lack of micro-data does encumber our exploration of channels of impact. In Section 5.1, we discuss in detail our strategy to address the challenge of isolating mechanisms.

3. Empirical strategy

3.1. Baseline specification

The main dataset is a cross-section where the unit of observation is an applicant *i* to the Fund. We present results of regressions performed both including and excluding the 12 companies (0.61% of all applicants) eventually selected for investment by the Fund.

Our baseline specification measures the correlation between the assignment to due diligence and the venture's subsequent growth. We estimate the following type of regression:

$$Y_i = \gamma + \rho Due\ diligence_i + \boldsymbol{Z}_i + \varepsilon_i \qquad (1)$$

where Y_i is the post-application outcome for applicant *i*, $Due\ diligence_i$ indicates the companies assigned to due diligence, and $\boldsymbol{Z}_i$ is a vector of controls at the time of the application, including log transformations (log[1+x]) of variables in the application files (age, target amount to raise, target days to close the funding, total addressable market, and total serviceable market). We condition on location fixed effects in all specifications to consider the level of randomization.[21] Robust standard errors are reported throughout.

The coefficient ρ captures the effect of the Fund's due-diligence assignment on subsequent venture growth. When $\rho > 0$ we conclude that assignment to due diligence adds value to entrepreneurs by increasing venture growth. The major empirical challenge is that due-diligence selection by investors is endogenous. Given time constraints, investors are likely to pick to conduct due-diligence on the candidates they perceive as having the higher-potential for growth. This endogeneity would generate a positive correlation between ε_i and $Due\ diligence_i$ in equation (1) and an upward bias to the estimate of ρ.

3.2. Identification strategy

To address potential endogeneity, we need an instrument that affects the likelihood of due-diligence assignment but does not affect venture growth through any other mechanism. Our setting provides us with a natural instrument. For every applicant, we estimate the exact probability of due-diligence assignment based on two exogenous factors: the scoring generosity of the three randomly assigned reviewers, and the corresponding rule for aggregating reviewers' scores (which differs based on the time of the application and the location of the applicant).[22]

This instrument correctly captures how the random assignment to a reviewer who tends to provide high scores matters most for due-diligence selection when the other two reviewers tend to offer low scores. It also captures how such an assignment will also matter more when the selection rule over-weights top scores, as under the "Champion model" commonly used by VC firms and applicable to the Fund's London applicants after May 2018.

In detail, we estimate our instrument—the Due-diligence Assignment Probability (DAP)—for each applicant *i* as follows:

[21] In a previous version of this paper, we reported results from regressions excluding location controls, which are available for inspection upon request. The results reported here include location controls; they are qualitatively similar but more conservative in economic magnitude.

[22] Our identification strategy is like the one used in the "judge leniency" literature, starting with Kling (2006), who uses random assignment of judges to estimate the effects of incarceration on employment. More recently, González-Uribe and Reyes (2020) employ the random assignment of judge panels to assess the impact on venture performance of participation in a business accelerator. Our main departure between these approaches is that the Fund aggregates the reviewers' scores using non-linear selection rules, whereas the business accelerator uses reviewers' average scores. In that sense, the paper closest to ours is Galasso and Schankerman (2014), who use the random assignment of (multiple) judges to estimate the effects of patent invalidation on citations and construct an invalidation index based on the judges' majority rule. The two main conceptual differences between the two settings are that (i) reviewers in our setting provide a numerical score from 1 to 4 rather than a binary decision, and (ii) the rule used by the Fund to aggregate scores is not a simple majority. Nevertheless, the basic assumption behind the different identification strategies is that reviewers differ in their scoring generosity.

$$DAP_i = \sum_{s_1 \in \{1,2,3,4\}} \sum_{s_2 \in \{1,2,3,4\}} \sum_{s_3 \in \{1,2,3,4\}} p_{1(-i)}^{s_1} p_{2(-i)}^{s_2} p_{3(-i)}^{s_3} f(s_1, s_2, s_3) \qquad (2)$$ [23]

where $f(s_1, s_2, s_3)$ corresponds to the selection rule used by the Fund to aggregate the scores of the three reviewers. The variable $p_{h(-i)}^{s_h}$ corresponds to the fraction of the applications (*not* including applicant *i*) given a score of s_h by reviewer *h* of applicant *i*. For example, if a reviewer of applicant *i* assessed 10 applicants besides *i*, and the reviewer assigned a score of 2 to four of those applications, then $p_{1(-i)}^{2} = \frac{4}{10} = 0.4$.

Note that by design the score for applicant *i* does not enter the computation of its instrument for due-diligence assignment, thus removing the dependence on the endogenous regressor for applicant *i* (as in the jackknife instrumental variable [IV] of Angrist, Imbens, and Krueger, 1999). This feature of our instrument allows us to control for any additional effects that applicant-specific unobservables may have on the decision to select the business for due diligence. To be sure, by dropping the review of applicant *i* from the construction of the DAP instrument for applicant *i*, any additional information revealed during the assessment by the reviewers (e.g., web page searches about the company during the review process) or any discussions among reviewers about the applicant (for example, potential collusion, or influence by senior staff if reviewers figure out the identity of their co-reviewers outside of the reviewing software; see Section 2.4.1 for a discussion on the low probability of this event) is removed from the instrument's construction and thus does not contaminate it.

Because the level of randomization is the region, we include location fixed effects in all specifications. In some of the analyses, we also use an adjusted DAP that considers the location of applicants in the estimation of the instrument directly. Specifically, for each applicant *i* we estimate the "regional DAP" using equation (2) but adjusting the variables $p_{h(-i)}^{s_h}$ so that they correspond to the fraction of applications assigned a score of s_h by reviewer *h* of applicant *i and* that share the same location as applicant *i*, excluding applicants *i*'s score from the computation. For example, if the first reviewer of applicant *i* assessed eight applicants besides *i* that are in the same location as applicant *i*, and the reviewer assigned a score of 2 to three of those applications, then $p_{1(-i)}^{2} = \frac{3}{8} = 0.375$. We discuss the robustness of the results to using regional DAP in Section 6.

There is substantial variation in the distribution of DAP (mean of 0.22, range from 0.00 to 0.78). Figure 6 shows the distribution of DAP across the sample of applicants. Our main estimation approach instruments due-diligence assignment with DAP using two-stage least squares (2SLS). In robustness

[23] $DAP_i = p_{1(-i)}^{1} p_{2(-i)}^{1} p_{3(-i)}^{1} f(1,1,1) + p_{1(-i)}^{1} p_{2(-i)}^{2} p_{3(-i)}^{1} f(1,2,1) + \cdots + p_{1(-i)}^{4} p_{2(-i)}^{4} p_{3(-i)}^{4} f(4,4,4)$.

checks, we also present results using the predicted probability of assignment obtained from the probit model $\widehat{DAP} = P(DAP, Z)$ as the instrument for due-diligence assignment. When the endogenous regressor is a dummy, as due diligence is in our case, the estimator $\widehat{DAP}$ is asymptotically efficient in the class of estimators where instruments are a function of DAP and other covariates. However, the linear model has the advantage of facilitating the interpretability of the estimates when we include controls like location fixed effects in our regression.

Specifically, we estimate the following two-stage model:

$$Due\ diligence_i = \mu + \beta DAP_i + \boldsymbol{Z}_i + e_i \quad (3)$$

$$Y_i = \theta + \alpha \widehat{Due\ diligence}_i + \boldsymbol{Z}_i + \omega_i \quad (4)$$

where the set of controls $\boldsymbol{Z}_i$ is the same in both stages and the same as in equation (1). We condition on location fixed effects in all specifications to control for the level of randomization (see Section 2.4.1). We report heteroskedasticity-robust standard errors for our estimates. In unreported analysis, the results are robust to using bootstrapped standard errors. In Section 6, we discuss the robustness of results to using Poisson models (see Cohn et al., 2022).

The coefficient of interest is α, which estimates the Local Average Treatment Effect (LATE) of due-diligence assignment for "marginal applicants", that is, applicants whose assignment is affected by DAP. The identification conditions necessary to interpret these 2SLS estimates as the causal impact of due-diligence assignment are: (i) that DAP is associated with due-diligence assignment (i.e., first-stage), (ii) that DAP only impacts venture outcomes through the due-diligence assignment probability (i.e., exclusion restriction), and (iii) that applicants assigned to due diligence by a low DAP would also have been assigned to due diligence had they had a higher DAP (i.e., monotonicity). We present supportive evidence of the identification conditions in the next sections.

While the 2SLS estimates measure the causal impact of due-diligence assignment for marginal applicants under the identification conditions, they have little to say about the causal impacts of "going through due diligence", which is an unobservable and endogenous variable. As we have no complete micro-data of the due-diligence process between the screening assessment and the pre-IC assessment, we cannot distinguish the applicants who indeed began the due-diligence process with the Fund after receiving the formal invitation from those who did not engage in the due-diligence process. Moreover, the number and quality of interactions during due diligence are possibly correlated to applicant quality; it is likely that applicants who had more due-diligence meetings with the Fund are also of better quality and would therefore have performed better in any case. How useful are our estimates? In practice, understanding the effects of due-diligence assignment, rather than actual participation, seems crucial. On the other hand, while the 2SLS estimates produce internally valid estimates of the effects of due-diligence assignment by the Fund, the external validity—that is, the predictive value of the estimates for due-diligence assignment in other contexts—is not directly addressed by the IV framework in equations (3) and (4). We return to this point in Section 6.

3.2.1. First stage

Figure 7 provides a visual representation of the first stage. Panel A shows a positive unconditional correlation between DAP and due-diligence assignment: due diligence increases along the 15-quantiles of DAP. Because the level of randomization is the region, Panel B shows the same positive correlation after controlling for location by using the regional DAP. Finally, Panel C shows a positive *conditional* correlation: for any level of applicant potential, applicants with above-median DAP have higher or equal probability of due-diligence assignment than applicants with below-median DAP. We proxy applicants' potential using adjusted scores (see Section 2.4.2). Panel C ranks companies on the x-axis in 15-quantiles of adjusted score. Panel C also shows that DAP has a stronger impact on due-diligence assignment for applicants with higher potential, as revealed by the vertical difference between the due-diligence assignment curves for above- and below-median DAP. The DAP is less likely to affect the due-diligence assignment of the very bottom applicants, as these are cases that the Fund clearly rejects as not venture-backable. Instead, the DAP is more binding for companies that stand a chance of selection given their potential as perceived by reviewers.

We formally test the first stage, that is, the relevance of DAP, using the standard F-tests of the excluded instruments (Stock and Yogo, 2005). Table 2 summarizes results from several specifications of equation (3), including different models (linear, Panel A; probit, Panel B), samples (full and excluding portfolio companies), and combinations of controls as specified in the bottom rows of each panel. There are two main takeaways from Table 2. Across all specifications, the coefficient of DAP is positive and statistically significant, and the F-test of the excluded instruments is above the rule of thumb of 10. In terms of economic magnitude, our most conservative estimate of 0.94 in column 5 implies that a 10-percentage point increase in DAP is associated with a 9.4 percentage point increase in the likelihood of due-diligence assignment. In terms of standard deviations, the coefficient in column 5 implies that an increase of one standard deviation in DAP increases the due-diligence assignment probability by 0.27 standard deviations.[24] We obtain similar results using a probit model (Panel B). The implied marginal effect from the probit regressions in column 5 is 0.85 (evaluated at the mean), which is not far from the

[24] 0.27=0.94×0.13/0.46, where 0.13 is the standard deviation of DAP and 0.46 is the standard deviation of due diligence.

linear estimates in Panel A, given that the mean of due-diligence assignment is 0.31 and far from 0 and 1.[25]

3.2.2. Exclusion restriction

The institutional details discussed in Section 1.4.1 suggest that the assignment of applicants to reviewers is plausibly quasi-random (i.e., conditional on location fixed effects). Figure 8 and Table 3 provide additional evidence in support of the assumption that DAP is as good as if randomly assigned (conditional on location). Figure 8 shows a flat relationship between DAP and company potential, as measured by the applicant adjusted scores (see Section 2.4.2); the x-axis ranks applicants in 15-quantiles of the adjusted score. Table 3 shows indistinguishable applicant characteristics across different quartiles in the DAP distribution.

The quasi-random assignment of reviewers is enough for a causal interpretation of the reduced form results reported in Appendix 6. That is, our reduced-form estimates can be interpreted as the causal impact of being evaluated under a stringent standard (i.e., as measured by the reviewers' generosity and the selection rule). However, it is not sufficient for a causal interpretation of the 2SLS estimates of due-diligence assignment. For such an interpretation, we would require the exclusion restriction assumption to hold, that is, DAP impacts applicants' outcomes exclusively through the single channel of due-diligence assignment and not through any other mechanism.

This exclusion restriction would fail if the outcomes of applicants with a high DAP were affected in some additional independent way other than through an increased likelihood of due-diligence assignment.[26] For example, a higher DAP could be associated with more hands-on treatment if reviewers who tended to score applicants generously also spent more time on due diligence, and this additional effort had an independent effect on applicants' growth.[27] However, three pieces of evidence suggest the exclusion restriction is reasonable in our setting. First, Appendix 7 shows that DAP does not predict investment by the Fund or selection into opportunity assessment by the Fund, which is contrary to the assumption that higher DAP leads to better-quality due diligence. Second, Appendix 7 shows that DAP is not correlated with opportunity assessment performance, as would be expected if DAP proxied for due-diligence quality. Third, neither DAP nor reviewers' generosity correlates with

[25] A marginal effect of 0.85 implies that a one standard deviation increase in DAP (0.13) is associated with an increase of 11 percentage points in the likelihood of due diligence (0.85×0.13=11.05%). This economic magnitude is comparable to that found by Galasso and Schankerman (2014).
[26] Because applicants are not made aware of their DAP, as they do not know the generosity of their reviewers, the selection rules, or even their scores, entrepreneurial reactions to DAP are not possible.
[27] DAP can also reflect better underlying venture potential if it proxied for selection skills. However, scoring generosity is not correlated with predicting ability, as discussed in Section 4.2 and Appendix 2.

the content of reviewers' comments, as shown in Appendices 8 and 3, respectively, which could indicate (via note-taking proficiency) the quality of due diligence.

Despite this evidence, we acknowledge that the assumption that DAP only systematically affects applicants' outcomes through due-diligence assignment is fundamentally untestable, and our estimates should be interpreted with this caveat in mind. Therefore, we deploy two main types of robustness tests (explained in detail in Section 6) that relax this identification assumption: adding controls for Investment Leads and estimating models that exploit selection regime changes, rather than differences in the generosity of reviewers.

3.2.3. Monotonicity

The final condition to interpret our results as the LATE of due-diligence assignment is that the impact of DAP on due diligence assignment is monotonic across applicants. In our setting, the monotonicity assumption requires that a higher DAP does not decrease the likelihood of due diligence. Consistent with this assumption, Figure 7 shows graphical evidence of the increasing correlation between DAP and the likelihood of due diligence. Despite this evidence, the monotonicity assumption could still be violated, for example, if reviewers differ in the types of applicants they score more generously, and these differences are averaged out in the pooled plots of Figure 7.

We present a battery of tests in Appendix 9 in support of the monotonicity assumption. We show that the first-stage results are consistently same-signed and similarly sized across different subsamples based on the applicant's characteristics at application: gender of founder(s), location, education background of founder(s), and stage of business development. Along the same line of reasoning, we show similar reviewers' generosity across observably different applicants. To produce this evidence, for each applicant characteristic at application (e.g., gender), we estimate two generosity measures defined as the reviewers' generosity estimated using each subsample of applicants (e.g., at least one female founder vs. all-male). Consistent with the monotonicity assumption, for each characteristic we find that generosity measures in the two subsamples are strongly positively correlated. We show similar results from tests at the reviewer trio level, as explained in Appendix 9. Finally, in robustness checks we also relax the monotonicity assumption by letting the variables $p_{h(-i)}^{s_h}$ in equation (2) differ across applicant characteristics (e.g., using regional DAP rather than DAP), in the spirit of Mueller-Smith (2015). The results from these robustness checks are quantitatively similar to our main results, as we discuss in greater detail in Section 6.

4. The impact of due-diligence assignment on venture growth

In this section, we begin by describing the main findings. We then discuss the implied economic magnitudes of the estimated coefficients, and the difference in coefficient estimates across the OLS and

IV models. We round off the discussion by presenting results from several sample cuts. We leave the interpretation of the findings and the discussion about mechanisms for Section 5.

4.1. Main findings

Table 4 presents ordinary least squares (OLS) and 2SLS estimates of the impact of the Fund's due-diligence assignment on future funding from other VCs. Panel A uses the entire sample, while Panel B excludes the 12 companies in the Fund's portfolio. Given the large skewness in the outcome measures, the last eight columns in each panel present results using extensive-based measures of the outcomes—i.e., dummy variables that light up when the respective outcome measures are different from zero.

The OLS estimates show that applicants assigned to due diligence have significantly higher subsequent funding (by VCs other than the Fund) than other applicants (see the odd-numbered columns). This positive association between due-diligence assignment and fundraising holds across all different funding proxies, across both web-based and administrative UK data (columns 7 and 15). Notably, the positive correlation is there even when we exclude the Fund's 12 portfolio companies, implying that these portfolio companies do not drive the OLS results (see Panel B).

The 2SLS estimates improve upon our OLS estimates by exploiting the plausibly exogenous variation in due-diligence assignment (see the even-numbered columns). Across all variables, the 2SLS estimates are positive and statistically significant. They confirm that applicants assigned to due diligence raise more funding than otherwise similar applicants who were rejected for due diligence by the Fund. In terms of magnitudes, Column 2 in Panel A shows a sizable increase of 281 percentage points in funding after due diligence, which corresponds to a 51 percent increase from the mean of the post-application log funding distribution.[28] Columns 4 and 6 show that the funding effects are explained by both higher numbers of subsequent financing rounds and participation by a larger number of investors. The results in column 8 imply similar increases for funding as measured by administrative data.[29] Results are indistinguishable if we use the coefficient estimates in Panel B that exclude portfolio companies.

Tables 5 and 6 replicate the OLS and 2SLS regressions of Table 4 using real, rather than financial, growth variables: asset growth, employment and survival (Table 5) and technology adoptions and A/B testing (Table 6). Given the large skewness in the outcome measures, we present results using both the level variables as well as dummies indicating positive value/growth as indicated in the top rows of each column. Across all specifications, the 2SLS estimates are positive and statistically significant. The only exception is the variable *Survival* in Table 5, for which we find evidence of negative effects. Panel B shows that due-diligence leads to a 10 percentage point decrease in the probability of survival, a 12%

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[28] 51%=2.81/5.56, where 5.56 is the mean of the log funding distribution post-application; see Table 1.

[29] The estimates imply a 39%=1.21/3.12 (19%=1.21/6.24) increase in equity issuance, where 3.12 (6.24) is the mean (75th percentile) of the log equity issuance distribution post-application (the median is 0); see Table 1.

increase relative to the average continuation in the sample. The results thus offer evidence of nuanced due-diligence effects: positive at the intensive margin, and negative at the continuation margin.

4.2. Economic magnitudes

Table 7 presents a summary table of the implied economic magnitudes of the coefficient estimates for the different growth variables. For ease of exposition, the first two rows summarize the coefficient estimates from Tables 4-6, using the full sample of applicants and excluding the portfolio companies.

In terms of funding, column 1 shows that assignment to due diligence leads to an additional £655K in equity financing within two years of applying to the Fund, which roughly correspond to securing a seed round. To produce this estimate, we compare the coefficient estimate (2.74) with the mean in post-application log funding distribution (5.56) and multiply it by the mean of the post-application fundraising distribution (£1,330K). For the rest of the funding variables, the implied economic magnitudes in columns 2-3 (relative to the mean) are also sizable: 0.25 (19%) more rounds and 0.11 (10%) additional investors. Columns 5-8 summarize the economic magnitude for real growth variables. The implied percentage (level) increases in the number of employees and asset growth are 21 (1.48) and 43 (£73K), respectively. The implied increases in technological adoptions and A/B testing are 37% and 225%, respectively, which imply increases in 5.89 technologies and 1.87 A/B tests. Said another way, assignment to due diligence drives a significant expansion to the ventures' tech stack.

An alternative approach that compares the coefficient estimates to the 75th percentile of the outcome variables rather than the mean leads to more conservative economic magnitudes. For example, in terms of funding the implied amount is an increase of £142K.[30] The smaller implied magnitudes are as expected given that most growth variables are highly skewed with means that exceed the 75th percentiles. Using this approach, our most conservative estimates imply that assignment to due diligence increases venture growth within two years of application by an average of 22% across growth proxies.

We also look more carefully at the effects at the top tails of the distributions of outcomes to complement the analysis on magnitudes. We estimate equation (1) and the system of equations (3) and (4) using indicator variables of "high growth", that is, dichotomous variables indicating when companies are within the top 25 percent of the sample for each dependent variable (except for the already dichotomous variables including *Survival*). We summarize results in Table 8 showing that due-diligence assignment helps usher applicants to the upper echelons of business growth. Across most outcome variables, we find evidence that assignment to due diligence makes firms more likely to rank in the top 25th percentile

[30] An approach based on the means points to an implied magnitude of £655K=2.74/5.56×£1,330K, where £1,330K is the mean of the funding distribution; see Table 1.

of sample companies. These results are consistent with the sizable economic magnitudes we find, and with the skewness in the growth distribution of startups.

4.2.1. Due diligence selection effects: OLS and IV

We note that for some of the growth variables, the LATE estimates exceed the OLS coefficients, although the positive difference is not statistically significant: equity issuance (Panel A) in Table 4 and change in assets in Table 5. In Section 3.1, we explained how the potential ability of investors to discern high-growth potential could instead generate a positive correlation between ε_i and $Due\ diligence_i$ in equation (1) and therefore an upward bias to the estimate of ρ in a homogenous treatment model. Does the evidence of the positive difference between the LATE and OLS estimates imply that the Fund reviewers have no ability to discern high-potential? As it happens, no. One important reason is that in the case of the Fund, the OLS may not necessarily be biased upwards, even if reviewers can discern high-potential. Why? Because the Fund's process to aggregate scores did not consider the differences in scoring generosity across reviewers, and therefore, applicants assigned to due-diligence are not necessarily those that the reviewers perceived to have the highest potential. To be sure, some lucky applicants that were assigned to generous reviewers (that tend to provide high scores on average) made it to due-diligence although they shouldn't have if the reviewers' scores had been adjusted to correct for generosity. Likewise, some unlucky applicants were rejected for due-diligence when they should have been assigned to due-diligence because they were assigned to reviewers that tend to provide low scores on average, and the Fund did not correct for this tendency when aggregating the scores. Precisely these selection mistakes create the variation we exploit in this paper to estimate causal effects of due-diligence assignment. To substantiate further this first explanation, in unreported regressions we show evidence that the Fund's reviewers are indeed able to discern high-growth potential. To produce this evidence, we regress applicants' performance against adjusted scores, controlling for due diligence, opportunity assessment, and investment. We show that adjusted scores are highly predictive of subsequent performance.[31]

4.3. Sample cuts

Table 9 resents OLS and 2SLS results after cutting the sample by applicant location (London versus out of London; Panel A) and founders' educational background (Russell indicates tertiary education from a Russell Group university; Panel B). Applicant location is an important margin given the Fund's investment approach, which emphasizes selecting top performers from outside London. Founder

[31] Conceptually, a second potential explanation has to do with the local nature of the LATE estimates, which makes them difficult to compare to OLS if there is treatment heterogeneity (cf. Imbens and Angrist, 1994). To be sure, due-diligence effects could be higher among marginal applicants whose assignment is affected by DAP, reflecting the more substantial frictions that they encounter when attempting to access due diligence elsewhere. In Section 6, however, we find only weak evidence of heterogenous treatment effects along applicant potential.

education is an important margin, as research has found that entrepreneurial growth is shaped by the social and human capital derived from the university where one studies (Klingler-Vidra et al., 2021; Kenney et al., 2013; Batjargal, 2007). The university has been found to affect entrepreneurs' social networks, which can in turn affect their entrepreneurial orientation, capabilities, and performance (Klofsten et al., 2019).

The results show no evidence of different causal effects of due-diligence assignment across London and non-London companies. The only exception is in the web-based funding proxy (Column 2, Panel A, Table 6), where the IV results point to lower funding effects from due diligence for London applicants. However, the effects are not robust across different funding or economic growth proxies. Panel B shows that the average growth of companies assigned to due diligence does not vary significantly with founders' educational background, either.[32] In unreported regressions, we also find no difference in impact when we cut the samples by other applicant characteristics, including founders' MBA degree attainment or gender, and businesses' development stage or type (e.g., deep technology, sales engine, or platform). Our preferred interpretation for the lack of heterogeneity in impact is that it reflects the homogeneity across applicants' business development, which trumps any effects from differences in entrepreneurs' education profiles and location. We return to this point in Section 6 where we explore impact heterogeneity more formally by using marginal treatment effects (Heckman and Vytlacil, 2005).

5. Information Frictions and Venture Capital

Why are there such considerable benefits from the Fund's due-diligence assignment for startups' growth? Our preferred interpretation is that seed-stage VC due diligence helps entrepreneurs mitigate their information frictions by providing high-stake opportunities to learn about their business.

We have no micro-data to fully rule out the alternative mechanisms that (i) due diligence reduces information frictions by connecting and certifying companies, (ii) due diligence increases (rather than decrease) information frictions by leading to window-dressing, or, (iii) due diligence increases (or has limited effects on) information frictions because founders are (or become) overconfident. To be sure, the Fund kept no systematic records of due-diligence meetings and the topics discussed in those meetings, and while we have conducted several interviews with partners at the Fund, the terms of our partnership preclude us from surveying applicants and providing qualitative evidence from founders' perceptions.

However, learning is the mechanism that is most consistent with the overall results. For one, learning is consistent with the results on closure (Howell, 2021); all other mechanisms would predict higher

[32] In unreported regressions, we find no impact heterogeneity across founders with or without an MBA. Fewer than 10% of founders in our sample have an MBA degree.

business continuation. Learning is also consistent with the changes in tech-stack. To be sure, increases in technology adoptions, and specially A/B testing, are a strong indication of learning that results in an active effort by entrepreneurs to change and experiment with their businesses (see Koning, Hasan, and Chatterji, 2019). Instead, all other mechanisms would predict no substantive changes in the business from due-diligence. One concern with the tech-stack findings, is that they may be driven by (subsequent) fundraising, rather than by due diligence. To address this concern, the number of technology adoptions and testing is restricted to be within 12 months of application (fundraising is instead measured within an average of 24 months). In our most acid (unreported) test, we drop all technology adoptions following fundraising, for those companies that manage to raise financing, and find similar effects.

We deploy several tests to provide further evidence against the first-order importance of the alternative mechanisms. Against the relative importance of due diligence reducing information frictions through certification, in unreported regressions we find no evidence of increased traffic to applicant businesses' web pages after the due-diligence assignment. These results are as expected given that the Fund's due diligence assignment decisions are privately informed to applicants rather than widely publicized. Therefore, a de-facto certification role for due diligence is unlikely to be primary relative to other settings where signals are publicly observed, like business plan competitions (Howell, 2020).

Against the relative importance of due diligence reducing information frictions by connecting entrepreneurs with VCs networks, in unreported regressions we show that due-diligence does not lead participants raising financing from investors in the Fund's network as we would expect if networking effects played a first-order role. We measure the Fund's as the VCs with whom the Fund syndicates (and strives to syndicate) its investments (the Fund indicated a set of thirteen VC funds with whom they strive to co-invest).

Further reducing the credence that due diligence increases information frictions by making founders overconfident, in Appendix 10 we show no effects from assignment to informal meetings with the Fund by exploiting differences in the propensity across judges to provide the low scores. Instead, we would expect similar (albeit possibly smaller) effects from selection to informal meetings in that such invitation could also be interpreted as "venture backable" validation. Further, in unreported regressions, we explore the heterogeneity of results across founders: we would expect any overconfidence effects of due-diligence to concentrate among those founders with a higher predisposition for overconfidence. Yet, we find no supportive evidence. Following Howell (2021), we proxy overconfidence propensity using the gender of the founders. Being male is associated with many types of overconfidence, including excessive optimism and excessively precise prior (Beyer and Bowden, 1997; Barber and Odean, 2001; Niederle and Vesterlund, 2007; Mobius et al., 2014). We find no differences in effects across teams with and without female founders in unreported regressions. We note that this is not to say there is no evidence that overconfidence may limit learning. Panel D in Table 10 shows that results are somewhat weaker for overconfidence-prone founders. We classify founders as prone to overconfidence when they perceive their venture to be at a further along stage of development than the reviewers.[33]

Overall, while the lack of micro-data limits our ability to fully rule out alternative channels, the empirical patterns seem most consistent with VC due diligence reducing information frictions by enabling entrepreneurs to learn about their business.

6. External validity

The results so far indicate that assignment to due diligence by the Fund improves venture growth for marginal applicants whose due-diligence assignment is affected by the instrument. To what extent can we extrapolate these results to other types of applicants and VCs?

Our IV strategy identifies the Fund's due-diligence impact on marginal applicants whose DAP alters due-diligence assignment. This LATE may or may not reflect the average treatment of due diligence for all applicants to the Fund. To investigate heterogenous treatment effects across unobservable applicant characteristics, we estimate marginal treatment effects (MTEs; Heckman and Vytlacil, 2005). In our setting, the MTEs illustrate how the outcomes for applicants on the margin of due diligence change as we move from low to high DAP, that is, as we go from stricter to more generous reviewers and rules. Thus, the MTE estimates shed light on the types of applicants who benefit most from due diligence, and whether our LATEs are likely to apply to applicants farther from the margin.

Panel B in Figure 9 shows that the MTE estimates are generally flat with respect to the predicted probability of due diligence across the different outcome variables (solid lines; dashed lines depict the corresponding 2SLS estimates for reference). Their flat shape suggests that the due-diligence assignment effects on the different outcomes do not vary systematically across applicants' unobservable characteristics. For some outcome variables there is a weak indication of heterogenous effects, as evidenced by slightly downward MTE functions in equity issuance and growth in assets (see also Section 4.1). However, the evidence is at best weak, as the standard errors are too wide to statistically reject a slope of zero for all the outcome variables. From the lack of supporting evidence of heterogeneous treatment effects, it follows that the LATEs are more likely than not to apply to applicants farther from the margins of due diligence, thus strengthening the case for the external validity of results for non-marginal Fund applicants.

To produce the MTE estimates in Figure 9, we follow the two-step approach by Dobbie and Chang (2015). In the first step, we predict the probability of due diligence using a probit model that captures

[33] Founders include in their application their own assessment of the stage. As part of the review process, reviewers also annotate their views on the stage of development of the applicant.

the variation in due diligence solely due to the instrument (i.e., no controls). As instrument we use the regional DAP, given that the level of reviewer randomization is regional (see Section 3.2).[34] The instrument achieves a wide variation in the probability of predicted due diligence, from 0.01 to 0.99, as shown in Panel A of Figure 9. Panel A plots actual due diligence against predicted due diligence using regional DAP as a predictor. Each dot corresponds to the average actual (y-axis) and predicted (x-axis) due diligence for a given 15-quantile of predicted probability of due diligence.[35] In the second step, we use a quadratic estimator to predict the relationship between a given outcome variable and the predicted probability of due diligence. Using the regression coefficients, we estimate the MTEs by evaluating the first derivative of this relationship at each percentile of the predicted probability of due diligence. We calculate standard errors using the standard deviation of MTE estimates with a bootstrap procedure with 250 iterations using a bandwidth of 0.15. Panel B plots the MTEs and the confidence intervals for the different outcome variables against the predicted probability of due diligence.

In terms of extrapolation of results outside of the Fund, we note that the Fund is representative of a shift towards investments at the seed stage (Klingler-Vidra, 2016). As argued above, the Fund, like others investing at the seed stage, has a systems-based approach for sorting applicants and focuses strongly on a highly interactive due-diligence process. Along with long-established VC funds now investing at the seed stage, the new intermediaries operating in a similar fashion include other funds (like dedicated seed and pre-seed funds), as well as super angels and accelerators. These early-stage intermediaries seek to identify and train the most promising of the increasingly inexperienced new founders raising specialized financing. We thus argue that our results are most representative of investing in companies at the seed stage, especially those funds recently established and seeking to secure high-quality deal flow in the future by building their reputation as value-add investors.

The lack of evidence in support of the heterogenous impact of due-diligence assignment depicted in Figure 9 may seem inconsistent with related studies in the context of business accelerators. For example, González-Uribe and Reyes (2020) find that participation in a Colombian accelerator (one that provides no cash) leads to stronger venture growth effects for applicants with already established ventures rather than just business ideas at application. However, contextual differences can help explain the differences

[34] Results are quantitatively similar if we use DAP. We do not report the results to conserve space, but they are available upon request.

[35] In an earlier draft, we reported a different version of the plot in Panel A of Figure 9. In the previous plot, each dot represented the average actual (y-axis) and predicted (x-axis) due diligence for a given bin of predicted probability of due diligence (increments of 0.05 along the x-axis), rather than a given 15-quantile. There was an apparent non-monotonic relation between the actual and predicted probability of due diligence, which could be at odds with the monotonicity assumption (although the original plot was not intended to visualize the monotonic relation between the instrument and the outcome as it included no controls for location, that is, the level of randomization). However, this apparent non-monotonic relation is a by-product of the small sample and the non-uniform distribution of firms along the different values of predicted due-diligence probability. The new plot controls for these issues by reporting average probabilities over 15-quantiles, rather than value-bins, of predicted due diligence. We thank a thoughtful discussant for pointing out this apparent inconsistency.

in results regarding impact heterogeneity across the two studies. Applicants to the Fund are more homogeneous than applicants to the Colombian accelerator: none apply with just a business idea and only a few have secured institutional investment at application. This homogeneity in the sample may be indicative of similar degrees of information frictions among applicants to the Fund, and therefore have similar expected effects of due-diligence assignment relative to the more diverse group of applicants to open accelerators like the Colombian one.

6.1. Implications

The first implication of the results is that entrepreneurs face information frictions that impede their growth, and assignment to seed VCs' due diligence can help resolve them. Our results are consistent with previous work pointing to the existence of informational frictions in early-stage markets, and the role of accelerators and business plan competitions in helping resolve these frictions. What incentives do VCs have to perform due diligence and thus add value to non-portfolio companies? Ex-ante, before the investment decision is made, the Fund has incentives to perform due diligence to help mitigate the uncertainty and information asymmetries they face themselves. The effect on founders is most likely a by-product, that is, an externality imposed on ecosystems. The Fund, however, can also benefit indirectly from providing value-add through due diligence, for example, by building a value-add reputation that can improve future deal flows and returns (Hsu, 2004; Sorensen, 2008).

The second important implication is that the role of VC investors in innovation goes beyond their value-add to the portfolio companies in which they invest. Extant literature strives to understand the role of VCs on innovation, often seeking to unpack the extent to which it is VCs' ability to make decisions (or, in industry parlance, to "pick winners") that drives their growth (Gompers et al., 2020), or their efforts to "build winners" through the feedback and networking they offer to portfolio companies (Baum and Silverman, 2004). Our findings point to a different implication: the due-diligence element of the VC selection process impacts a broader ecosystem of ventures, offering a new mechanism for potential spillover effects of VC investment. Through their due-diligence process, VCs meet with, ask questions of, and possibly exchange further information and resources with many more companies than just the ones in which they invest. These interactions, as we show, add value to the startups, even if they fail to secure investment from a fund.

How important are due-diligence effects? Are they first-order or a minor curiosity? To partially answer these questions, we perform a back-of-the-envelope calculation comparing the magnitude of our estimated due-diligence effects on the Fund's non-portfolio companies with the Fund's "total investment effects" on its portfolio firms (including both selection and treatment effects). We measure the total investment effects as growth differences between firms in the investment portfolio of the Fund and he rest of the applicants that did not secure investment from the Fund (using an OLS regression controlling for covariates; see Appendix 11), which include any potential portfolio selection effects of the Fund. We find that due-diligence effects are on average across growth proxies, roughly 40% of the total investment effects. The exception is number of employees for which there are no significant total investment effects in our data. Taking these calculations at face value implies that due-diligence effects are of a similar order of magnitude as total investment effects, rather than a minor oddity.

The evidence that VCs add value to portfolio companies highlights the importance of VC for venture growth but remains silent on the implications of participation in the process to secure VC funding. Our study supports the growing evidence that frictions in the process through which entrepreneurs connect with VCs can have profound implications for innovation and growth. Rather than a sunk cost or distraction for founders, engagement in due-diligence processes acts as a value-add for their growing ventures. Our analysis points to how high-potential entrepreneurs may not reach their full potential if they remain outside the fringes of VC networks (cf. Lerner and Nanda, 2020).

7. Robustness checks

Threats to the exclusion restriction. Interpreting our 2SLS estimates as the causal impact of the Fund's due-diligence assignment requires our DAP instrument to affect applicants' outcomes only through the channel of due-diligence assignment rather than through alternative channels, such as higher-quality due diligence. To further explore this issue, we relax our exclusion restriction by running two tests. First, controlling for Investment Lead fixed effects in unreported analysis, which mitigates concerns that differences across due-diligence processes led by Investment Leads with different generosities drives the results. Second, by including reviewer trio fixed effects in estimating equations (3) and (4) that hold constant the generosity of reviewers and identify due-diligence effects based on the change in selection regime.

One limitation of this methodology is the small subset of companies that are used to estimate the effects: as shown in Figure 5, very few firms receive scores at the margin of the selection rules. Nevertheless, Appendix 12 shows that results continue to hold for this alternative identification approach when we restrict the sample to London applicants post-May 2018, who face the most stringent selection rule, although the lower statistical power helps explain why estimates are much higher. We also present results using an alternative specification that uses the residual variation in DAP as an instrument after netting out the reviewers' generosity. Intuitively, this identification strategy also holds constant the generosity of reviewers; the main difference is that it does not hold constant the trio of reviewers for that purpose. Instead, it holds constant the average generosity of the reviewer trio (as estimated by the average reviewer fixed effects in Appendix 2). A vital identification assumption in these alternative models is that the reviewers' scoring generosity does not change across selection rules. Figure 5 and Appendix 2 show evidence in this regard, as explained in Sections 1.2.2 and 2.2.2. Taken together, these results provide additional evidence that due-diligence assignment positively affects venture growth.

Alternative specifications. We also explore the sensitivity of our main results to alternative specifications. In unreported analysis, we see that our main results are robust to including controls for company potential as measured by the applicants' adjusted scores (see Section 2.4.2). These results are similar to our preferred specification, indicating that potential bias from omitted variables is likely slight in our setting. In unreported analysis, we also confirm that results are quantitatively similar when using untransformed dependent variables (i.e., no logarithms) in Poisson regressions, alleviating concerns that the count nature of the outcome data biases our main results (cf. Cohn, Liu, and Wardlaw, 2022). Finally, we also experiment with refinements of our DAP instrument to control for potential expertise differences across reviewers in evaluating applicants with different observable characteristics. Appendix 13 shows that results are robust to controlling for region in the estimation of DAP, that is, using regional DAP (see Section 3.2). In unreported analysis, we show that results also hold with other refinements to DAP at the industry and industry cross-regional level. None of the estimates in the robustness checks suggest that our preferred estimates are invalid.

8. Conclusion

The main thrust of research investigating the global prevalence of VCs in innovation clusters focuses on the effects these investors have on their portfolio companies. We know that VCs provide smart money to young companies that might otherwise have difficulty attracting financing. In this paper, we open a new line of research into the venture growth effects of VC due diligence—the process through which VCs engage with new ventures to determine whether, and on which terms, to invest. Our novel data comprises nearly 2,000 ventures applying for funding to a UK-based VC seed fund. For identification, we exploit the Fund's process of screening applicants for due diligence, which features pre-determined selection rules based on the scores given by quasi-randomly allocated reviewers.

We find that assignment to due diligence leads to higher growth, but also increased closure, even among applicants rejected for investment. The results suggest that VC due diligence helps entrepreneurs reduce their information frictions, possibly by enabling entrepreneurs to learn about their business.

The results provide evidence that assignment to VCs' due diligence adds value in the form of improved venture growth. This new evidence implies that VCs' role in innovation goes beyond their value-added effects on their portfolio companies. The VC due-diligence process is a systemic opportunity to add value to the larger number of ventures (approximately 30 out of 100) that enter the early-stage financing funnel. Therefore, frictions in the process through which ventures seek VC financing can profoundly impact the innovation and economic growth capabilities of a wider set of startups than previously acknowledged.

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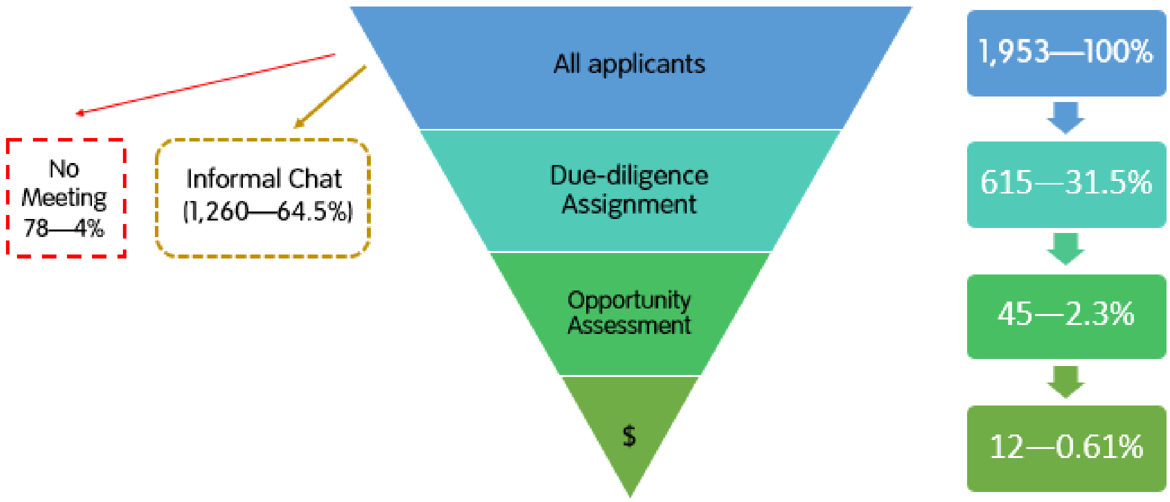
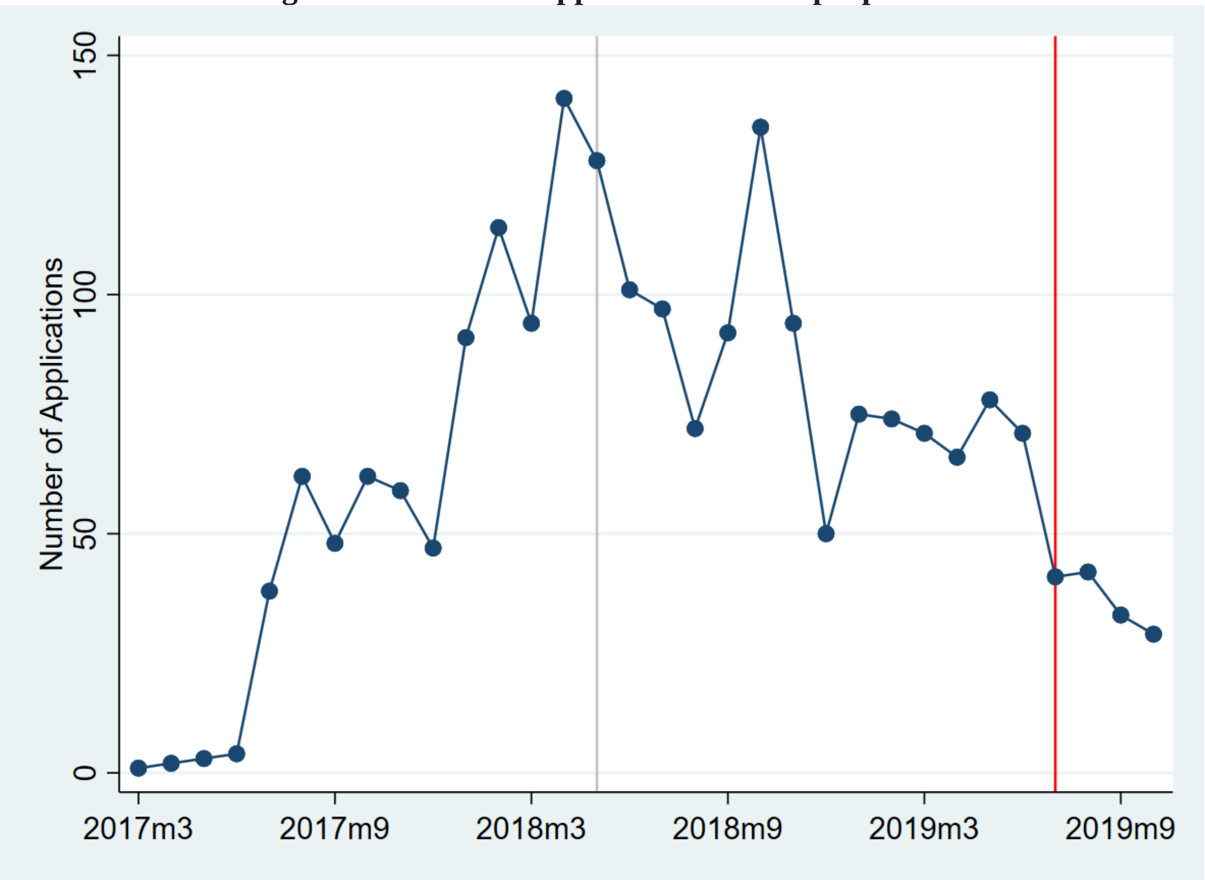
Figure 1. Selection Funnel



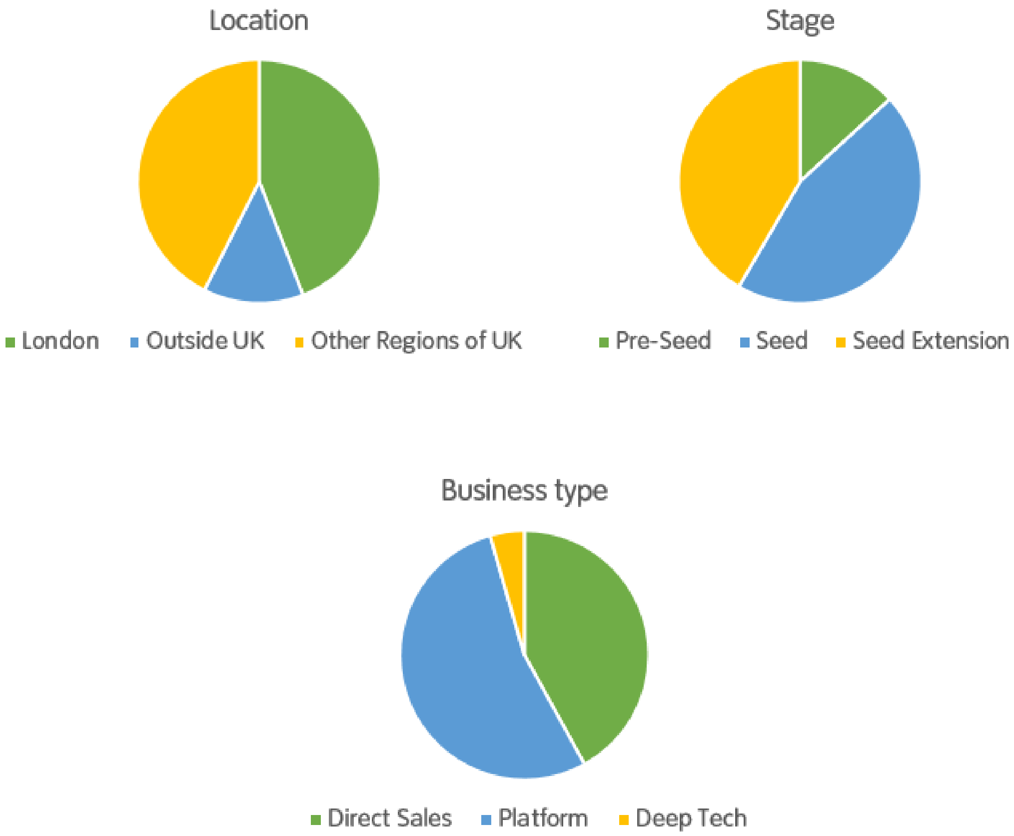
The figure plots the selection funnel of the Fund for the period between March 2017 and June 2019. Opportunity assessment corresponds to the third stage in the due diligence process includes hiring industry experts for external reviews and calling on other parties, including references provided by the founders; see Section 1 for more details.

Figure 2. Number of applicants over sample period



This figure plots the distribution of Fund applicants over the sample period. The grey line indicates the date where the Fund changes the selection regime—May 28 2018; see Section 2.4.3 for more details. The red line indicates the end of our sample, which coincides with the end of the investment period of the Fund.

Figure 3. Characteristics of Businesses at Application



This figure shows the distribution of applicants across locations, development stage and business type at the time of application. The details of the distribution are in the table below.

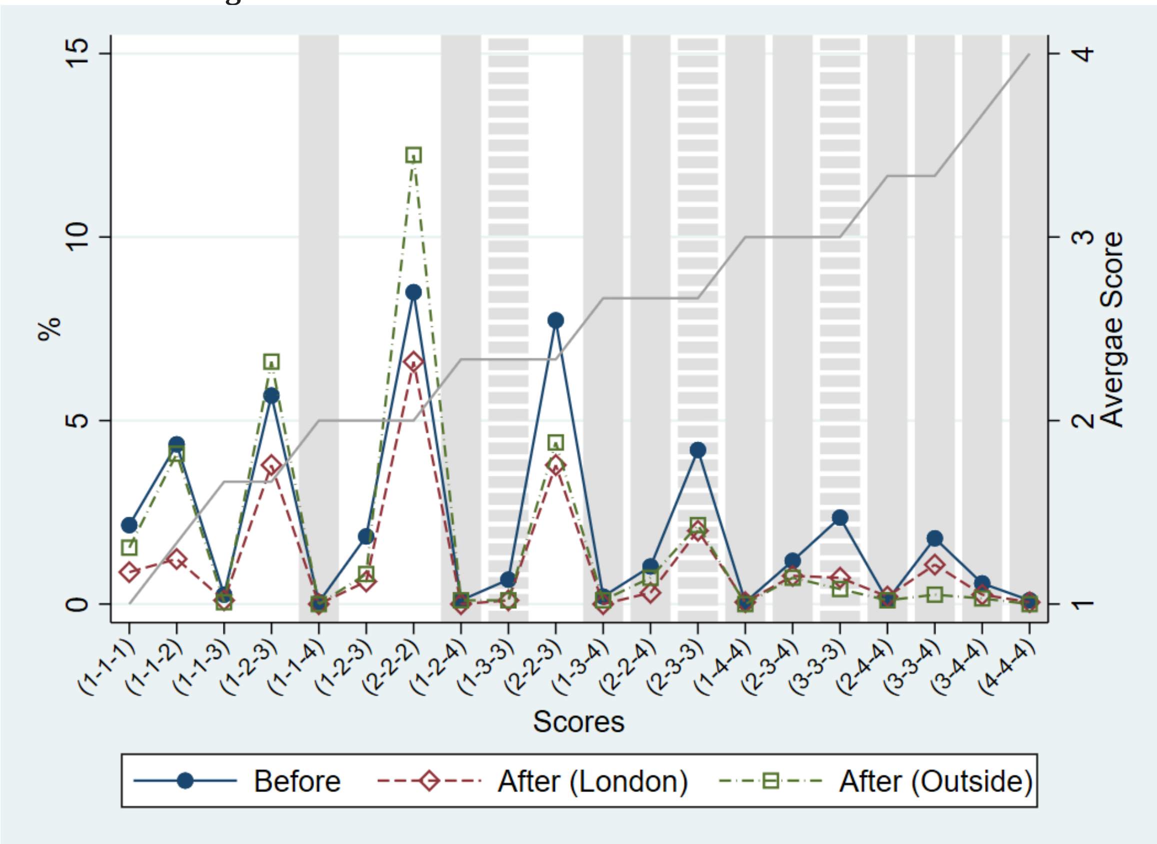
	Number of Companies	Percent
	By Location	
London	862	44.14%
Outside UK	412	21.10%
Other Regions of UK	679	34.77%
	By Stage	
Pre-Seed (under £100k)	250	12.80%
Seed (£100k-1m)	865	44.29%
Seed Extension (£200k-2m)	838	42.91%
	By Business Type	
Deep Tech	83	4.26%
Direct Sales Led	836	42.92%
Platform	1,029	52.82%

Figure 4. Due Diligence Selection Rules over Time and Location

				Average Score	Pre—May 2018	Post—May 2018	
						London	Outside
1	1	1	1	1.00	No Meeting	No Meeting	No Meeting
2	1	1	2	1.33	Informal Chat	Informal Chat	Informal Chat
3	1	1	3	1.67	Informal Chat	Informal Chat	Informal Chat
4	1	2	2	1.67	Informal Chat	Informal Chat	Informal Chat
5	1	1	4	2.00	Due diligence	Due diligence	Due diligence
6	1	2	3	2.00	Informal Chat	Informal Chat	Informal Chat
7	2	2	2	2.00	Informal Chat	Informal Chat	Informal Chat
8	1	2	4	2.33	Due diligence	Due diligence	Due diligence
9	1	3	3	2.33	Due diligence	Informal chat	Informal Chat
10	2	2	3	2.33	Informal Chat	Informal Chat	Informal Chat
11	1	3	4	2.67	Due diligence	Due diligence	Due diligence
12	2	2	4	2.67	Due diligence	Due diligence	Due diligence
13	2	3	3	2.67	Due diligence	Informal Chat	Informal Chat
14	1	4	4	3.00	Due diligence	Due diligence	Due diligence
15	2	3	4	3.00	Due diligence	Due diligence	Due diligence
16	3	3	3	3.00	Due diligence	Informal Chat	Due diligence
17	2	4	4	3.33	Due diligence	Due diligence	Due diligence
18	3	3	4	3.33	Due diligence	Due diligence	Due diligence
19	3	4	4	3.67	Due diligence	Due diligence	Due diligence
20	4	4	4	4.00	Due diligence	Due diligence	Due diligence

The figure summarizes the selection rules used by the Fund to aggregate reviewers' scores over time and location. The scores are sorted by average score. See Section 2.4.3 for more details.

Figure 5. Distribution of Scores over Time and Location

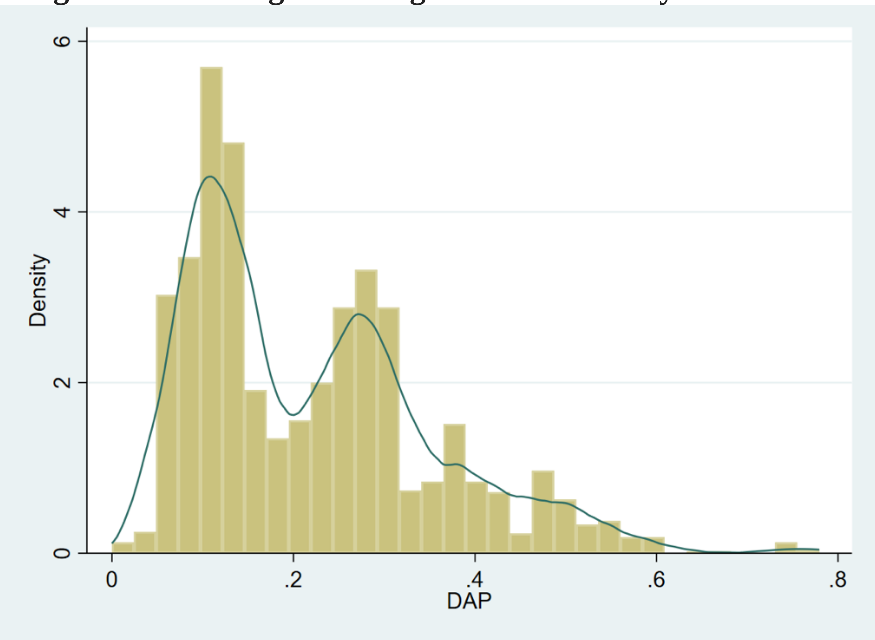


This figure plots the distribution of scores over time and locations. The left axis plots the fraction of scores for each score combination over the different selection regimes. The right axis plots the average score for each score combination; score combinations are sorted by average score. The bars in grey represents scores that lead to due diligence according to the rule. The dashed bars in grey represents scores whose mapping into due diligence are effectively affected by the selection regime change (See Figure 4). The score distributions are not statistically different over time. We perform Kolmogorov-Smirnov tests comparing the distribution scores across time and locations. We summarize results below.

Trio Scores	Two-Sample Kolmogorov-Smirnov Test	
	Stat.	P Value
London (Before) vs. Outside (Before)	0.132	0.001
London (After) vs. Outside (After)	0.149	0.000
London (Before) vs. London (After)	0.103	0.021
Outside (Before) vs. Outside (After)	0.120	0.001

Individual Score	Two-Sample Kolmogorov-Smirnov Test	
	Stat.	P Value
London (Before) vs. Outside (Before)	0.089	0.000
London (After) vs. Outside (After)	0.113	0.000
London (Before) vs. London (After)	0.084	0.000
Outside (Before) vs. Outside (After)	0.109	0.000

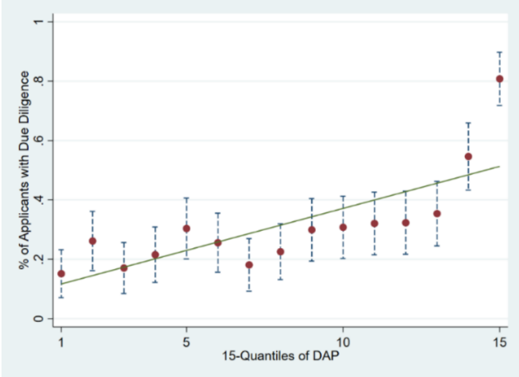
Figure 6. Due Diligence Assignment Probability Distribution



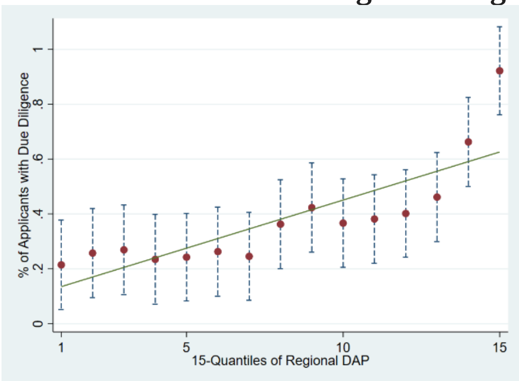
This figure plots the distribution of the Due Diligence Assignment Probability (DAP) across the sample applicants. For more details, see Section 3.2.

Figure 7. DAP and Due Diligence Assignment

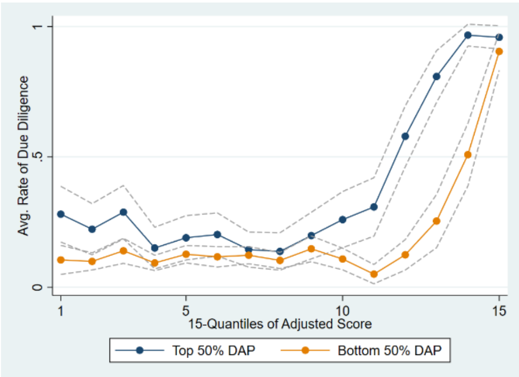
Panel A-Unconditional correlation between due-diligence assignment and DAP



Panel B-Unconditional correlation between due-diligence assignment and regional DAP

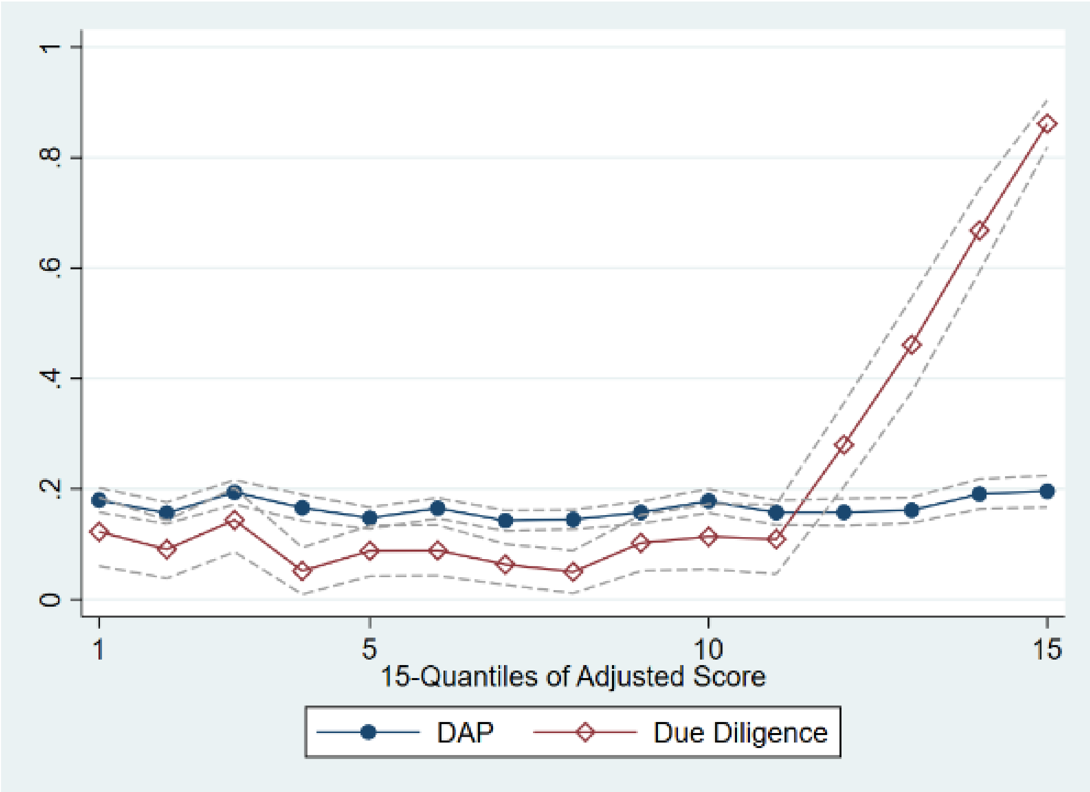


Panel C-Conditional correlation between Due-diligence assignment and DAP



Panel A plots the estimated due-diligence assignment for each 15-quartile DAP dummies. We regress due-diligence assignment against 15-quartile coefficient estimates of 15-quartile DAP dummies. The plot includes coefficient estimates and standard error confidence dashed bars. Panel B replicates Panel A but using regional DAP to take into account the level of randomization in the instrument for illustration purposes (see Section 3.2). Panel C plots the average rate of due diligence assignment (demeaned by region and rescaled for illustration purposes) against deciles of adjusted score for two subsamples: applicants with DAP above and below the median DAP of 0.22. The adjusted scores correspond to the applicant fixed effects and are estimated in models regressing reviewer scores against full set of applicant and reviewer fixed effects; for more details see Section 2.4.2 and Appendix 3.

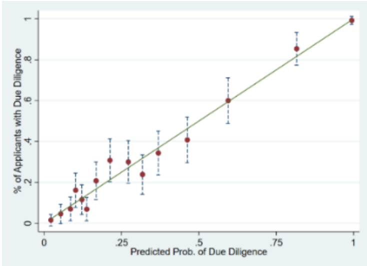
Figure 8. DAP and Company Characteristics at Application



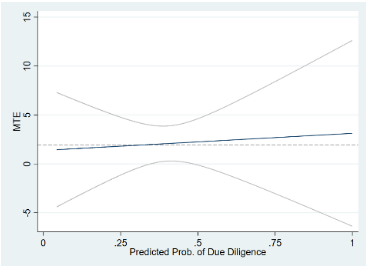
This figure plots the average due diligence assignment (demeaned by region and rescaled for illustration purposes) and DAP against deciles of applicant fixed effects. The applicant fixed effects are estimated in models regressing reviewer scores against full set of applicant and reviewer fixed effects; for more details see Section 1.2 and Appendix 3

Figure 9. Marginal Treatment Effects

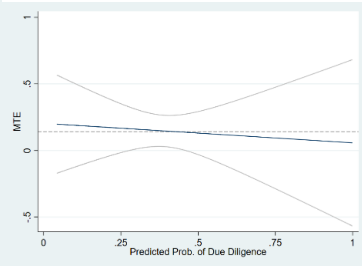
Panel A – Actual and Predicted Due Diligence Assignment



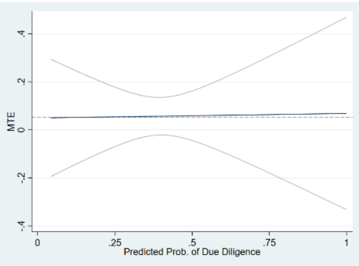
Panel B -MTE Functions



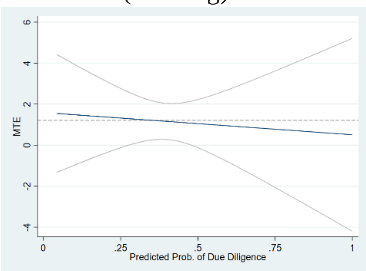
ln(Funding)



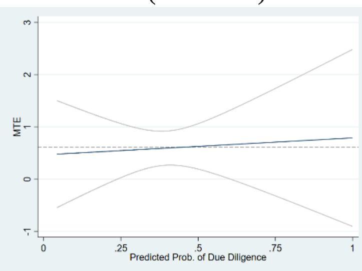
ln(# Rounds)



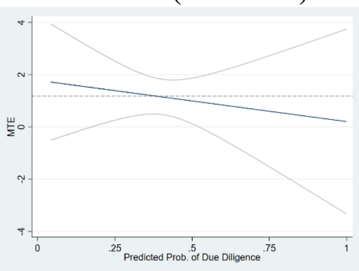
ln(# Investors)



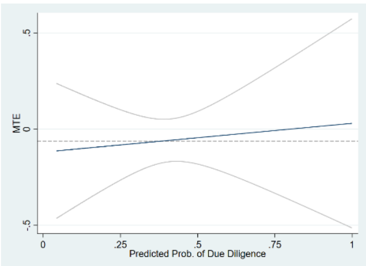
ln(Equity Issuance)



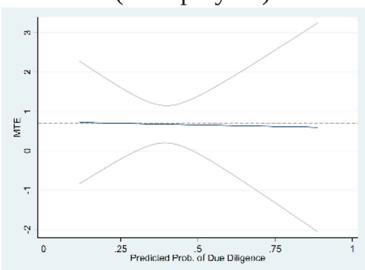
ln(# Employees)



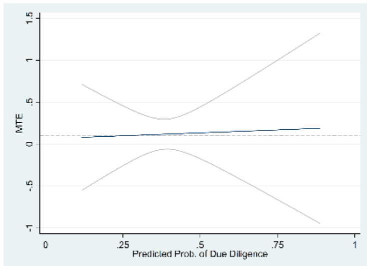
Growth in Assets



Survival (UK)



ln(# Tech Adoptions)



ln(# A/B Testing)

Panel A plots actual due-diligence against predicted probability using regional DAP. Panel B plots marginal treatment effects and associated 95% confidence intervals. We predict the relationship between each outcome and the predicted probability of due diligence assignment using a quadratic estimator. The estimates of the first derivative of this relationship are then evaluated at each percentile of predicted probability. Standard errors are calculated using a bootstrap with 250 iterations and bandwidth of 0.15. For more details see Section 5.2.

Table 1. Summary Statistics

Source	Variable	Mean	Std. Dev.	p5	p25	p50	p75	p95	N
	Application and Selection								
Application files	Age Business (since incorporation)	2.61	2.96	0.00	1.00	2.00	4.00	7.00	1,953
	Target Amount (£1000s)	1,692	2,537	100	365	1,000	2,000	5,500	1,950
	Target Close Date (Days)	80	70	25	48	70	96	165	1,946
	Total Addressable Market (£Billion)	345	1,725	0.02	1.00	8.00	50	1,000	1,435
	Total Serviceable Market (£ Billion)	45	269	0.00	0.08	0.50	3.45	80	1,435
LinkedIn	Female Founder	0.13	0.33	0.00	0.00	0.00	0.00	1.00	1,785
	Russell Education Founder	0.17	0.37	0.00	0.00	0.00	0.00	1.00	1,953
	MBA Founder	0.10	0.30	0.00	0.00	0.00	0.00	1.00	1,953
Fund’s Selection	Due diligence(%)	31.49	46.46	0.00	0.00	0.00	100.00	100.00	1,953
	Opportunity assessment(%)	2.30	15.49	0.00	0.00	0.00	0.00	100.00	1,953
	Investment(%)	0.61	7.81	0.00	0.00	0.00	0.00	0.00	1,953
	Company Characteristics (All Companies, Web Sources)								
	Pre- Application								
Crunchbase	Number of funding rounds (# Rounds)	0.47	1.06	0.00	0.00	0.00	0.00	3.00	1,953
	Total funding ($1000s) (Funding)	306	1,105	0.00	0.00	0.00	0.00	2,000	1,953
	Number of Investors (# Investors)	0.83	2.48	0.00	0.00	0.00	0.00	5.00	1,953
	ln(# Rounds)	0.73	0.29	0.00	0.00	0.00	0.00	1.39	1953
	ln(Funding)	2.90	5.00	0.00	0.00	0.00	0.00	7.60	1953
	ln(# Investors)	0.78	0.47	0.00	0.00	0.00	0.00	1.79	1953
	No. of Years Before App.	2.61	2.96	0.00	1.00	2.00	4.00	7.00	1,953
LinkedIn	Serial Entrepreneur	0.26	0.44	0.00	0.00	0.00	1.00	1.00	1,953
	No. of Companies Created by the Founder	0.40	0.80	0.00	0.00	0.00	1.00	2.00	1,953
Builtwith	Total # of Web Tech Adoptions	18.95	26.69	0.00	0.00	12.00	30.00	61.00	1,953
	ln(Total # of Web Tech Adoptions)	2.00	1.63	0.00	0.00	2.56	3.43	4.13	1,953
	Num. of A/B Testing	3.88	26.09	0.00	0.00	0.00	0.00	11.00	1,029
	ln(A/B Testing)	0.23	0.88	0.00	0.00	0.00	0.00	2.48	1,029
	Post-Application								
Crunchbase	Number of funding rounds (# Rounds)	1.28	1.90	0.00	0.00	0.00	2.00	5.00	1,953
	Total funding ($1000s) (Funding)	1,330	3,362	0.00	0.00	0.00	698	8,634	1,953
	Number of Investors (# Investors)	1.02	1.19	0.00	0.00	1.00	2.00	3.00	1,953
	ln(# Rounds)	0.93	0.40	0.00	0.00	0.00	1.10	1.79	1953
	ln(Funding)	5.56	6.56	0.00	0.00	0.00	13.46	15.97	1953

	ln(# Investors)	0.87	0.28	0.00	0.00	0.69	1.10	1.39	1953
Linkedin	Number of Employees (# Employees)	6.09	11.38	1.00	1.00	2.00	7.00	27.00	1,953
	ln(# Employees)	1.21	1.16	0.00	0.00	1.10	2.08	3.33	1,953

Table 1 (Continued). Summary Statistics

Source	Variable	Mean	Std. Dev.	p5	p25	p50	p75	p95	N
Builtwith	Total # of Web Tech Adoptions	15.83	23.60	0.00	0.00	9.00	24.00	54.00	1,953
	ln(Total # of Web Tech Adoptions)	1.88	1.54	0.00	0.00	2.30	3.22	4.01	1,953
	1(Total # of Web Tech Adoptions>0)	0.66	0.47	0.00	0.00	1.00	1.00	1.00	1,953
	Num. of A/B Testing	0.80	6.88	0.00	0.00	0.00	0.00	0.00	1,029
	ln(A/B Testing)	0.12	0.57	0.00	0.00	0.00	0.00	0.00	1,029
	1(A/B Testing>0)	0.05	0.21	0.00	0.00	0.00	0.00	0.00	1,029
	Adoptions/Testing Before Fundraising Post-Application:								
	Total # of Web Tech Adoptions	13.81	21.97	0.00	0.00	7.00	20.00	51.00	1,953
	ln(Total # of Web Tech Adoptions)	1.74	1.50	0.00	0.00	2.08	3.04	3.95	1,953
	1(Total # of Web Tech Adoptions>0)	0.64	0.48	0.00	0.00	1.00	1.00	1.00	1,953
	Num. of A/B Testing	0.67	6.69	0.00	0.00	0.00	0.00	0.00	1,029
	ln(A/B Testing)	0.10	0.51	0.00	0.00	0.00	0.00	0.00	1,029
	1(A/B Testing>0)	0.04	0.19	0.00	0.00	0.00	0.00	0.00	1,029
	Company Characteristics (UK Companies, Administrative Data)								
	Pre-Application								
Companies House	Assets (£1000s)	641	15,635	0.00	0.00	23	167	1,044	1,548
	ln(Assets)	2.89	2.61	0.00	0.00	3.18	5.12	6.95	1,548
	Equity Issuance (£1000s)	316	1,216	0.00	0.00	0.00	166	1,700	1,548
	ln(Equity Issuance)	2.39	2.70	0.00	0.00	0.00	5.12	7.44	1,548
	No. of Years Before App.	2.67	2.67	0.00	1.00	2.00	4.00	8.00	1,548
	Post-Application								
	Assets (£1000s)	1,066	18,470	0.00	1.00	86	545	3,199	1,548
	ln(Assets)	3.94	2.85	0.00	0.69	4.46	6.30	8.07	1,548
	Equity Issuance (£1000s)	770	1,866	0.00	0.00	0.00	510	4,774	1,548
	ln(Equity Issuance)	3.12	3.07	0.00	0.00	0.00	6.24	8.47	1,548
	Survival	0.81	0.39	0.00	1.00	1.00	1.00	1.00	1,548
	No. of Years After App.	1.93	0.64	1.00	2.00	2.00	2.00	3.00	1,548
	Post- relative to Pre-Application								
	Growth in Assets	1.05	2.45	-2.82	0.00	0.61	2.08	5.91	1,548
	Instrumental Variables								
Constructed	DAP	0.22	0.13	0.06	0.11	0.19	0.30	0.48	1,953

Regional DAP	0.25	0.21	0.01	0.08	0.18	0.37	0.67	1,953

he table presents summary statistics of the variables used in the analysis. The variables are organized by source and time period as indicated by the first and second column of the table. The sample includes all 1,953 applicants to the Fund that were evaluated by the reviewers. Only a subsample of these companies are incorporated in UK, and for these ventures we collect abridged balance sheet information from Companies House. For more details on data sources see Section 1.1.

Table 2. DAP and Due Diligence Assignment

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Panel A-OLS				
DAP	1.09***	1.33***	1.09***	1.32***	0.94***	1.19***	0.93***	1.19***
	(0.08)	(0.07)	(0.08)	(0.07)	(0.07)	(0.06)	(0.07)	(0.06)
Applicant FE					0.35***	0.37***	0.34***	0.37***
					(0.02)	(0.01)	(0.02)	(0.02)
F-test of excl. IV	185.64	361.00	185.64	355.59	180.33	393.36	176.51	393.36
Controls		Yes		Yes		Yes		Yes
Portfolio Companies	Yes	Yes			Yes	Yes		
Obs.	1953	1953	1941	1941	1953	1953	1941	1941
R-sq.	0.0981	0.3589	0.0976	0.3618	0.0551	0.2916	0.2679	0.5390
				Panel B-Probit				
DAP	3.09***	4.53***	3.08***	4.52***	3.14***	6.09***	3.12***	6.07***
	(0.23)	(0.28)	(0.23)	(0.28)	(0.26)	(0.37)	(0.26)	(0.37)
Applicant FE					1.17***	1.89***	1.15***	1.87***
					(0.07)	(0.10)	(0.07)	(0.10)
F-test of excl. IV	180.49	261.75	179.33	260.59	145.85	270.91	144.00	269.14
Controls		Yes		Yes		Yes		Yes
Portfolio Companies	Yes	Yes			Yes	Yes		
Obs.	1953	1953	1941	1941	1953	1953	1941	1941
Pseudo R-sq.	0.08	0.32	0.08	0.33	0.23	0.55	0.23	0.55

The table presents results from estimating Eq. (3). The outcome variable is Due diligence, which corresponds to a dummy indicating the applicants assigned to further due diligence. DAP is the due diligence assignment probability estimated as in Eq. (2). Reviewer and applicant FE correspond to the fixed effects estimated in models regressing scores against applicant and reviewer fixed effects; see Appendix 3. Controls include the log transformations (log(1+x)) of variables in the application files: age, target amount to raise, target days to close the funding, total addressable market and total serviceable market. Region fixed effects are included in the regressions. Standard errors are robust, except in columns with reviewer or applicant FE where we bootstrap standard errors. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 3—Balance of Covariates Across DAP Quartiles

Variable	Q1	Other Q	*p-value diff. in mean*	Q2	Other Q	*p-value diff. in mean*	Q3	Other Q	*p-value diff. in mean*	Q4	Other Q	*p-value diff. in mean*
App. Info												
Age	2.30	2.71	*0.00*	2.42	2.67	*0.85*	2.73	2.57	*0.43*	2.98	2.48	*0.02*
ln(Age)	0.98	1.08	*0.00*	1.01	1.07	*0.42*	1.09	1.05	*0.58*	1.14	1.03	*0.06*
Female Founder	0.14	0.12	*0.62*	0.12	0.13	*0.11*	0.14	0.13	*0.91*	0.11	0.13	*0.22*
Russell Education of Founder	0.14	0.18	*0.46*	0.17	0.17	*0.99*	0.17	0.17	*0.93*	0.20	0.16	*0.41*
Amount	1690.78	2416.15	*0.33*	1606.34	2444.41	*0.78*	3948.15	1663.73	*0.07*	1694.31	2413.00	*0.58*
ln(Amount)	6.72	6.60	*0.18*	6.58	6.65	*0.42*	6.67	6.62	*0.67*	6.55	6.66	*0.92*
Target Close Days	83.18	80.05	*0.50*	81.83	80.50	*0.40*	78.93	81.47	*0.79*	79.37	81.32	*0.67*
ln(Target Close Days)	4.23	4.22	*0.29*	4.24	4.22	*0.26*	4.22	4.22	*0.18*	4.19	4.23	*0.19*
Total Addressable Market	152.47	862.41	*0.67*	3269.07	39.36	*0.08*	3.91	1011.05	*0.53*	4.62	1073.79	*0.50*
ln(Total Addressable Market)	0.62	0.42	*0.64*	0.53	0.44	*0.08*	0.40	0.48	*0.73*	0.35	0.51	*0.08*
Total Serviceable Market	247.10	6.77	*0.39*	9.03	63.04	*0.69*	11.33	67.00	*0.11*	1.30	75.24	*0.67*
ln(Total Serviceable Market)	0.31	0.18	*0.09*	0.21	0.21	*0.14*	0.21	0.21	*0.06*	0.15	0.24	*0.09*
London	0.41	0.45		0.40	0.45		0.46	0.43		0.50	0.42	
Seed/Pre-Seed	0.47	0.44	*0.25*	0.46	0.44	*0.57*	0.42	0.45	*0.94*	0.42	0.45	*0.10*
Platform	0.46	0.55	*0.03*	0.53	0.53	*0.31*	0.56	0.52	*0.38*	0.56	0.52	*0.12*
Deep Tech	0.03	0.05	*0.10*	0.02	0.05	*0.95*	0.04	0.04	*0.47*	0.07	0.03	*0.08*
CH Info. Before App.												
Asset (£1000s)	217.48	767.68	*0.51*	194.55	785.47	*0.57*	1808.90	247.39	*0.06*	320.16	760.96	*0.51*
Annual Equity Issuance (£1000s)	177.83	740.68	*0.52*	105.08	774.86	*0.54*	1849.26	193.80	*0.05*	287.00	732.26	*0.50*
Equity Issuance (£1000s)	289.17	325.19	*0.15*	284.61	327.35	*0.72*	338.83	309.49	*0.11*	349.03	304.83	*0.62*
ln(Equity Issuance)	2.25	2.43	*0.19*	2.34	2.40	*0.54*	2.37	2.39	*0.69*	2.55	2.32	*0.75*
Web Info. Before App.												
Num. of Funding Rounds	1.09	1.22	*0.09*	1.22	1.18	*0.43*	1.19	1.18	*0.87*	1.24	1.17	*0.45*
ln(# Rounds)	0.70	0.75	*0.16*	0.74	0.73	*0.91*	0.74	0.73	*0.59*	0.76	0.73	*0.45*
Total Funding (£1000s)	280.42	437.74	*0.57*	368.39	408.36	*0.94*	356.07	412.44	*0.52*	589.22	334.94	*0.20*
ln(Funding)	2.50	3.04	*0.39*	2.75	2.95	*0.78*	2.96	2.88	*0.45*	3.40	2.74	*0.18*
Num. of Companies Created	0.40	0.40	*0.36*	0.41	0.40	*0.92*	0.37	0.41	*0.96*	0.42	0.39	*0.28*
ln(# Companies Created)	0.24	0.23	*0.20*	0.23	0.23	*0.99*	0.21	0.24	*0.83*	0.24	0.23	*0.28*
Serial Entrepreneur	0.27	0.26	*0.22*	0.26	0.26	*0.96*	0.25	0.27	*0.57*	0.27	0.26	*0.48*
Num. of Tech Adoptions	21.15	18.21	0.91	20.41	18.46	0.94	19.76	18.67	0.97	14.45	20.44	0.82

ln(Tech Adoptions)	2.17	1.94	0.89	2.07	1.98	0.95	2.02	1.99	0.99	1.74	2.09	0.83
Num. of A/B Testings	1.82	3.17	0.95	2.94	2.79	0.99	3.86	2.48	0.95	2.69	2.87	0.99
ln(# A/B Testings)	0.13	0.19	0.94	0.16	0.18	0.98	0.24	0.16	0.91	0.17	0.18	0.99

The table compares applicants' characteristics (at application) across the different quartiles of Due Diligence Assignment Probability (DAP).

Table 4—Due Diligence Assignment and Funding

Panel A—Full sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Dep. Var.	ln(Funding)		ln(# Rounds)		ln(# Investors)		ln(Equity Issuance)		I(Funding>0)		I(Rounds>0)		I(Investors>0)		I(Equity Issuance>0)	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Due diligence	2.94***	2.81***	0.20***	0.18**	0.10***	0.09*	1.18***	1.21**	0.196***	0.200**	0.175***	0.127*	0.168***	0.131*	0.104***	0.139**
	(0.36)	(0.85)	(0.02)	(0.06)	(0.02)	(0.04)	(0.18)	(0.43)	(0.03)	(0.06)	(0.03)	(0.06)	(0.03)	(0.06)	(0.02)	(0.05)
N	1953	1953	1953	1953	1953	1953	1548	1548	1953	1953	1953	1953	1953	1953	1548	1548
R-sq.	0.1313	0.1039	0.1457	0.1156	0.0704	0.0415	0.1053	0.0709	0.1126	0.0878	0.1198	0.0914	0.0763	0.0443	0.0759	0.0367
F Stat.	401.49		401.49		401.49		355.83		401.49		401.49		401.49		355.83	

Panel B—Excluding Portfolio companies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Dep. Var.	ln(Funding)		ln(# Rounds)		ln(# Investors)		ln(Equity Issuance)		I(Funding>0)		I(Rounds>0)		I(Investors>0)		I(Equity Issuance>0)	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Due diligence	2.86***	2.74**	0.19***	0.18**	0.10***	0.09*	1.13***	1.11*	0.192***	0.196**	0.170***	0.123*	0.162***	0.125*	0.102***	0.135**
	(0.37)	(0.86)	(0.02)	(0.06)	(0.02)	(0.04)	(0.18)	(0.44)	(0.03)	(0.06)	(0.03)	(0.06)	(0.03)	(0.06)	(0.02)	(0.05)
N	1941	1941	1941	1941	1941	1941	1537	1537	1941	1941	1941	1941	1941	1941	1537	1537
R-sq.	0.1298	0.1032	0.1419	0.1120	0.0689	0.0405	0.1031	0.0694	0.1116	0.0877	0.1177	0.0897	0.0747	0.0431	0.0751	0.0358
F Stat.	397.38		397.38		397.38		352.01		397.38		397.38		397.38		352.01	

The table presents results from estimating Eq. (4). The outcome variable is specified in the title of each column. Due diligence is a dummy indicating the applicants assigned to further due diligence. The IV models instrument Due diligence with DAP, the due diligence assignment probability estimated as in Eq. (2). All columns include as controls the log transformations (log(1+x)) of variables in the application files: age, target amount to raise, target days to close the funding, total addressable market and total serviceable market. Region fixed effects are also included in the regressions. The F-stat corresponds to the F-statistic of the excluded instrument (DAP) in the respective first stage Eq. (3). Standard errors are robust. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 5 –Due Diligence and Economic Growth

Panel A—Full sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	ln(# Employees)		Growth in Assets		Survival		I(Asset Growth>0)		I(#Employees>5)	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Due diligence	0.51***	0.46**	0.54***	0.93**	0.07**	-0.11	0.10***	0.10	0.18***	0.20**
	(0.07)	(0.16)	(0.15)	(0.34)	(0.02)	(0.06)	(0.03)	(0.07)	(0.03)	(0.06)
N	1953	1953	1548	1548	1548	1548	1548	1548	1953	1953
R-sq.	0.1629	0.1382	0.0846	0.0662	0.0495	-0.0042	0.0354	0.0134	0.1472	0.1262
F Stat.	401.49		355.83		355.83		355.83		401.49	

Panel B—Excluding Portfolio companies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	ln(# Employees)		Growth in Assets		Survival		I(Asset Growth>0)		I(#Employees>5)	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Due diligence	0.50***	0.44**	0.50***	0.89*	0.07**	-0.11*	0.09**	0.09	0.18***	0.20**
	(0.07)	(0.16)	(0.15)	(0.34)	(0.02)	(0.06)	(0.03)	(0.07)	(0.03)	(0.06)
N	1941	1941	1537	1537	1537	1537	1537	1537	1941	1941
R-sq.	0.1598	0.1357	0.0821	0.0636	0.0489	-0.0062	0.0345	0.0128	0.1438	0.1229
F Stat.	397.38		352.01		352.01		352.01		397.38	

The table presents results from estimating Eq. (4). The outcome variable is specified in the title of each column. Due diligence is a dummy indicating the applicants assigned to further due diligence. The IV models instrument Due diligence with DAP, the due diligence assignment probability estimated as in Eq. (2). Controls include the log transformations (log(1+x)) of variables in the application files: age, target amount to raise, target days to close the funding, total addressable market and total serviceable market. Region fixed effects are also included in the regressions. The F-stat corresponds to the F-statistic of the excluded instrument (DAP) in the respective first stage Eq. (3). Standard errors are robust. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 6. Due Diligence and Technology Adoptions and A/B Testing

Panel A Full Sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ln(Tech Adoptions)		**1**Tech Adoptions>0)		ln(A/B Testing)		**1**(A/B Testing>0)	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Due Diligence	0.20***	0.70***	0.06*	0.18**	0.18***	0.27*	0.07***	0.11*
	(0.05)	(0.13)	(0.03)	(0.06)	(0.05)	(0.13)	(0.02)	(0.05)
N	1953	1953	1953	1953	1029	1029	1029	1029
R-sq	0.0241	-0.0317	0.0253	-0.0006	0.0476	0.0248	0.0488	0.0278
F Stat.		401.49		401.49		148.73		148.73

Panel B—Excluding Portfolio companies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ln(Tech Adoptions)		**1**Tech Adoptions>0)		ln(A/B Testing)		**1**(A/B Testing>0)	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Due Diligence	0.20***	0.70***	0.06*	0.18**	0.18***	0.28*	0.07***	0.11*
	(0.05)	(0.13)	(0.03)	(0.06)	(0.05)	(0.13)	(0.02)	(0.05)
N	1941	1941	1941	1941	1021	1021	1021	1021
R-sq	0.0242	-0.0320	0.0250	-0.0001	0.0479	0.0252	0.0493	0.0282
F Stat.		397.38		397.38		143.10		143.10

The table presents results from estimating Eq. (4). The outcome variable is specified in the title of each column. The outcome variables are constructed based on the number of technology adoptions on the applicant's website within 12 months after the application. There are two types of outcome variable: Total number of technology adoptions and A/B testing technologies for platform businesses. Due diligence is a dummy indicating the applicants assigned to further due diligence. The IV models instrument Due diligence with DAP, the due diligence assignment probability estimated as in Eq. (2). All columns include as controls the log transformations (log(1+x)) of variables in the application files: age, target amount to raise, target days to close the funding, total addressable market and total serviceable market. Region fixed effects are also included in the regressions. The F-stat corresponds to the F-statistic of the excluded instrument (DAP) in the respective first stage Eq. (3). Standard errors are robust. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 7 - Implied Economic Magnitudes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Funding	# Rounds	# Investors	Equity issuance	# Employees	Growth in Assets	Tech. adoptions	A/B testing
Point estimate	2.81	0.18	0.09	1.21	0.46	0.93	0.70	0.27
Point estimate non-portfolio companies	2.74	0.18	0.09	1.11	0.44	0.89	0.70	0.28
log mean	5.56	0.93	0.87	3.12	1.21	1.05	1.88	0.12
level mean (£K)	1,330	1.28	1.02	770	6.09	641	15.83	0.80
log P75	13.46	1.1	1.1	6.24	2.08	2.05	3.22	-
level P75 (£K)	698	2	2	510	7	167	24	-
Economic magnitudes relative to the mean								
Percentage	51%	19%	10%	39%	38%	89%	37%	225%
Level	672	0.25	0.11	299	2.32	568	5.89	1.80
Percentage non-portfolio companies	49%	19%	10%	36%	36%	85%	37%	233%
Level non- portfolio companies	655	0.25	0.11	274	2.21	543	5.89	1.87
Economic magnitudes relative to the P75								
Percentage	21%	16%	8%	19%	22%	45%	22%	-
Level	146	0.33	0.16	99	1.55	76	5.22	-
Percentage non-portfolio companies	20%	16%	8%	18%	21%	43%	22%	-
Level non- portfolio companies	142	0.33	0.16	91	1.48	73	5.22	-

The table summarizes the implied economic magnitudes of the estimated coefficients reported in Tables 4-6. To back out the implied economic magnitudes for a given coefficient estimate, we compare the estimate to the mean or 75th percentile of the corresponding level and logarithmic outcome distribution.

Table 8 – Effects on the Upper Tail (25th percentile)

Panel A Full Sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	ln(Funding)		ln(# Rounds)		ln(# Investors)		ln(Equity Issuance)		ln(# Employees)		Asset growth		Tech Adoptions		A/B testing	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Due Diligence	0.19***	0.15*	0.18***	0.19***	0.07***	0.05	0.17***	0.13*	0.16***	0.14*	0.05*	0.12*	0.06*	0.18**	0.07***	0.11*
	(0.03)	(0.06)	(0.02)	(0.05)	(0.02)	(0.05)	(0.03)	(0.06)	(0.03)	(0.06)	(0.03)	(0.06)	(0.03)	(0.06)	(0.02)	(0.05)
N	1953	1953	1953	1953	1953	1953	1548	1548	1953	1953	1548	1548	1953	1953	1029	1029
R-sq.	0.126	0.096	0.112	0.084	0.033	0.017	0.094	0.068	0.147	0.126	0.095	0.076	0.025	-0.001	0.049	0.028
F Stat.		401.63		401.63		401.63		355.96		401.63		355.96		401.63		148.73

Panel B Excluding Portfolio Companies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	ln(Funding)		ln(# Rounds)		ln(# Investors)		ln(Equity Issuance)		ln(# Employees)		Asset growth		Tech Adoptions		A/B testing	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Due Diligence	0.18***	0.14*	0.18***	0.18***	0.07***	0.06	0.16***	0.12	0.16***	0.13*	0.05	0.11	0.06*	0.18**	0.07***	0.11*
	(0.03)	(0.06)	(0.02)	(0.05)	(0.02)	(0.05)	(0.03)	(0.06)	(0.03)	(0.06)	(0.03)	(0.06)	(0.03)	(0.06)	(0.02)	(0.05)
N	1941	1941	1941	1941	1941	1941	1537	1537	1941	1941	1537	1537	1941	1941	1021	1021
R-sq.	0.122	0.093	0.110	0.082	0.032	0.017	0.091	0.066	0.145	0.125	0.095	0.074	0.025	-0.001	0.049	0.028
F Stat.		397.52		397.52		397.52		352.13		397.52		352.13		397.52		143.10

The table presents results from estimating Eq. (4). The outcome variable corresponds to dichotomous variables indicating firms in the top 25th percentile of the sample distribution of the variable specified in the title of each column. Due diligence is a dummy indicating the applicants assigned to further due diligence. The IV models instrument Due diligence with DAP, the due diligence assignment probability estimated as in Eq. (2). All columns include as controls the log transformations (log(1+x)) of variables in the application files: age, target amount to raise, target days to close the funding, total addressable market and total serviceable market. Region fixed effects are also included in the regressions. The F-stat corresponds to the F-statistic of the excluded instrument (DAP) in the respective first stage Eq. (3). Columns 9 and 10 replicate the results in the respective columns of Table 5 to ease the comparison. Standard errors are robust. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 9-The Impacts of Due Diligence for Non-portfolio Companies: sample cuts

Panel A—Location

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
	ln(Funding)		ln(# Rounds)		ln(# Investors)		ln(Equity Issuance)		ln(# Employees)		Growth in Assets		Survival		ln(Tech Adoptions)		ln(A/B Testing)	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Due diligence	1.77***	7.73***	0.10***	0.32**	0.05**	0.09	0.07	3.11**	0.13	0.71	-0.15	1.89	0.07*	-0.42*	0.16*	0.90***	0.06	-0.03
	(0.40)	(1.96)	(0.02)	(0.11)	(0.02)	(0.08)	(0.22)	(1.17)	(0.09)	(0.42)	(0.19)	(0.98)	(0.03)	(0.17)	(0.07)	(0.26)	(0.06)	(0.21)
Due diligence*London	1.35*	-6.29**	0.13**	-0.16	0.06*	0.02	1.55***	-2.02	0.58***	-0.17	0.97***	-0.92	0.04	0.40*	0.14	-0.14	0.22*	0.46
	(0.65)	(2.29)	(0.04)	(0.14)	(0.03)	(0.09)	(0.33)	(1.32)	(0.12)	(0.47)	(0.27)	(1.08)	(0.04)	(0.19)	(0.10)	(0.30)	(0.09)	(0.27)
London	1.25***	3.69***	0.08***	0.17***	0.06***	0.07*	0.17	1.52**	-0.04	0.24	0.11	0.87*	0.00	-0.15*	-0.03	0.03	-0.03	-0.09
	(0.33)	(0.78)	(0.02)	(0.04)	(0.01)	(0.03)	(0.18)	(0.51)	(0.07)	(0.18)	(0.14)	(0.42)	(0.03)	(0.07)	(0.05)	(0.09)	(0.03)	(0.08)
N	1941	1941	1941	1941	1941	1941	1537	1537	1941	1941	1537	1537	1537	1537	1941	1941	1021	1021
R-sq	0.117	0.008	0.131	0.089	0.053	0.050	0.082	-0.033	0.145	0.114	0.079	0.000	0.037	-0.145	0.015	-0.057	0.042	0.033
F Stat.		27.49		27.49		27.49		17.68		27.49		17.68		17.68		41.88		14.00

Panel B—Founders' Educational Background

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
	ln(Funding)		ln(# Rounds)		ln(# Investors)		ln(Equity Issuance)		ln(# Employees)		Growth in Assets		Survival		ln(Tech Adoptions)		ln(A/B Testing)	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Due diligence	3.00***	2.46*	0.19***	0.18**	0.10***	0.10*	1.16***	1.01*	0.50***	0.37*	0.54**	0.88*	0.07**	-0.11	0.17**	0.62***	0.18**	0.28
	(0.40)	(0.97)	(0.03)	(0.06)	(0.02)	(0.04)	(0.20)	(0.50)	(0.08)	(0.19)	(0.17)	(0.40)	(0.02)	(0.07)	(0.06)	(0.15)	(0.06)	(0.16)
Due diligence*Russell	-0.79	1.57	0.02	-0.03	-0.04	-0.08	-0.28	0.35	-0.04	0.26	-0.26	-0.13	-0.01	-0.01	0.19	0.53	0.03	-0.00
	(0.86)	(2.77)	(0.06)	(0.17)	(0.04)	(0.13)	(0.42)	(1.31)	(0.14)	(0.47)	(0.32)	(1.01)	(0.05)	(0.16)	(0.14)	(0.47)	(0.11)	(0.31)
Russell	0.88	0.08	0.03	0.05	0.01	0.03	0.93***	0.71	0.42***	0.31	0.64***	0.58	0.07*	0.07	-0.11	-0.25	-0.01	-0.01
	(0.47)	(1.00)	(0.03)	(0.06)	(0.02)	(0.05)	(0.24)	(0.50)	(0.08)	(0.17)	(0.18)	(0.37)	(0.03)	(0.06)	(0.08)	(0.18)	(0.04)	(0.11)
N	1941	1941	1941	1941	1941	1941	1537	1537	1941	1941	1537	1537	1537	1537	1941	1941	1021	1021
R-sq	0.131	0.101	0.143	0.113	0.070	0.040	0.115	0.080	0.178	0.152	0.090	0.072	0.053	-0.003	0.026	-0.037	0.048	0.025
F Stat.		22.16		22.16		22.16		22.71		22.16		22.71		22.71		21.50		55.96

The table presents results from estimating Eq. (4). The outcome variable is specified in the title of each column. Due diligence is a dummy indicating the applicants assigned to further due diligence. The IV models instrument Due diligence with DAP, the due diligence assignment probability estimated as in Eq. (2). All columns include as controls the log transformations (log(1+x)) of variables in the application files: age, target amount to raise, target days to close the funding, total addressable market and total serviceable market. Region fixed effects are also included in the regressions. The F-stat corresponds to the F-statistic of the excluded instrument (DAP) in the respective first stage Eq. (3). Standard errors are robust. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 10-Due-diligence and Disagreement among reviewers

Panel A-Summary Statistics of Disagreement measures

Variable	Mean	SD	p5	p25	p50	p75	p95	N
Disagreement Residual Score	0.226	0.156	0.026	0.069	0.217	0.344	0.490	1953
Disagreement Stage	0.353	0.345	0.000	0.000	0.333	0.667	1.000	1953
Disagreement Earlier Stage	0.273	0.342	0.000	0.000	0.000	0.667	1.000	1953
Disagreement Later Stage	0.080	0.208	0.000	0.000	0.000	0.000	0.667	1953

Panel B Disagreement (by Adjusted Score) Across Reviewers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
	ln(Funding)		ln(# Rounds)		ln(# Investors)		ln(Equity Issuance)		ln(# Employees)		Growth in Assets		Survival		ln(Tech Adoptions)		ln(A/B Testing)	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Due diligence	4.07***	5.50**	0.26***	0.39***	0.17***	0.23**	1.79***	2.13*	0.69***	0.66*	0.80**	1.28	0.04	-0.10	0.19*	1.02***	0.15*	0.23
	(0.60)	(1.70)	(0.04)	(0.11)	(0.03)	(0.08)	(0.31)	(0.83)	(0.12)	(0.32)	(0.25)	(0.70)	(0.04)	(0.11)	(0.10)	(0.26)	(0.06)	(0.14)
Due diligence* Dis.(Residual Score)	-4.45*	-9.51	-0.25*	-0.79*	-0.27**	-0.54	-2.59**	-3.87	-0.71	-0.62	-1.20	-1.53	0.12	-0.03	0.09	-1.20	-0.16	-0.52
	(1.90)	(6.43)	(0.12)	(0.37)	(0.08)	(0.28)	(0.98)	(3.20)	(0.39)	(1.32)	(0.89)	(2.89)	(0.13)	(0.44)	(0.32)	(0.99)	(0.19)	(0.47)
Dis.(Residual Score)	-2.99**	-1.45	-0.18**	-0.01	-0.04	0.05	-0.33	0.10	-0.38	-0.41	0.13	0.16	-0.16	-0.07	-0.22	0.08	-0.02	0.09
	(1.02)	(2.16)	(0.06)	(0.12)	(0.05)	(0.10)	(0.57)	(1.16)	(0.21)	(0.47)	(0.48)	(1.03)	(0.09)	(0.16)	(0.17)	(0.36)	(0.06)	(0.16)
N	1941	1941	1941	1941	1941	1941	1537	1537	1941	1941	1537	1537	1537	1537	1941	1941	1941	1941
R-sq	0.143	0.114	0.154	0.114	0.078	0.045	0.111	0.076	0.169	0.145	0.084	0.065	0.051	-0.002	0.025	-0.042	0.021	0.007
F Stat.		41.88		41.88		41.88		33.53		41.88		33.53		33.53		41.88		41.88

Panel C Disagreement about Stage Between Entrepreneur and Reviewers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
	ln(Funding)		ln(# Rounds)		ln(# Investors)		ln(Equity Issuance)		ln(# Employees)		Growth in Assets		Survival		ln(Tech Adoptions)		ln(A/B Testing)	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Due diligence	3.68***	4.67***	0.24***	0.31***	0.12***	0.10	1.52***	1.76**	0.59***	0.90**	0.66***	0.85	0.08**	-0.05	0.18**	0.83***	0.12*	0.34**
	(0.49)	(1.27)	(0.03)	(0.09)	(0.02)	(0.06)	(0.25)	(0.65)	(0.10)	(0.28)	(0.20)	(0.52)	(0.03)	(0.08)	(0.07)	(0.20)	(0.05)	(0.12)
Due diligence* Dis.(Stage)	-2.77**	-5.43*	-0.18**	-0.35*	-0.07	-0.06	-1.42**	-1.87	-0.35	-1.17*	-0.55	-0.81	-0.06	-0.14	0.07	-0.39	-0.03	-0.69**

	(0.93)	(2.50)	(0.06)	(0.15)	(0.04)	(0.11)	(0.46)	(1.27)	(0.18)	(0.52)	(0.41)	(1.16)	(0.06)	(0.18)	(0.14)	(0.40)	(0.09)	(0.23)
Dis.(Stage)	-1.82***	-1.09	-0.11***	-0.06	-0.06**	-0.07*	-0.77**	-0.62	-0.37***	-0.12	-0.01	0.08	-0.04	-0.03	0.06	0.23	0.03	0.21**
	(0.47)	(0.78)	(0.03)	(0.05)	(0.02)	(0.03)	(0.25)	(0.43)	(0.09)	(0.17)	(0.21)	(0.39)	(0.04)	(0.06)	(0.08)	(0.13)	(0.04)	(0.07)
N	1941	1941	1941	1941	1941	1941	1537	1537	1941	1941	1537	1537	1537	1537	1941	1941	1941	1941
R-sq	0.086	0.054	0.097	0.061	0.063	0.034	0.085	0.050	0.084	0.046	0.024	0.009	0.025	-0.024	0.022	-0.039	0.018	-0.028
F Stat.		101.21		101.21		101.21		81.24		101.21		81.24		81.24		101.21		101.21

Panel C Disagreement about Stage (Earlier) Between Entrepreneur and Reviewers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
	ln(Funding)		ln(# Rounds)		ln(# Investors)		ln(Equity Issuance)		ln(# Employees)		Growth in Assets		Survival		ln(Tech Adoptions)		ln(A/B Testing)	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Due diligence	3.37***	4.30***	0.24***	0.34***	0.12***	0.11*	1.47***	1.68**	0.56***	0.87***	0.56**	0.81	0.08**	-0.05	0.23***	0.87***	0.13**	0.21*
	(0.46)	(1.15)	(0.03)	(0.08)	(0.02)	(0.05)	(0.23)	(0.59)	(0.09)	(0.25)	(0.19)	(0.48)	(0.03)	(0.07)	(0.07)	(0.18)	(0.04)	(0.11)
Due diligence* Dis.(Earlier Stage)	-2.01*	-5.00*	-0.18**	-0.53***	-0.09*	-0.11	-1.43**	-1.72	-0.27	-1.23*	-0.32	-0.91	-0.08	-0.19	-0.11	-0.70	-0.08	-0.39
	(0.94)	(2.49)	(0.06)	(0.15)	(0.04)	(0.11)	(0.46)	(1.24)	(0.18)	(0.50)	(0.42)	(1.14)	(0.07)	(0.19)	(0.15)	(0.41)	(0.10)	(0.21)
Dis.(Earlier Stage)	-1.60***	-0.82	-0.07**	0.02	-0.05*	-0.05	-0.46	-0.36	-0.23*	0.05	-0.25	-0.08	-0.03	-0.02	0.07	0.26*	0.03	0.11
	(0.45)	(0.74)	(0.03)	(0.04)	(0.02)	(0.03)	(0.25)	(0.41)	(0.09)	(0.16)	(0.21)	(0.37)	(0.04)	(0.06)	(0.08)	(0.13)	(0.04)	(0.06)
N	1941	1941	1941	1941	1941	1941	1537	1537	1941	1941	1537	1537	1537	1537	1941	1941	1941	1941
R-sq	0.078	0.045	0.090	0.041	0.062	0.033	0.077	0.041	0.072	0.030	0.025	0.009	0.026	-0.022	0.022	-0.041	0.018	-0.001
F Stat.		98.28		98.28		98.28		92.16		98.28		92.16		92.16		98.28		98.28

Panel D Disagreement about Stage (Later) Between Entrepreneur and Reviewers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
	ln(Funding)		ln(# Rounds)		ln(# Investors)		ln(Equity Issuance)		ln(# Employees)		Growth in Assets		Survival		ln(Tech Adoptions)		ln(A/B Testing)	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Due diligence	3.13***	3.38***	0.20***	0.18**	0.10***	0.08	1.14***	1.37**	0.52***	0.57**	0.56***	0.54	0.06**	-0.11	0.17**	0.61***	0.10**	0.19*
	(0.40)	(0.96)	(0.03)	(0.06)	(0.02)	(0.04)	(0.19)	(0.48)	(0.08)	(0.20)	(0.16)	(0.39)	(0.02)	(0.06)	(0.06)	(0.14)	(0.04)	(0.09)
Due diligence* Dis.(Later Stage)	-2.47	-3.30	-0.02	0.37	0.03	0.12	-0.15	-1.89	-0.26	-0.42	-0.74	1.19	0.06	0.19	0.47	1.05	0.13	-0.92*
	(1.54)	(4.94)	(0.10)	(0.33)	(0.07)	(0.21)	(0.77)	(2.75)	(0.25)	(0.93)	(0.77)	(2.84)	(0.09)	(0.36)	(0.26)	(0.81)	(0.17)	(0.44)
Dis.(Later Stage)	-0.61	-0.36	-0.10**	-0.20*	-0.03	-0.06	-0.90*	-0.37	-0.39**	-0.34	0.71	0.13	-0.01	-0.07	-0.04	-0.17	0.01	0.31

	(0.80)	(1.52)	(0.04)	(0.09)	(0.03)	(0.06)	(0.39)	(0.92)	(0.13)	(0.30)	(0.37)	(0.92)	(0.06)	(0.12)	(0.12)	(0.23)	(0.07)	(0.16)
N	1941	1941	1941	1941	1941	1941	1537	1537	1941	1941	1537	1537	1537	1537	1941	1941	1941	1941
R-sq	0.067	0.038	0.078	0.038	0.052	0.022	0.066	0.028	0.070	0.043	0.025	0.004	0.023	-0.025	0.023	-0.033	0.018	-0.026
F Stat.		12.57		12.57		12.57		6.55		12.57		6.55		6.55		12.57		12.57

We construct two sets of measurement of disagreement: (1) disagreement across reviewers and (2) disagreement between the entrepreneur and reviewers regarding the stage and business type. The first type of disagreement is measured by the standard deviation of the three (adjusted) score divided by the average of the three adjusted scores (the adjusted score is the raw score subtracted the generosity of each reviewer). The second type of disagreement is based on the comparison of claimed stage (or business type) and perceived stage (or business type) by the reviewers. For each reviewer on a given application, an indicator of reviewer-entrepreneur disagreement on the stage (or business type) is equal to 1 if the claimed stage (or business type) is different from the perceived stage (or business type) by the reviewers. Then for each application, the disagreement of stage (or business type) is calculated as the average of the three reviewer-entrepreneur indicators of disagreement. We further decompose the disagreement of funding stage into two types: earlier or later. “Earlier” (“Later”) means the reviewer thinks the stage of the venture is before (after) the claimed stage by the entrepreneur.

ONLINE APPENDIX

Appendix 1—Randomization Checks

There are 12 reviewers in our data, including three female reviewers. The average (median) number of applicants assessed by reviewers is 400 (566), and the minimum (maximum) is 30 (796). In terms of "reviewer trios", there are 132 in total, with 44 (30) mean (median) and 3 (150) minimum (maximum) reviews per trio. Figure A11 below shows the distribution of applications, over the 12 reviewers (Panel A) and over the 132 trios (Panel B).

The proprietary software assigns numbers to incoming applications and classifies them according to the location of the business as self-reported by the applicants. There is a total of 16 regions, following the standard 12 region and nations classification of the UK, plus a further breakdown to best reflect local entrepreneurship clusters, and non-UK applicants. The locations are Cambridge, East Midlands, East of England, London, Non-UK, North East, North West, Northern Ireland, Republic of Ireland, Scotland, South Central, South East, South West, Wales, West Midlands and Yorkshire and the Humber.

Some reviewers (6 out of 12) have an explicit geographical focus. Table A11 shows the regional sample composition for each reviewer, and details reviewers' regional focus. The table shows that the reviewers with the regional focus are more likely to be assigned applicants that are located within their regions. For example, the table shows that the regional distribution of applicants for reviewer 12 is concentrated relative to the overall regional distribution of applicants in London, Southwest and Wales (50.9% vs. 44.%, 8.1% vs. 4.2%, and 1.8% vs. 0.9%), which correspond to this reviewers' geographical focus areas.

Yet, the regional focus match between applicants and reviewers is neither sufficient nor necessary for an assignment. Table A11 shows that all but two reviewers (Reviewer 1 and 2) assess applicants from all 16 regions. The remaining two reviewers assess 10 (Reviewer 1) and 14 (Reviewer 2) regions, respectively. These reviewers are also those with the fewest number of applications as they are newer to the firm, and which helps explain why their assessment sample not cover all the regions.

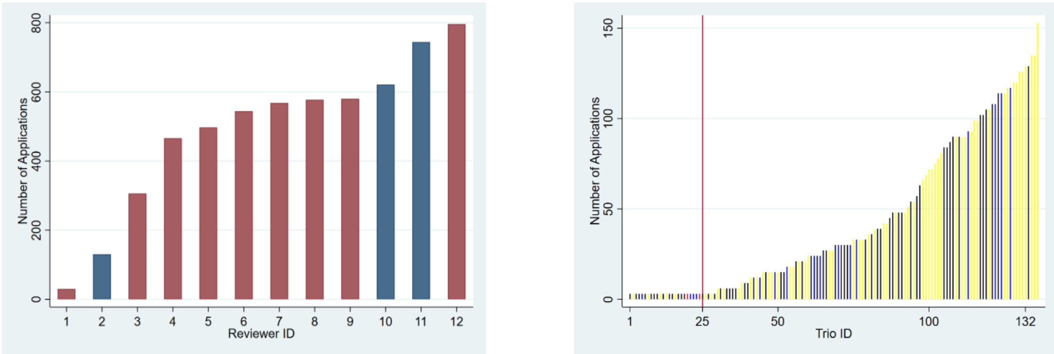
The pool of reviewers for applicant assignment is 12 for 9 of the 16 locations (56.3%), 11 for 6 of the 16 locations (37.5%), and 10 for 1 of the 16 locations (6.25%). The regions with 11 reviewers in the pool are: East of England, Non-UK, North East, Northern Ireland, Scotland, South Central. The region with 10 reviewers in the pool is Wales. For regions with designated investment leads, the average number of companies with an investment lead that has a regional focus is 64% (Cambridge has the minimum with 23% and Scotland is the maximum with 86%).

We provide evidence to support the assertion that the assignment of applications to reviewers is random conditional on the location of the applicant. We regress businesses' and applicants' characteristics at application against reviewer fixed effects. We test for balance in sample composition across reviewers by assessing the joint significance of the reviewer fixed effects. The dependent variables are: the age of the business, the gender of the founding team (female equals 1 if at least one founder is female), the stage of development (a dummy indicating a pre-seed or seed company), the business model (a dummy indicating companies doing direct sales), the total addressable and serviceable markets and the target amounts (all as reported by the applicants), and the location of the business (a dummy that equals one for businesses in London).

Table A12 below reports the F-tests and p-values of the reviewer fixed effects across the different business and applicant characteristics. We reject the equality of the reviewer fixed effects for all variables. The only exception is the location variable, where consistent with the regional allocation we reject of equality of reviewer fixed effects when we use as dependent variable an indicator variable for businesses in London.

Figure A11—Distribution of Applications across Reviewers and Trios

Panel A—Distribution over Reviewers **Panel B—Distribution over Trios**



The figure plots the number of applications evaluated by each reviewer (Panel A) and by each trio of reviewers (Panel B).

Table A11 Regional Composition of Each Reviewer's Assessment Samples

Reviewer ID	No. of Reviewed Applications	Wales	Republic of Ireland	Northern Ireland	East Midlands	North East	Eeast England	Cambridge	Yorkshire & Humber	South Central	West Midlands	North West	South West	South East	Scotland	Non-UK	London	**Geographic focus**
ALL	***5859***	***0.9%***	***1.1%***	***1.4%***	***1.2%***	***1.4%***	***1.5%***	***1.8%***	***2.2%***	***2.6%***	***4.0%***	***4.5%***	***4.2%***	***4.4%***	***4.9%***	***20.0%***	***44.2%***	
12	795	***1.8%***	0.8%	0.8%	1.0%	1.0%	1.0%	1.0%	1.0%	1.9%	2.0%	2.1%	***8.1%***	3.1%	1.9%	21.6%	***50.9%***	London, Southwest + Wales
11	742	0.9%	0.4%	0.4%	***2.3%***	0.5%	1.5%	1.8%	1.3%	5.7%	***7.8%***	2.3%	3.0%	3.4%	2.4%	19.0%	***47.3%***	London, Midlands + Oxford
10	618	0.5%	0.5%	1.5%	1.0%	1.0%	0.6%	1.5%	1.3%	0.8%	3.7%	2.8%	3.1%	7.8%	3.7%	15.9%	***54.5%***	London
8	582	1.2%	0.7%	1.5%	0.7%	1.5%	1.4%	1.7%	2.2%	3.4%	4.6%	4.8%	4.8%	6.0%	5.0%	13.6%	46.7%	
9	580	0.7%	1.0%	1.0%	1.2%	2.1%	1.7%	1.7%	1.9%	2.2%	4.3%	4.5%	3.1%	3.6%	3.8%	24.0%	43.1%	
7	568	0.4%	1.6%	1.9%	0.4%	1.1%	1.2%	1.1%	2.6%	1.6%	3.2%	***8.6%***	4.0%	1.1%	***14.3%***	26.1%	31.0%	Scotland + Northwest
6	538	***1.3%***	1.3%	1.3%	1.3%	0.4%	1.7%	2.2%	2.0%	1.7%	3.0%	3.5%	4.5%	5.4%	5.6%	20.3%	44.6%	
5	498	0.2%	1.4%	1.6%	2.2%	1.6%	1.0%	1.8%	2.6%	2.0%	4.0%	7.0%	4.2%	4.4%	7.0%	13.9%	45.0%	
4	468	0.2%	2.8%	***4.1%***	0.2%	***4.1%***	1.3%	1.3%	6.2%	3.0%	2.6%	5.3%	2.6%	3.6%	2.4%	27.4%	33.1%	Northeast + Northern Ireland
3	307	1.6%	0.7%	0.7%	0.3%	1.3%	***4.6%***	***4.2%***	1.3%	3.6%	2.9%	5.2%	1.6%	3.3%	5.9%	26.4%	36.5%	Cambridge
2	134	0.0%	1.5%	0.0%	3.0%	2.2%	3.7%	6.0%	1.5%	1.5%	5.2%	5.2%	5.2%	10.4%	4.5%	4.5%	45.5%	
1	29	0.0%	3.4%	3.4%	3.4%	0.0%	0.0%	3.4%	6.9%	0.0%	10.3%	17.2%	10.3%	10.3%	0.0%	0.0%	31.0%	

This table presents the regional composition of each reviewers' assessment samples. The underlined and italic cells indicate the regions of focus of the different reviewers.

Table A12—Randomization Checks across Business and Founder Characteristics

Dependent Variable	Obs.	Reviewer F.E.		Reviewer F.E. Conditional on Speciality of Region		Reviewer F.E. Conditional on Region	
		F Stat.	*p-Value*	F Stat.	*p-Value*	F Stat.	*p-Value*
Age	5837	1.646	(0.079)	1.618	(0.087)	1.291	(0.222)
ln(Age)	5837	1.284	(0.227)	1.252	(0.246)	1.025	(0.421)
Female Founder	5340	0.966	(0.475)	0.946	(0.494)	0.667	(0.771)
Russell Education of Founder	5837	1.058	(0.391)	0.839	(0.601)	0.432	(0.942)
Amount	4872	0.585	(0.843)	0.580	(0.847)	0.643	(0.793)
ln(Amount)	4872	0.389	(0.961)	0.367	(0.969)	0.377	(0.965)
Target Close Days	4881	1.031	(0.416)	1.010	(0.434)	0.962	(0.479)
ln(Target Close Days)	4869	1.272	(0.234)	1.250	(0.248)	1.153	(0.315)
Total Addressable Market	4285	0.566	(0.858)	0.563	(0.86)	0.517	(0.893)
ln(Total Addressable Market)	4285	2.095	(0.018)	2.039	(0.022)	1.678	(0.0719)
Total Servicable Market	4285	1.053	(0.396)	1.037	(0.411)	1.043	(0.405)
ln(Total Servicable Market)	4285	0.780	(0.660)	0.740	(0.701)	0.606	(0.826)
Seed/Pre-Seed	5837	1.258	(0.242)	1.260	(0.241)	1.081	(0.372)
Deep Tech	5837	1.719	(0.063)	1.699	(0.067)	1.261	(0.241)
Platform	5837	2.301	(0.008)	2.287	(0.009)	1.380	(0.175)
London	5837	9.883	(0.000)				
London (Reviewers Assigned by Region Rules)	3491	20.510	(0.000)				
London (Reviewers Assigned without Region Rules)	2346	1.389	(0.225)				
Financial Status Before App.							
Asset (£1000s)	4625	0.756	0.685	0.754	0.687	0.712	0.729
ln(Assets)	4625	1.147	0.319	1.148	0.319	1.014	0.431
Equity Issuance (£1000s)	4625	0.918	0.522	0.918	0.522	0.877	0.563
ln(Equity Issuance)	5837	0.653	0.784	0.653	0.784	0.668	0.770
Num. of Funding Rounds	5837	0.932	0.508	0.911	0.528	0.743	0.697
ln(# Rounds)	5837	0.809	0.631	0.773	0.668	0.579	0.847
Total Funding (£1000s)	5837	0.609	0.823	0.603	0.828	0.509	0.898
ln(Funding)	5837	0.630	0.804	0.635	0.801	0.578	0.848
Num. of Companies Created	5837	0.965	0.476	1.026	0.420	0.907	0.533
ln(# Companies Created)	5837	0.957	0.484	0.996	0.447	0.874	0.565
Serial Entrepreneur	5837	0.817	0.623	0.832	0.608	0.744	0.697
Num. of Tech Adoptions	5837	0.379	0.965	0.382	0.964	0.319	0.982
ln(Tech Adoptions)	5837	0.681	0.758	0.679	0.760	0.643	0.793
Num. of A/B Testings	5837	0.910	0.530	0.893	0.546	0.615	0.818
ln(# A/B Testings)	5837	0.794	0.646	0.786	0.655	0.517	0.893

The table shows the F test of the joint significance of reviewer fixed effects for different dependent variables. The last two rows represent two subsamples: reviewers assigned by geographical focus rules and reviewers assigned without geographical rules. Specification (1) includes no controls; specification (2) include a dummy "specialty" indicating if the region is focused by any reviewers; specification (3) includes region specific fixed effects.

Appendix 2—Reviewer Heterogeneity in Scores

We provide evidence of systematic differences across reviewers in scoring generosity by exploiting the multiple reviewers assignment per applicant to run fixed effects models of application scores against reviewer and applicant fixed effects. Our approach is similar to the methodologies in papers assessing the importance of managers in corporations (cf. Bertrand and Schoar, 2003) and general partners in limited partnerships (Ewens and Rhodes-Kropf, 2015). The idea is that reviewer fixed effects would be jointly significant if reviewers systematically vary in their tendency to assign high or low scores to applicants.

We begin by decomposing individual scores into applicant and reviewer fixed effects using the following regression:

$$Score_{i,h} = \mu_h + \alpha_i + X_{i,h} + \epsilon_{i,h} \quad \text{(A21)}$$

where $Score_{i,h}$ denotes the score assigned by reviewer h to company i; μ_h and α_i are full sets of reviewer and applicant FE. $X_{i,h}$ denote control variables we include in the estimation to reflect the level of randomization level—i.e., location of applicants.[1] The reviewer fixed effects are meant to capture heterogeneity across reviewers in their scoring generosity. By contrast, the applicant fixed effects can be understood as the underlying potential and fit of the applicants that all reviewers agree on; they represent "adjusted scores" after controlling for potential systematic differences in scoring generosity across reviewers.

Figure A21 plots the distribution of fixed effects across reviewers. Figure A22 plots the distribution of applicant fixed effects.

There are three main findings from estimating equation (A21):

First, there is statistically significant heterogeneity in scoring generosity across reviewers: the *F*-test on the joint significance of the reviewer fixed effects is 10.63 (p-value of 0.00). By contrast, if reviewer heterogeneity was irrelevant (or nonsystematic), then reviewer fixed effects would not be jointly significant (as reviewers are quasi-randomly assigned by design). Consistent with the quasi-random assignment of reviewers to applicants, Table A21 confirms that the scoring heterogeneity is not related to differences in the types of applicants that reviewers assess: the sample of applicants is balanced across different quartiles of reviewer generosity.

[1] In some specifications we also include other controls like the reviewers' perception of the stage and business type of the business, but these controls are immaterial.

To address concerns regarding the validity of *F*-tests in the presence of high serial correlation (Wooldridge, 2002), we scramble the data 500 times, each time randomly assigning reviewers' scores to different applicants in the same spirit as in Fee, Hadlock, and Pierce (2013).[2] In this scrambled samples we hold constant the number of projects evaluated by each reviewer, make sure that each applicant receives three scores from reviewers specialized in the same location and available at the time of application.[3] Then we proceed to estimate the "scrambled" applicants' and reviewers' fixed effects and test the joint significance of the latter in each scrambled sample. The distribution of the scrambled *F*-tests is plotted in Figure A24 (Panel A). Lending credence to the statistically significant reviewer heterogeneity in our setting, we reject the null of "no joint significance of the reviewer fixed effects" in only 4.4% of the placebo assignments (the largest estimated placebo *F*-test is 3.12).

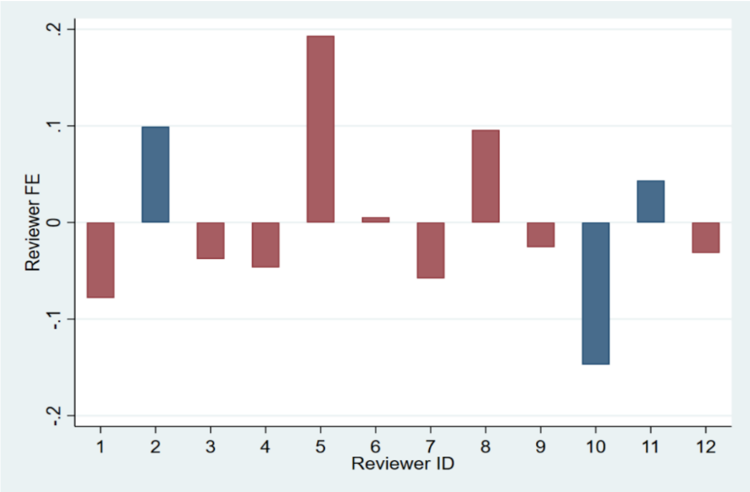
The second finding is the sizable *economic* significance of the scoring generosity heterogeneity. Figure A23 shows that generous reviewers (with positive FE) are twice as likely to assign a score of "3" or "4" than stricter reviewers with negative FE across all applicant fixed effects deciles. On average, this probability is 31.1% for applicants with generous reviewers and 17.9% for applicants with stricter reviewers

The third finding is that these systematic differences across reviewers are unrelated to the reviewers' skill in distinguishing high potential applicants and instead reflect reviewers' propensities to assign high or low application scores. Figure A25 shows a nil correlation between reviewers' generosity and their ability to correctly rank applicants. We measure reviewers' ranking ability using the correlation between a "reviewer' s ranks" and "actual ranks." To produce this correlation, for every reviewer we rank the companies she evaluated based on (i) average annual funding post application ("actual rank") and (ii) the reviewer's score ("reviewer's rank). Figure A25 is a scatterplot of each reviewer's generosity and ranking ability for the 12 reviewers in our sample.

[2] In the parallel literature, when seeking to identify the "style" of managers using an endogenous assignment of (movers) managers to multiple companies (e.g., Bertrand and Schoar, 2003), concerns have been raised regarding the validity of *F*-tests in the latter settings on the grounds of (a) the particularly acute endogeneity in samples of job movers and (b) the high level of serial correlation in most of the variables of interest (see Fee, Hadlock, and Pierce, 2013). The first reason for concern is not at play in our setting, as reviewers are randomly assigned by design, but the second concern may still apply. Regarding the second concern, Heckman (1981) and Greene (2001) discuss the ability of small sample sizes per group to allow for meaningful estimates of fixed effects with a rule of thumb of eight observations per group.

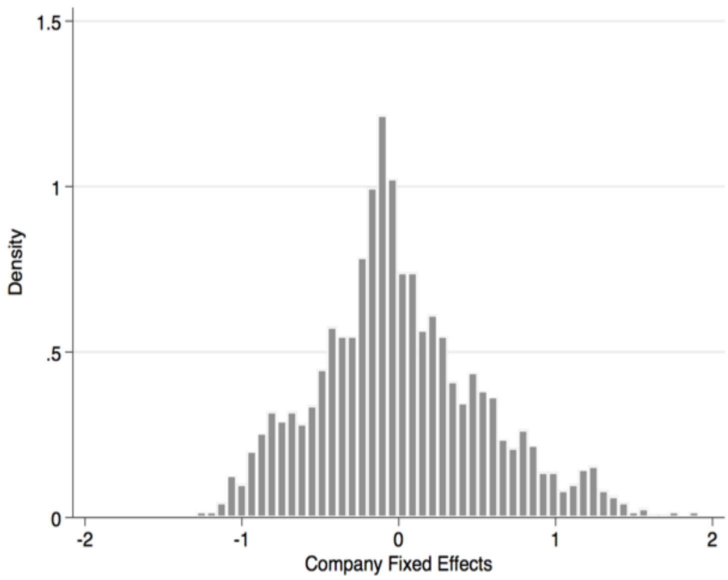
[3] We make sure the reviewer was assigned at least one application to review within 3 months of the company's application date.

Figure A21—Distribution of Reviewer Fixed Effects



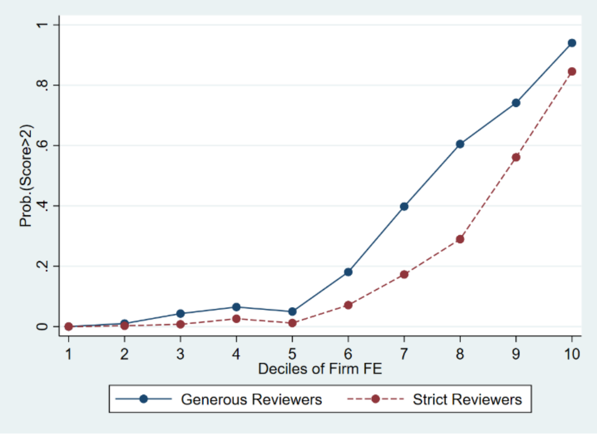
The figure plots the reviewer fixed effects for each reviewer in the sample based on the estimates of equation A21. Blue columns indicate female reviewers.

Figure A22—Distribution of Applicant Fixed Effects



The figure plots the applicant fixed effects for each applicant in the sample based on the estimates of equation A21.

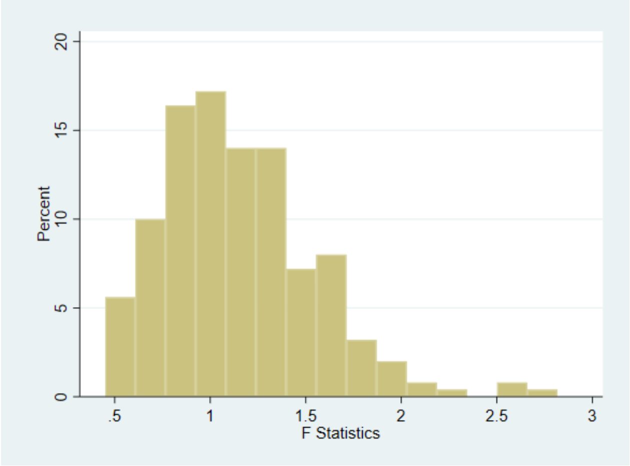
Figure A23—Frequency of Scores Above 2 and Reviewer FE



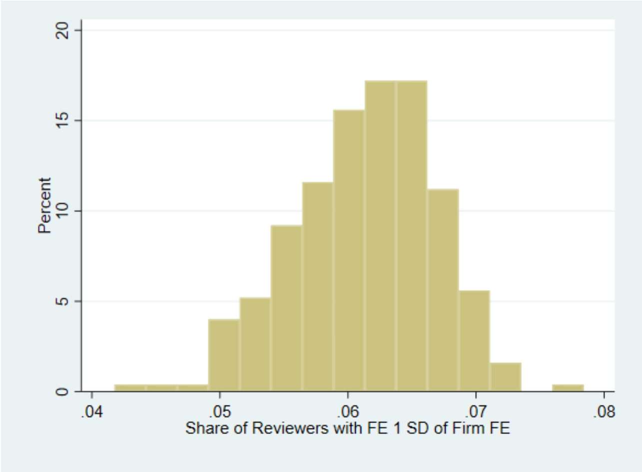
The figure plots the probability of a score higher than 2, separately for reviewers with positive and negative fixed effects (from Eq. A21).

Figure A24—Placebo Tests Reviewer Fixed Effects

Panel A— Distribution of *F*-values

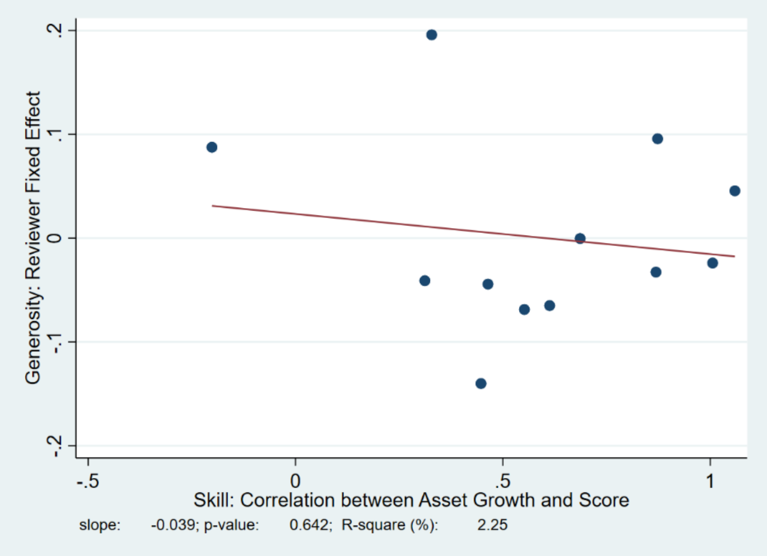


Panel B— Fixed Effects One Standard Deviation Above/Below Applicant Effect



This figure plots the distribution of *F*-tests on the joint significance of the reviewer fixed effects in 500 placebo assignments.

Figure A25—Reviewer Fixed Effects and Ranking Ability of Reviewers



This plot is a scatter plot of reviewers' scoring generosity and ranking ability. We measure reviewer' ranking ability using the correlation between a "reviewer's rank" and "actual rank". To produce this correlation, for every reviewer we rank the applicants she evaluated based on 1) average annual funding post application ("actual rank") and 2) the reviewer's score ("reviewer's rank").

Table A21—Balance of Covariates Across Generosity Quartiles

Variable	Q1	Other Q	*p-value diff. in mean*	Q2	Other Q	*p-value diff. in mean*	Q3	Other Q	*p-value diff. in mean*	Q4	Other Q	*p-value diff. in mean*
App. Info												
Age	2.61	2.61	*0.51*	2.49	2.65	*0.22*	2.55	2.63	*0.95*	2.85	2.55	*0.03*
ln(Age)	1.05	1.06	*0.44*	1.03	1.06	*0.64*	1.05	1.06	*0.70*	1.10	1.04	*0.07*
Female Founder	0.12	0.13	*0.91*	0.13	0.13	*0.86*	0.14	0.12	*0.30*	0.11	0.13	*0.19*
Russell Education of Founder	0.15	0.17	*0.31*	0.15	0.17	*0.22*	0.18	0.16	*0.12*	0.18	0.16	*0.52*
Amount	2542.83	2153.36	*0.57*	1728.48	2422.04	*0.27*	2210.44	2245.20	*0.96*	2623.39	2132.98	*0.49*
ln(Amount)	6.58	6.64	*0.26*	6.67	6.62	*0.71*	6.63	6.63	*0.68*	6.64	6.63	*0.73*
Target Close Days	82.08	80.51	*0.92*	82.16	80.34	*0.37*	80.30	81.08	*0.63*	78.67	81.40	*0.58*
ln(Target Close Days)	4.23	4.22	*0.80*	4.23	4.22	*0.63*	4.22	4.22	*0.45*	4.20	4.23	*0.25*
Total Addressable Market	1147.71	618.44	*0.61*	942.66	655.37	*0.72*	807.58	697.59	*0.94*	6.54	946.75	*0.32*
ln(Total Addressable Market)	0.46	0.45	*0.87*	0.48	0.45	*0.33*	0.46	0.45	*0.97*	0.42	0.47	*0.20*
Total Servicable Market	78.78	44.17	*0.08*	63.96	47.08	*0.19*	56.63	49.30	*0.86*	5.63	65.20	*0.56*
ln(Total Servicable Market)	0.24	0.20	*0.10*	0.22	0.20	*0.80*	0.19	0.21	*0.62*	0.18	0.22	*0.37*
Seed/Pre-Seed	0.45	0.44	*0.27*	0.45	0.44	*0.95*	0.44	0.44	*0.49*	0.43	0.45	*0.75*
Platform	0.51	0.53	*0.10*	0.51	0.53	*0.84*	0.55	0.52	*0.08*	0.53	0.52	*0.95*
Deep Tech	0.03	0.05	*0.08*	0.04	0.04	*0.91*	0.04	0.04	*0.44*	0.06	0.04	*0.07*
CH Info. Before App.												
Asset (£1000s)	240.57	744.68	*0.40*	1220.37	434.29	*0.11*	667.45	628.52	*0.99*	278.42	740.50	*0.39*
Annual Equity Issuance (£1000s)	230.17	709.69	*0.43*	1175.80	409.59	*0.13*	643.19	595.98	*0.96*	239.40	713.07	*0.38*
Equity Issuance (£1000s)	254.53	333.07	*0.15*	353.71	303.76	*0.18*	320.74	315.11	*0.87*	325.95	314.39	*0.81*
ln(Equity Issuance)	2.30	2.41	*0.36*	2.39	2.39	*0.56*	2.37	2.39	*0.50*	2.49	2.36	*0.27*
Web Info. Before App.												
Num. of Funding Rounds	1.13	1.20	*0.08*	1.18	1.19	*0.98*	1.20	1.18	*0.57*	1.22	1.18	*0.20*
ln(# Rounds)	0.72	0.74	*0.12*	0.73	0.74	*0.68*	0.74	0.73	*0.50*	0.75	0.73	*0.17*
Total Funding (£1000s)	381.68	402.71	*0.85*	400.61	397.51	*0.99*	367.47	412.53	*0.44*	459.00	382.50	*0.49*
ln(Funding)	2.72	2.95	*0.36*	2.92	2.90	*0.67*	2.84	2.93	*0.68*	3.16	2.84	*0.31*
Num. of Companies Created	0.38	0.41	*0.23*	0.38	0.41	*0.42*	0.42	0.39	*0.29*	0.41	0.40	*0.32*
Ln(# Companies Created)	0.21	0.24	*0.08*	0.22	0.23	*0.65*	0.25	0.22	*0.22*	0.24	0.23	*0.32*
Serial Entrepreneur	0.24	0.27	*0.13*	0.26	0.26	*0.92*	0.28	0.25	*0.19*	0.27	0.26	*0.47*
Num. of Tech Adoptions	19.07	18.95	1.00	18.86	19.02	1.00	19.66	18.73	0.97	18.09	19.22	0.97
ln(Tech Adoptions)	2.00	2.00	1.00	2.00	2.00	1.00	2.06	1.98	0.96	1.94	2.02	0.96
Num. of A/B Testings	2.93	2.85	1.00	3.31	2.76	0.98	2.31	3.09	0.97	3.09	2.82	0.99
ln(# A/B Testings)	0.17	0.18	0.99	0.19	0.17	0.99	0.17	0.18	0.99	0.18	0.18	1.00

The table compares applicants' characteristics (at application) across the different quartiles of reviewers' generosity.

Appendix 3 – Measuring Comments' Style and its Heterogeneity Across Reviewers

We use text analysis tools to analyse the content of the reviewers' comments. We build a text classification model based on the pre-trained model, Bidirectional Encoder Representations from Transformers (BERT). BERT has been trained on a large corpus of unlabelled text including the entire Wikipedia and Book Corpus.[4]

We fine-tune the BERT model to classify reviewers' comments in terms of their sentiment and practical advice by using a random sample that we read manually. BERT is designed to pre-train deep bidirectional representations from unlabelled text. For more details, see Devlin et. Al (2018) and Vaswani (2017).

In detail, we randomly select 1000 comments and read them manually to classify them as positively, negatively or neutrally toned. We also classify the comments into two additional non-mutually exclusive categories, depending on whether the comments provide any practical advice on financing opportunities (e.g. participate in other programs, such as the seed enterprise investment scheme that is a tax incentive program for individual investments in UK startups), or employment decisions (e.g. hire a chief technology officer or other key persons), and product improvements or market strategy. We then use this manual classification to train BERT and construct four measures of comments' content: *Sentiment* (increasing in positive tone), *Finance and Hiring*, *Product and Strategy*, and *Length* (word count). Table A31 presents summary statistics of the comments' content measures so-constructed.

Having classified comments in terms of their length, sentiment and practical advice, we then start by investigating the relation between scoring generosity and comments' content. Table A32 shows no evidence of a statistically significant correlation between the content of reviewers' comments and their generosity, although more generous reviewers write shorter comments on average.

The lack of variation in comments' content by reviewers' generosity does not necessarily imply that reviewers do not vary in the ways in which they provide comments. We turn to investigating further whether reviewers vary in terms of their comments to applicants.

We run regressions of the different measures of comments' content against applicant and reviewer fixed effects. Like our exploration of heterogeneity in reviewers' scoring, the idea behind this approach is that reviewer fixed effects would be jointly significant if reviewers systematically vary in their length and style of comments to applicants.

We run the following type of regression:

$$Content_{i,h} = \mu_h + \alpha_i + X_{i,h} + \epsilon_{i,h} \quad \text{(A31)}$$

where $Content_{i,h}$ denotes different proxies for the content of the comments provided by reviewer h to company i; μ_h and α_i are full sets of reviewer and applicant FE. $X_{i,h}$ denote location fixed effects, score

[4] BERT is designed to pre-train deep bidirectional representations from the unlabelled text by jointly conditioning on both left and right contexts. As a result, the pre-trained BERT model can be fine-tuned with just one additional output layer to create state-of-the-art models for a wide range of NLP tasks. For more details, see Devlin et. Al (2018) and Vaswani (2017).

fixed effects, and log transformation (log (1+x)) of variables in the application files: age, target amount to raise, target days to close the funding, total addressable market and total serviceable market.

The reviewer fixed effects are meant to capture heterogeneity across reviewers in their comments' length and style. By contrast, the applicant fixed effects can be understood as the underlying comments that all reviewers agree on; they represent "adjusted comments" after controlling for potential systematic differences in comment styles' across reviewers.

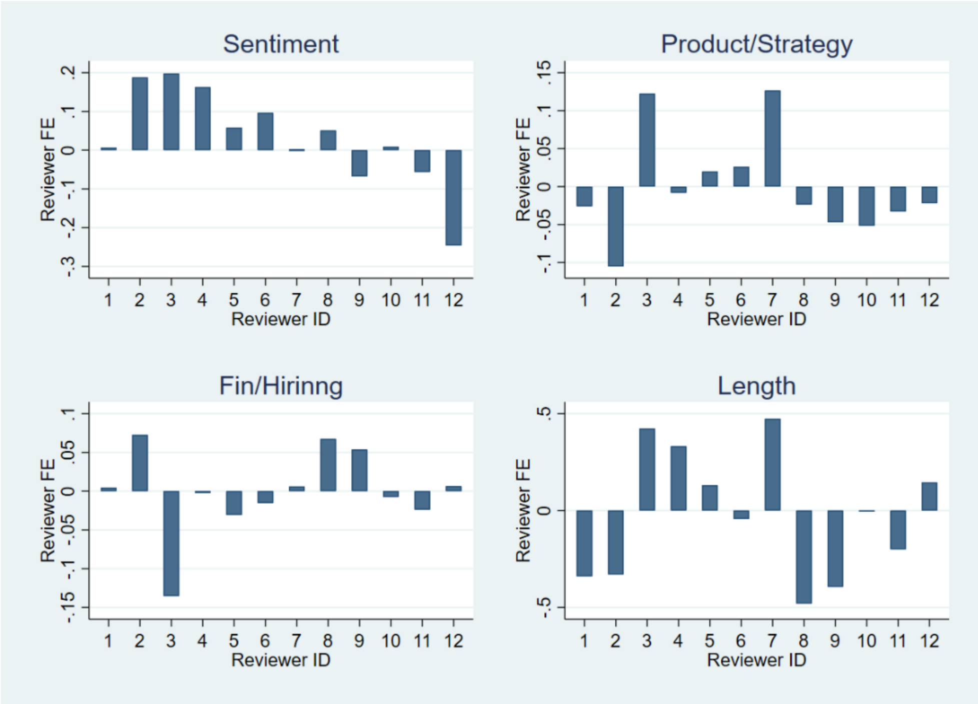
Figure A31 plots the distribution of fixed effects across reviewers. Figure A32 plots the distribution of applicant fixed effects.

We find statistically significant heterogeneity in comments' styles across reviewers: the F-test on the joint significance of the reviewer fixed effects is 73.08 (p-value of 0.00) for sentiment, 12.64 (p-value of 0.00) for finance/hiring, 8.77 (p-value of 0.00) for product/strategy and 111.47 (p-value of 0.00) for length. By contrast, if reviewer heterogeneity in comments' content was irrelevant (or nonsystematic), then reviewer fixed effects would not be jointly significant (as reviewers are quasi randomly assigned by design).[5]

We provide additional evidence of the lack of systematic variation in the type of comments across between more and less generous reviewers by correlating the generosity of reviewers (as measured by the reviewer fixed effects from regression A21) and the reviewer fixed effects we estimate in regression A31. We find no significant correlation between generosity and any of the reviewer fixed effects based on the content proxies, including length. Figure A33 shows the nil correlation between reviewers' generosity and the different proxies of the content in reviewers' comments.

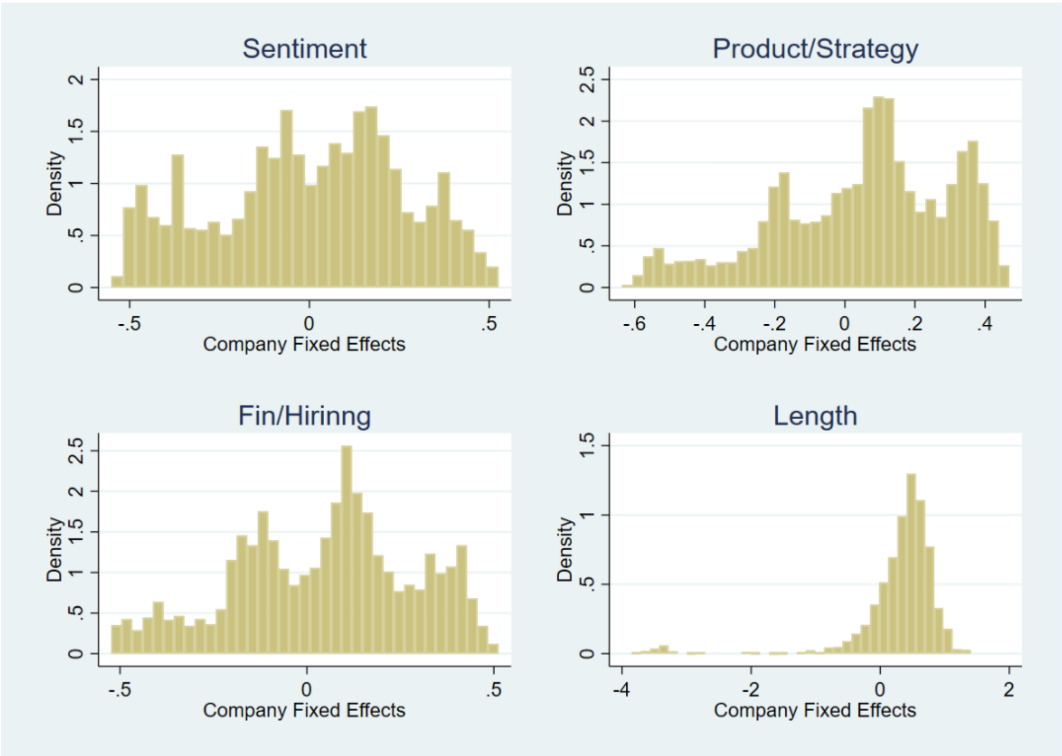
[5] In unreported analysis, we condition on scores to investigate whether comments vary across reviewers for a given score. We expand equation A31 to include reviewer-score fixed effects. We find evidence of heterogeneity conditional on score: the F-test on the joint significance of the reviewer-score fixed effects is 38.84 (p-value of 0.00) for tone, 4.97 (p-value of 0.00) for finance, 5.35 (p-value of 0.00) for operations and 32.16 (p-value of 0.00) for length.

Figure A31 – Distribution of Reviewer Fixed Effects



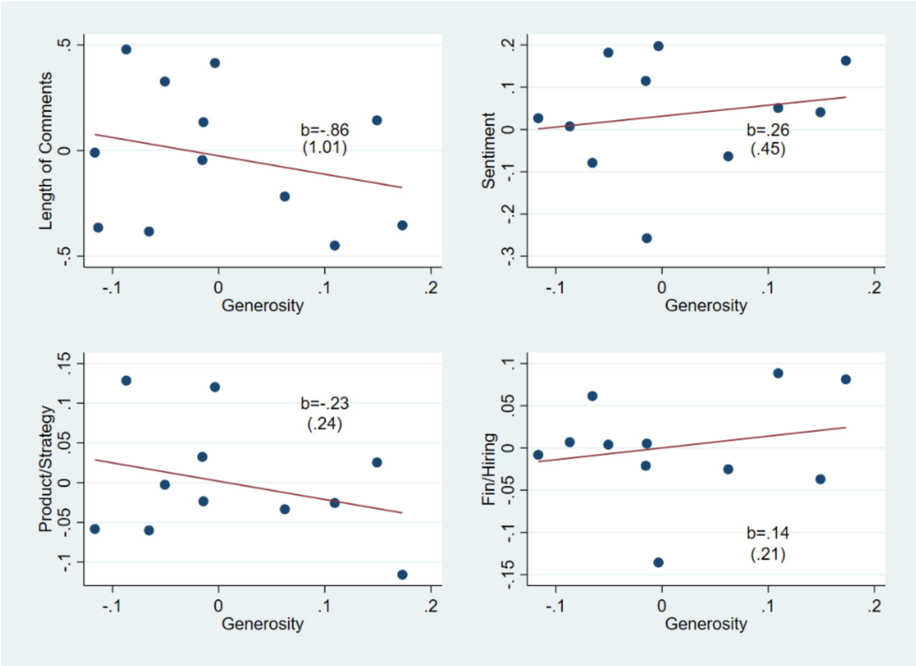
The figure plots the reviewer fixed effects for each reviewer in the sample based on the estimates of equation A31.

Figure A32 – Distribution of Applicant Fixed Effects



The figure plots the applicant fixed effects for each applicant in the sample based on the estimates of equation A31.

Figure A33 – Reviewers' Generosity and Comments' Content



The figure shows scatter plots of reviewers' scoring generosity and different proxies of the content in reviewers' comments.

Table A31 – Summary Statistics Comments' Content Measures

	Mean	Sd	p5	p25	p50	p75	p95	Obs.
Sentiment	0.492	0.377	0.020	0.060	0.641	0.870	0.900	5177
Product/Strategy	0.629	0.377	0.037	0.185	0.843	0.963	0.980	5177
Fin/Hiring	0.538	0.365	0.027	0.103	0.722	0.848	0.962	5177
Length of Comments	3.547	1.347	0.000	3.332	3.932	4.357	4.875	5794
Word Counts	55.393	40.120	0	27	50	77	130	5794

The table shows the summary statistics of comments' content measures. Length of comments is the log transformation (log(1+x)) of word counts of non-symbol words (such as comma, question mark etc.) in the comment text. There are missing observations in the variables for two reasons: (1) the reviewer didn't make comments; (2) there is not enough information in the comment text for the algorithm to assign values to these observations.

Table A32 – Reviewers' Generosity and Comments

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Sentiment		Product / Strategy		Financial / Hiring		Length of Comments	
Generosity	0.08	0.11	-0.08	-0.08	0.02	0.00	-1.25***	-1.23***
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.11)	(0.11)
Constant	0.43***	0.48***	0.75***	0.67***	0.57***	0.56***	3.96***	3.91***
	(0.05)	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)	(0.09)	(0.07)
N	5177	5177	5177	5177	5177	5177	5794	5794
R^2	0.1150	0.1173	0.0594	0.0580	0.0353	0.0364	0.1031	0.1031
Controls	No	Yes	No	Yes	No	Yes	No	Yes

The table correlates the content of reviewer comments and generosity. The observations are at the applicant-reviewer level, and generosity correspond to the reviewer fixed effects estimated in Appendix 2 (equation A21). In the regressions, we include as controls the log transformations (log(1+x)) of variables in the application files:

age, target amount to raise, target days to close the funding, total addressable market and total serviceable market. Region and score fixed effects are also included in all regressions. The row Controls indicates the inclusion as controls of the applicant fixed effects estimated in Appendix 2 (equation A21). Standard errors are robust. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix 4 – Email templates
In this Appendix we present the email templates. For each email template the emphasis in **bold** is our own.
Due diligence email template:

Hi ,

Thanks for taking the time to share your ambition with us through the [application platform]... **We've completed our initial review and would like to meet to take our review further. Would work for you for a call or a coffee?**

We're well aware that your time is precious when building a startup, so we aim to review and provide you with what we hope is constructive feedback quickly.

We approach our initial review with the belief that any startup could be a generation-defining business. In order to surface those opportunities, we believe three separate minds are better than one. Three of our team members, including two Investment Leads and a member of the Executive Team, independently review the materials you've shared to consider whether we are the right investment partner for you at this point in your journey.

We aim to get this initial review done and share our feedback within a couple of days of receiving a full submission. We move forward if any one of the reviewers sees enough potential in the opportunity.

In the spirit of transparency, we've included each reviewer's feedback below which we can review in more detail when we meet.

The first reviewer's feedback is here;

The second reviewer's feedback is here;

The third reviewer's feedback is here;

Thanks again for considering us as a potential partner and for sharing your opportunity with us.
Best regards,

Informal Meeting email template:

Hi ,

Thanks for taking the time to share your ambition with us through the [application platform]…

We're well aware that your time is precious when building a startup, so we aim to review and provide you with what we hope is constructive feedback quickly.

We've completed our initial review and have concluded we're not currently the right investor for you. However, we would like to meet to share our feedback with you directly, learn more about your venture and stay in touch ahead of your next raise. Would work for you for a call or a coffee?

We approach our initial review with the belief that any startup could be a generation-defining business. In order to surface those opportunities, we believe three separate minds are better than one. Three of our team members, including two Investment Leads and a member of the Executive Team, independently review the materials you've shared to consider whether we are the right investment partner for you at this point in your journey.

We aim to get this initial review done and share our feedback within a couple of days of receiving a full submission. We move forward if any one of the reviewers sees enough potential in the opportunity.

In the spirit of transparency, we've included each reviewer's feedback below. We hope it's useful as you continue to pursue your venture.

The first reviewer's feedback is here;
The second reviewer's feedback is here;
The third reviewer's feedback is here;

Thanks again for considering us as a potential partner and for sharing your opportunity with us and I look forward to meeting you.

Best regards,

No meeting email template:

Hi ,

Thanks for taking the time to share your ambition with us through the [application platform]…

We're well aware that your time is precious when building a startup, so we aim to review and provide you with what we hope is constructive feedback quickly.

We approach our initial review with the belief that any startup could be a generation-defining business. In order to surface those opportunities, we believe three separate minds are better than one. Three of our team members, including two Investment Leads and a member of the Executive Team, independently review the materials you've shared to consider whether we are the right investment partner for you at this point in your journey.

We aim to get this initial review done and share our feedback within a couple of days of receiving a full submission. We move forward if any one of the reviewers sees enough potential in the opportunity.

We’ve completed our initial review and have concluded we’re not currently the right investor for you. If you feel that we have missed something substantial you can update your pitch, otherwise we are happy to consider your opportunity again after you have made further progress. We also recognise that you may prove our decision wrong with time.

In the spirit of transparency, we’ve included each reviewer’s feedback below. We hope it’s useful as you continue to pursue your venture.

The first reviewer’s feedback is here;
The second reviewer’s feedback is here;
The third reviewer’s feedback is here;

Thanks again for considering us as a potential partner and for sharing your opportunity with us.

Best regards,

Appendix 5—Example Data from the Fund

Web Application
Company name
Application date
What does the company do?
Web address
Contact email
Contact phone
City
Full name
Linked-In profile
When was the company founded?
Who is the customer?
What do you sell or plan to sell?
What stage is the company at?
What is the funding stage appropriate to the company?
How much are you hoping to raise?
Intended close date
Is this your first round of financing? If not please give a short history of funding since formation.
Please give links to any content you wish to share
Total addressable market (£)
Total serviceable market (£)
Document upload
Stage
How did you hear about us?
Business type

Initial review data
Date of application
Date of completion
Days to complete?
Reviewers
Reviews complete
Review score dates
(Internal) comments
External comments
Names with external comments
Actual review scores
All score array
Score array
Core score array
Max reviewer score
Min reviewer score
Reviewer scores

All reviewers
High scorer
Reviewer 2 random number
Reviewer 3 random number
Reviewer 4 random number
Review facilitator
Investment team reviewer
Score 1
Score 2
Score 3
TOTAL score
Recommended next step
Contact team by
Meet team by
Meet the team score
All perceived types
Perceived types by reviewers
Perceived stage by reviewers
Location - city
Location - region

"Future Gaze" due diligence questionnaire	
1. Unit of value	"What is the name of the thing that you will sell? (most basic thing that generates revenues)"
2. Market	What market are you in?
	Provide us a link backing your TAM calculation below:
	For how much does the market sell one unit
	How many units are in the market
	Total market (TAM)
3. Unit economics	How much do you sell one unit for?
	What is the cost of sale per unit? (this is either your COGs/COS and your CAC, not your operating costs)
	Gross Margin
	Gross profit per unit
	How fast will your unit sales grow per year?
	Units sold
	Percentage of the TAM
4. P&L (Profit & Loss)	Revenues
	Cost
	Gross Profit
	Opex
	Operating Profit
5. KPIs	Your key performance indicators (KPIs) should always be a manifestation of your unit economics. KPIs should relate to

	increasing revenue, either by growing volume, lowering costs or both.
6. Milestones & Fundraise	Once you've worked out the best KPIs, you can plan the MS and fundraise journey.

Opportunity assessment (pre-investment committee)
Investment committee member
Date added
Company name
Stage
Is this a crowded market?
Is the market ready for the product?
Can it produce venture scale returns?
Is the business model proven?
Is there traction?
Is there risk this cannot be built?
Are the team capable of executing the plan?
Is the solution already built?
How close is the cap table to the Fund's recommended norm? Does it need fixing?
Is the company built on the platform of a 3rd party and dependent upon continued good relations?
Are the management team sufficiently independent - i.e. do they have conviction?
Are the management team sufficiently open - i.e. do they listen to advice?
Is the company likely to need more capital in future than could reasonably be raised?
Is there a legal risk of being sued for patent or copyright infringement? Are there outstanding legal issues?
Is there a risk the company has material security issues? Has it had a security audit?
Risk Score
Review Score
Status
IR and Checklist
Risk of regulatory approvals or changes impacting the business
Future Enterprise Value
Enterprise Value Justification
Disposal Mechanism
Value at Fund's Exit

Appendix 6—Reduced Form

Table A61 - Reduced Form Estimates

	Panel A: Funding – Full Sample				
	ln(Funding)	ln(# Rounds)	ln(# Investors)	ln(Equity Issuance) (UK)	
	(1)	(2)	(3)	(4)	
DAP	3.73**	0.24**	0.12*	1.65**	
	(1.13)	(0.08)	(0.05)	(0.59)	
N	1953	1953	1953	1548	
R-sq.	0.103	0.1109	0.0516	0.0828	
	Panel B: Economic Growth & Tech Adoptions – Full Sample				
	ln(#Employees)	Growth in Assets (UK)	Survival (UK)	ln(# Tech Adoptions)	ln(# A/B Testings)
	(1)	(2)	(3)	(4)	(5)
DAP	0.62**	1.27**	-0.14	0.93***	0.33*
	(0.23)	(0.47)	(0.08)	(0.17)	(0.16)
N	1953	1548	1548	1953	1029
R-sq.	0.1319	0.0803	0.0461	0.0314	0.0356

The table presents reduced form estimates regressing the different outcome variables against DAP. Controls include the log transformations (log(1+x)) of variables in the application files: age, target amount to raise, target days to close the funding, total addressable market and total serviceable market. Region fixed effects are also included in the regressions. Standard errors are robust. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix 7—DAP and, Opportunity Assessment and Investment

Panel A—Probability of Opportunity Assessment and Investment

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Opportunity Assessment				Investment			
DAP	0.04	0.03	0.00	-0.00	0.01	0.01	0.01	0.01
	(0.03)	(0.03)	(0.03)	(0.03)	(0.01)	(0.01)	(0.01)	(0.01)
Applicant FE			0.07***	0.07***			0.01*	0.01
			(0.01)	(0.01)			(0.00)	(0.00)
Controls		Yes		Yes		Yes		Yes
Observations	1,953	1,953	1,953	1,953	1,953	1,953	1,953	1,953
R-sq.	0.0010	0.0151	0.0716	0.0799	0.0007	0.0145	0.0027	0.0159

Panel B—Opportunity Assessment Performance

Question	mean	sd	p25	p50	p75	Obs	Correlation with DAP	*p-value*
Is this a crowded market?	5.19	1.73	4.00	5.33	6.50	45	-0.10	(0.504)
Is the market ready for the product?	5.34	1.46	4.42	5.50	6.17	45	-0.14	(0.345)
Can it produce venture scale returns?	4.79	1.32	4.00	4.55	5.50	45	-0.18	(0.229)
Is the business model proven?	6.63	1.47	5.50	7.00	7.67	45	-0.01	(0.950)
Is there traction?	6.55	1.55	5.50	6.83	7.50	45	-0.02	(0.869)
Is there risk this cannot be built?	5.67	1.56	4.50	5.50	7.00	45	-0.07	(0.635)
Are the team capable of executing the plan?	5.40	1.40	4.67	5.50	6.50	45	-0.01	(0.23)
Is the solution already built?	5.34	1.41	4.13	5.50	6.10	45	-0.07	(0.626)
How close is the cap table to the Fund's recommended norm? Does it need fixing?	4.73	2.06	3.00	4.75	5.50	45	-0.23	(0.111)
Is the company built on the platform of a 3rd party and dependent upon continued good relations?	6.13	1.97	5.00	6.00	8.00	45	-0.17	(0.261)
Are the management team sufficiently independent - i.e. do they have conviction?	3.26	1.16	2.42	3.00	4.00	45	-0.12	(0.405)
Are the management team sufficiently open - i.e. do they listen to advice?	4.21	1.20	3.00	4.00	5.00	45	-0.14	(0.328)
Is the company likely to need more capital in future than could reasonably be raised?	6.62	1.27	6.00	7.00	7.50	45	0.06	(0.674)
Is there a legal risk of being sued for patent or copyright infringement? Are there outstanding legal issues?	4.44	1.78	3.00	4.00	5.75	45	0.05	(0.736)
Is there a risk the company has material security issues? Has it had a security audit?	5.10	1.85	3.50	5.00	6.54	45	0.11	(0.45)
Risk Score	422.45	56.00	385.88	420.17	465.00	45	-0.23	(0.120)

Panel A presents results from regressing Opportunity Assessment (a variable indicating applicants that made it to the Fund's third stage of due diligence) and Investment (a variable indicating applicants that are in the Fund's investment portfolio) against due diligence assignment probability(DAP).Controls include the log transformations (log(1+x)) of variables in the application files: age, target amount to raise, target days to close the funding, total addressable market and total serviceable market. Region fixed effects are also included in the regressions. Panel B shows the summary statistics of opportunity assessment results at the applicant level. The opportunity assessment involves scoring for 15 questions (scale of 10) and providing risk score. For each question and risk score, we first take the average across different reviewers for each company and summarize the statistics as shown above. In particular, we show their' correlation coefficients with DAP and the corresponding p-values.

Appendix 8—DAP and reviewers' comments

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Sentiment		Product / Strategy		Financial / Hiring		Length of Comments	
DAP	-0.04	-0.04	-0.10*	-0.09	0.03	0.03	-0.58***	-0.57***
	(0.04)	(0.04)	(0.05)	(0.05)	(0.05)	(0.04)	(0.08)	(0.08)
Constant	0.44***	0.49***	0.78***	0.69***	0.56***	0.56***	4.09***	4.02***
	(0.05)	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)	(0.09)	(0.07)
N	5177	5177	5177	5177	5177	5177	5794	5794
R-sq.	0.1149	0.1169	0.0600	0.0584	0.0354	0.0365	0.0886	0.0893
Controls	No	Yes	No	Yes	No	Yes	No	Yes

The table correlates the content of reviewer comments and DAP. The observations are at the applicant-reviewer level, and DAP is a constant measure for a given applicant across reviewers. In the regressions, we include as controls the log transformations (log(1+x)) of variables in the application files: age, target amount to raise, target days to close the funding, total addressable market and total serviceable market. Region and score fixed effects are included in all regressions. There are a few cases that reviewers don't have comments (results are robust to replacing the variables of comments' style with zero in those instance). Standard errors are robust. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

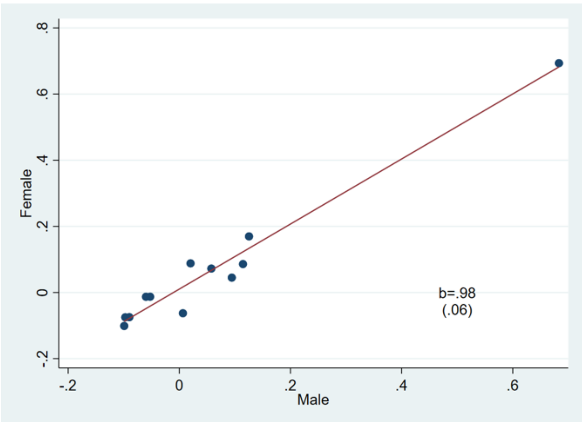
Appendix 9—Monotonicity Tests

Panel A- First Stage in Subsamples

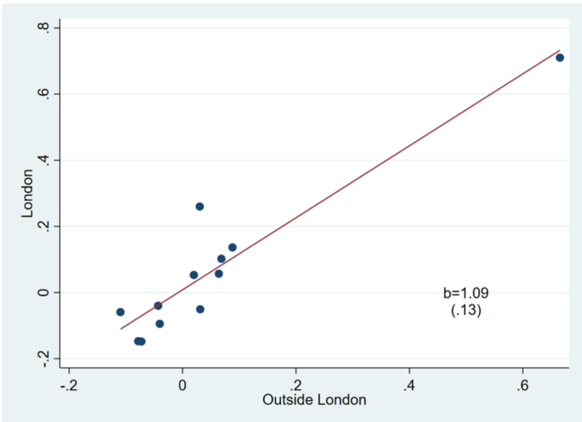
	(1) London	(2) Outside London	(3) Female Founder	(4) Male Founder	(5) Russell	(6) Non-Russell	(7) Pre-Seed/ Seed	(8) Post-Seed
DAP	1.39***	0.70***	0.87***	1.04***	0.96***	1.02***	1.04***	0.96***
	(0.10)	(0.11)	(0.18)	(0.08)	(0.19)	(0.08)	(0.09)	(0.14)
Constant	-0.03	0.18***	0.12**	0.08***	0.12*	0.09***	0.06**	0.19***
	(0.02)	(0.03)	(0.04)	(0.02)	(0.05)	(0.02)	(0.02)	(0.04)
F Stat. of excluded instruments	205.54	40.37	23.97	164.25	25.87	159.43	140.18	49.86
N	861	1087	397	1551	327	1621	1509	439
R-sq.	0.2301	0.0549	0.0949	0.1211	0.1184	0.1152	0.0972	0.0923

The table shows the correlation between

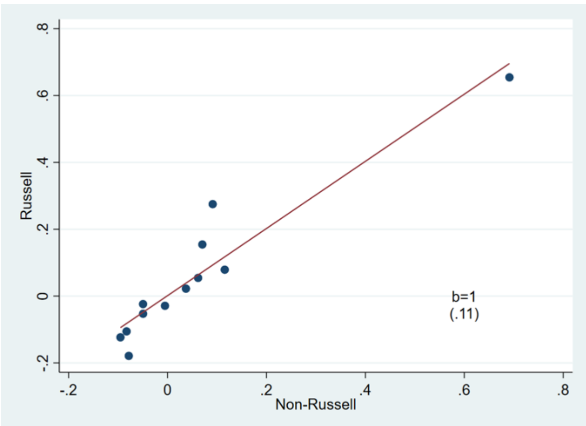
Panel B – Correlation Between Subgroup-Specific Reviewer-level Generosity Measures



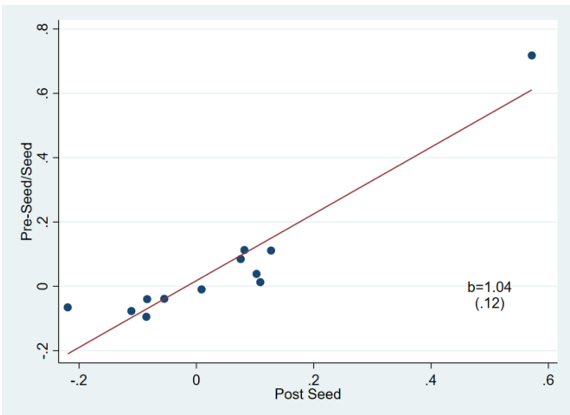
Female v.s. Male



London v.s. Non-London

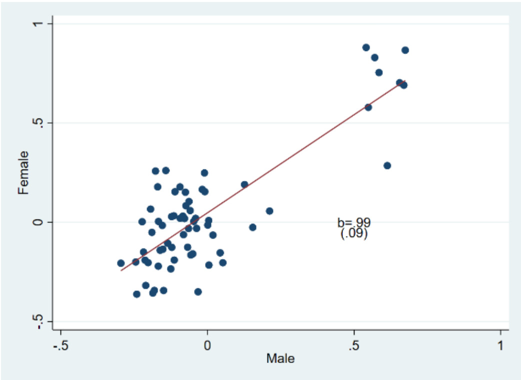


Russel v.s. Non-Russell

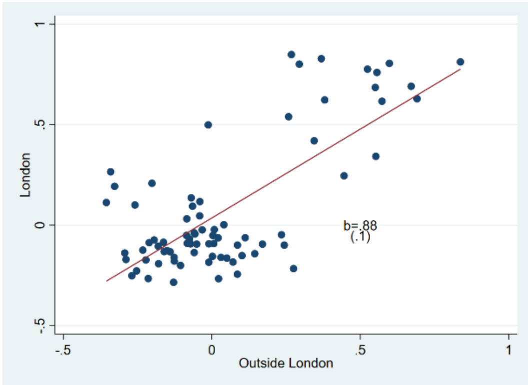


Pre-seed/Seed and Post-Seed

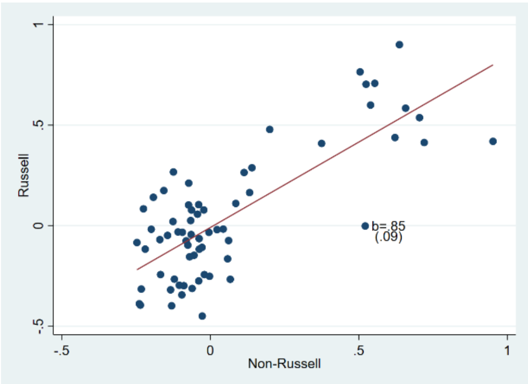
Panel C – Correlation Between Subgroup-Specific Trio-level Generosity Measures



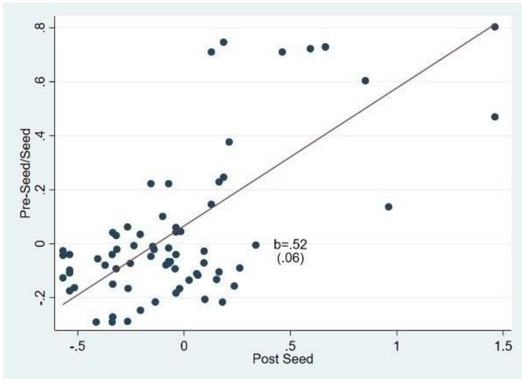
Female v.s. Male



London v.s. Non-London



Russel v.s. Non-Russell



Pre-seed/Seed and Post-Seed

The figure shows the correlations between trio level generosity for different groups of applicants. Trio level generosity is defined average rate of due diligence of the assigned trio controlling for applicant fixed effects. We take the average generosity for each group over all available years of data. The solid line shows the best linear fit estimated using OLS relating each trio generosity measure. The four pairs of groups of applicants are: female v.s. male founder, London v.s. Outside London companies, founder with v.s. without Russell group education, early stage (pre-seed and seed) v.s. advanced stage (seed extension).

Appendix 10—Informal Meetings

To show that no venture performance effects exist from informal meetings, we start by estimating baseline models exploring the impact of the allocation to informal meetings on subsequent venture performance. We run the following type of regressions

$$Y_i = \tilde{\gamma} + \tilde{\rho} Informal\ Meeting_i + \boldsymbol{Z}_i + \tilde{\varepsilon}_i \qquad (1b)$$

where $Informal\ Meeting_i$ is a dummy that indicates informal meeting assignment, and all other variables remain the same as defined in the main text.

The primary empirical challenge is that informal meeting selection is endogenous as the Fund only decides to meet with those that are "worth the time of the Fund." This endogeneity would generate a positive correlation between $\tilde{\varepsilon}_i$ and $Informal\ Meeting_i$ in equation (1b) and an upward bias to the estimate of $\tilde{\rho}$.

To address potential endogeneity, we need an instrument that affects the likelihood of informal meeting assignments but does not affect the venture performance through any other mechanism. To construct such an instrument, we exploit the random assignment of applicants to reviewers and the informal meeting selection rule. As explained in Section 2, across all selection regimes, the only combination of scores that leads to "no meeting" is {1 1 1}, that is a score of "1" by all the three reviewers of the applicant.

In detail, we estimate the following system of equations:

$$Informal\ Meeting_i = \tilde{\mu} + \tilde{\beta} IMAP_i + \boldsymbol{Z}_i + \tilde{e}_i \quad (3b)$$

$$Y_i = \tilde{\theta} + \tilde{\alpha} \widehat{Informal\ Meeting_i} + \boldsymbol{Z}_i + \widetilde{\omega_i} \quad (4b)$$

where $IMAP_i$ stands for "Informal Meeting Assignment Probability," which we estimate for every company as:

$$IMAP_i = 1 - p^1_{1(-i)} p^1_{2(-i)} p^1_{3(-i)} \qquad (5b)$$

where $p^1_{h(-i)}$ denotes the probability that applicant's i reviewer number h {1,2,3} gives a score of 1 (based on all other reviewed applicants except i). For example, if the second reviewer of applicant i assessed 20 applicants other than i, and the reviewer assigned a score of 1 to five of those applications, then $p^1_{2(-i)} = \frac{5}{20} = 0.25$.

Table A10 presents results from estimating equations (3b) and (4b) using two-stage least squares. Standard errors are heteroskedasticity robust.

The OLS estimates (columns 1, 3, 5, and 7) of equation (1b) show that, on average, applicants assigned to informal meetings outperform applicants assigned to no meeting within two years of application. These results are consistent with the Fund's assessment of which businesses are venture backable. However, the two-least squares estimates (columns 2, 4, 6, and 8) show little evidence of causal effects on performance from those meetings: no coefficient is statistically significant.

One issue with interpreting the results in Table A10 is statistical power: very few companies are not invited for an informal meeting, which may make it hard for us to distinguish the effects of rejection if any exist. However, unreported power tests suggest our sample is big enough to distinguish the effects of informal meetings (assuming an effect of the same size as the due-diligence effects reported in Tables 4 and 5). Another concern is that the signal from an informal meeting may be too weak, relative to the potential signal of due-diligence assignment, given that most companies get at least the chance of an informal meeting. However, the results from the Fund's selection are not publicly available, so it is not publicly known that only a few companies are not invited to meet with the Fund. Also against this concern, we find similar results, when we split the sample into two periods, and focus only on the first months when it is even less likely to be publicly known that the Fund extended an informal invitation to all almost all companies rejected from due-diligence.

Table A10. Informal Meetings and Funding

Panel A Funding

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ln(Funding)		ln(# Rounds)		ln(# Investors)		Δ(Equity Issuance) (UK)	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Informal Meeting	3.07***	-2.68	0.16***	-0.13	0.12***	-0.07	1.28***	8.70
	(0.47)	(5.01)	(0.02)	(0.29)	(0.02)	(0.21)	(0.28)	(4.48)
N	1338	1338	1338	1338	1338	1338	1025	1025
R-sq	0.0978	0.0303	0.1079	0.0459	0.0554	0.0001	0.0888	-0.2286
F Stat.		21.29		21.29		21.29		11.02
Reference:								
P75	13.46		1.10		1.10		6.24	

Panel B Economic Growth

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	ln(# Employees)		Growth in Assets (UK)		Survival (UK)		ln(#Tech Adoptions)		ln(# A/B Testings)	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Informal Meeting	0.38**	1.17	0.45	-2.21	0.12	-0.22	-0.07	0.19	0.10**	0.41
	(0.14)	(1.50)	(0.27)	(3.14)	(0.07)	(0.59)	(0.09)	(0.80)	(0.03)	(0.63)
N	1338	1338	1025	1025	1025	1025	1337	1334	698	696
R-sq	0.1630	0.1030	0.0769	0.0092	0.0516	0.0020	0.0204	-0.0024	0.0440	-0.0092
		21.29		11.02		11.02		21.22		9.79
Reference:										
P75	2.08		2.08					3.22		0.00

The table presents results from estimating Eq. (4b) in the sample of applicants rejected from due diligence. The outcome variable is specified in the title of each column. Informal Meeting is a dummy indicating the rejected applicants assigned to informal meetings. The IV models instrument Informal Meeting with IMAP, the informal meeting assignment probability estimated as in Eq. (5b). Controls include the log transformations (log(1+x)) of variables in the application files: age, target amount to raise, target days to close the funding, total addressable market and total serviceable market. Region fixed effects are also included in the regressions. The F-stat corresponds to the F-stat of the excluded regressor (IMAP) in Eq. (3b). Standard errors are robust. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix 11—Due diligence, Investment and Performance of Portfolio Companies

Table A11-Investment by the Fund and Venture Performance

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	ln(Funding)	ln(# Rounds)	ln(# Investors)	ln(Equity Issuance) (UK)	ln(# Employees)	Growth in Assets (UK)	Survival (UK)	ln(#Tech Adoptions)	ln(A/B Testing)
Investment by the Fund	7.14***	0.36*	0.18**	2.11*	0.57	1.87*	0.06	0.09	-0.10***
	(1.45)	(0.15)	(0.06)	(1.02)	(0.32)	(0.74)	(0.11)	(0.08)	(0.03)
N	1953	1953	1953	1548	1953	1548	1548	1953	1029
R-sq.	0.0822	0.0811	0.0259	0.0543	0.1074	0.0711	0.0265	0.0040	0.0144
Coefficients Comparisons:									
DD Effect (OLS)/Investment Effect (OLS)	0.41	0.56	0.56	0.56	0.89	0.29	1.17	0.45	-0.56
DD Effect (IV)/Investment Effect (OLS)	**0.39**	**0.50**	**0.50**	**0.57**	**0.81**	**0.50**	**-1.83**	**0.13**	**-0.35**

The table presents OLS estimates of the impacts of investment from the Fund on ventures' performance. In addition, in the bottom of the table, I provide comparisons between the investment effects and due diligence effect. The OLS and IV estimates of due diligence effects are the corresponding coefficients in Table 4 and 5.

Appendix 12—Robustness Checks Exclusion Restriction

Table A121-Funding

Panel A: Variation in DAP Due to Policy Change

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ln(Funding)		ln(# Rounds)		ln(# Investors)		ln(Equity Issuance) (UK)	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Due diligence	4.16***	15.96***	0.26***	0.83***	0.14***	0.68***	1.88***	5.57**
	(0.66)	(4.13)	(0.04)	(0.24)	(0.03)	(0.19)	(0.35)	(1.82)
N	829	829	829	829	829	829	777	777
R-sq.	0.2100	-0.2545	0.2244	-0.0975	0.1440	-0.4031	0.2187	-0.0906
F Stat.		15.06		15.06		15.06		12.10

Panel B: Use the Residual DAP as Instrument

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ln(Funding)		ln(# Rounds)		ln(# Investors)		ln(Equity Issuance) (UK)	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Due diligence	2.94***	3.80**	0.20***	0.21**	0.10***	0.21***	1.18***	0.34
	(0.36)	(1.22)	(0.02)	(0.08)	(0.02)	(0.05)	(0.18)	(0.58)
N	1953	1953	1953	1953	1953	1953	1548	1548
R-sq.	0.1313	0.1011	0.1457	0.1156	0.0704	0.0136	0.1053	0.0564
F Stat.		146.28		146.28		146.28		138.04

In Panel A, based on the main identification model, we add trio fixed effects, use regional-DAP estimated using reviewers' assessments over London-based companies only, and restrict the sample to London companies. In Panel B, by running the following regression: $DAP_i = \beta \sum_{h=1}^{3} Score_{i,h}/3 + \epsilon_i$, we obtain the residual DAP ($\widehat{\epsilon_i}$) and then use residual DAP as the instrument instead of DAP. We include year FE throughout. Standard errors are robust. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A122-Economic Growth

Panel A: Variation in DAP Due to Policy Change										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	ln(# Employees)		Growth in Assets (UK)		Survival (UK)		ln(# Tech Adoptions)		ln(# A/B Testing)	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Due diligence	0.75***	1.42**	1.19***	0.09	0.17***	0.01	0.20*	3.09**	0.22**	0.58
	(0.11)	(0.52)	(0.26)	(1.32)	(0.03)	(0.21)	(0.10)	(1.17)	(0.08)	(0.55)
N	829	829	777	777	777	777	829	829	478	478
R-sq.	0.2797	0.1171	0.2058	0.1007	0.1395	0.0325	0.1173	-1.1880	0.2469	-0.0221
F Stat.		15.06		12.10		12.10		10.92		5.65

Panel B: Use the Residual DAP as Instrument										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	ln(# Employees)		Growth in Assets (UK)		Survival (UK)		ln(# Tech Adoptions)		ln(# A/B Testing)	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Due diligence	0.51***	0.31	0.54***	0.42	0.07**	-0.16*	0.20***	0.89***	0.18***	0.02
	(0.07)	(0.22)	(0.15)	(0.47)	(0.02)	(0.08)	(0.05)	(0.19)	(0.05)	(0.21)
N	1953	1953	1548	1548	1548	1548	1953	1953	1029	1029
R-sq.	0.1629	0.1331	0.0846	0.0705	0.0495	-0.0329	0.0241	-0.0710	0.0476	0.0151
F Stat.		146.28		138.04		138.04		146.26		42.82

In Panel A, based on the main identification model, we add trio fixed effects, use location-based DAP, and restrict the sample to London companies. In Panel B, by running the following regression: $DAP_i = \beta \sum_{h=1}^{3} Score_{i,h}/3 + \epsilon_i$, we obtain the residual DAP ($\widetilde{\epsilon_i}$) and then use residual DAP as the instrument instead of DAP. We include year FE throughout. Standard errors are robust. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix 13—Robustness Checks Alternative Specification using regional DAP

Panel A—Funding, Full sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ln(Funding)		ln(# Rounds)		ln(# Investors)		ln(Equity Issuance) (UK)	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Due diligence	2.95***	1.94*	0.20***	0.14*	0.10***	0.05	1.18***	1.21**
	(0.36)	(0.91)	(0.02)	(0.06)	(0.02)	(0.04)	(0.18)	(0.45)
N	1953	1953	1953	1953	1953	1953	1548	1548
R-sq.	0.1316	0.1003	0.1458	0.1125	0.0701	0.0363	0.1055	0.0711
F Stat.		337.62		337.62		337.62		292.06

Panel B—Funding, Excluding portfolio companies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ln(Funding)		ln(# Rounds)		ln(# Investors)		ln(Equity Issuance) (UK)	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Due diligence	2.87***	1.81*	0.19***	0.13*	0.10***	0.05	1.13***	1.14*
	(0.37)	(0.92)	(0.02)	(0.06)	(0.02)	(0.04)	(0.18)	(0.46)
N	1941	1941	1941	1941	1941	1941	1537	1537
R-sq.	0.1301	0.0991	0.1420	0.1081	0.0686	0.0361	0.1033	0.0696
F Stat.		328.79		328.79		328.79		289.91

Panel C—Economic growth, Full sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	ln(# Employees)		Growth in Assets (UK)		Survival (UK)		ln(# Tech Adoptions)		ln(# A/B Testings)	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Due diligence	0.51***	0.61***	0.54***	1.18**	0.07**	-0.06	0.20***	0.69***	0.18***	0.23
	(0.07)	(0.17)	(0.15)	(0.36)	(0.02)	(0.06)	(0.05)	(0.14)	(0.05)	(0.12)
N	1953	1953	1548	1548	1548	1548	1953	1953	1029	1029
R-sq.	0.1632	0.1378	0.0846	0.0583	0.0496	0.0116	0.0241	-0.0301	0.0476	0.0283
F Stat.		337.62		292.06		292.06		337.62		155.75

Panel D—Economic growth, Excluding Portfolio companies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	ln(# Employees)		Growth in Assets (UK)		Survival (UK)		ln(# Tech Adoptions)		ln(# A/B Testings)	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Due diligence	0.50***	0.60***	0.50***	1.14**	0.07**	-0.07	0.20***	0.70***	0.18***	0.24*
	(0.07)	(0.17)	(0.15)	(0.36)	(0.02)	(0.06)	(0.05)	(0.14)	(0.05)	(0.12)
N	1941	1941	1537	1537	1537	1537	1941	1941	1021	1021
R-sq.	0.1602	0.1353	0.0821	0.0555	0.0490	0.0103	0.0242	-0.0310	0.0479	0.0285
F Stat.		328.79		289.91		289.91		328.79		145.72

The table presents results from estimating Eq. (4). The outcome variable is specified in the title of each column. Due diligence is a dummy indicating the applicants assigned to further due diligence. The IV models instrument Due diligence with regional DAP. All columns include as controls the log transformations (log(1+x)) of variables in the application files: age, target amount to raise, target days to close the funding, total addressable market and total serviceable market. Region fixed effects are also included in the regressions. The F-stat corresponds to the F-statistic of the excluded instrument (regional DAP) in the respective first stage Eq. (3). Standard errors are robust. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.