Attracting Early Stage Investors: Evidence from a Randomized Field Experiment

Shai Bernstein, Arthur Korteweg, and Kevin Laws*

Abstract

This paper uses a randomized field experiment to identify which start-up characteristics are most important to investors in early stage firms. The experiment randomizes investors’ information sets of fund-raising start-ups. The average investor responds strongly to information about the founding team, but not to firm traction or existing lead investors. In contrast, inexperienced investors respond to all information categories. Our results suggest that information about human assets is causally important for the funding of early stage firms, and hence, for entrepreneurial success.

JEL classification: G32, L26, D23

Keywords: Angel investors, early stage firms, entrepreneurship, crowdfunding, theory of the firm, portfolio selection, correspondence testing

Current Draft: May, 2015

* Shai Bernstein (shaib@stanford.edu) is from Stanford Graduate School of Business, Arthur Korteweg (korteweg@marshall.usc.edu) is from the University of Southern California Marshall School of Business, and Kevin Laws is from AngelList, LLC. We thank Michael Roberts (the editor), the associate editor, an anonymous referee, and Jean-Noel Barrot, Doug Cumming, Wayne Ferson, Amir Goldberg, Steve Kaplan, Ross Levine, Alexander Ljungqvist, John Matsusaka, Richard Roll, Rick Townsend, Danny Yagan, and seminar participants at Cornell, Harvard Business School, Northwestern University, UC Davis, UCLA, University of Illinois at Urbana-Champaign, University of Maryland, University of Southern California, University of Texas at Austin, the joint Stanford-Berkeley seminar, the 7th Coller Institute of Private Equity symposium, the 2015 Western Finance Association meetings, the 2015 SFS Cavalcade, and brown bag participants at the UC Berkeley Fung Institute and Stanford for helpful comments and suggestions. The authors have obtained IRB approval from Stanford University before conducting the field experiment.
Early stage investors provide financial capital to young entrepreneurial firms, enabling their birth and development, and thus contributing to innovation and growth in the economy (Solow (1957)). Start-up firms are particularly difficult to finance because their prospects are highly uncertain, they lack tangible assets that can be used as collateral, and they face severe information problems (Hall and Lerner (2010)). Given these problems, how do investors choose which start-ups to fund? What factors drive their selection process? While this issue is often debated among academics and practitioners (see Quindlen (2000), Gompers and Lerner (2001)), there is little systematic evidence on the selection process of early stage investors. This stands in sharp contrast to the wealth of evidence on investment decisions in public equity markets by institutional and retail investors.1 This paper provides, to the best of our knowledge, the first experimental evidence of the causal impact of start-up characteristics on investor decisions.

Based on competing theories of the firm, we focus on three key characteristics of start-ups: the founding team, the start-up’s traction (such as sales and user base), and the identity of current investors. The founding team is important if human assets are the critical resource that differentiates one start-up from another, as argued by Wernerfelt (1984), Rajan and Zingales (2001), and Rajan (2012). The importance of experimentation at the earliest stages of the firm further highlights the special role of the founding team (e.g., Schumpeter (1934), Kerr, Nanda and Rhodes-Kropf (2014), Manso (2015)). Alternatively, the property rights theories of Grossman and Hart (1986), and Hart and Moore (1990), amongst others, suggest that it is the non-human assets that are most important. Investors should then react most strongly to firm traction in order to identify early signs of the underlying idea’s success. A third possibility is that investors prefer to rely mostly on the behavior of other, earlier investors, rather than on their own

---

1 See, for example, Falkenstein (1996), Wermers (2000), and Gompers and Metrick (2001) for evidence on the investment behavior of mutual funds, and Barber and Odean (2000), and Ivkovic and Weisbenner (2005) for individual retail investors.
information, especially when earlier investors are high profile and successful. Such behavior may arise in various settings with information asymmetry and may lead to information cascades (Bikhchandani, Hirshleifer, and Welch (1992), and Welch (1992)). In these cases, investors pay most attention to the identity of existing investors.

Testing these hypotheses is challenging because it is difficult to separate the causal effects of different start-up characteristics. For example, are serial entrepreneurs more likely to attract financing due to their past experience, or because they tend to start companies that look attractive on other dimensions known to the investor but not to the researcher, such as the underlying business idea? This omitted variables problem is exacerbated by the fact that existing data sources for start-ups contain only a small fraction of investors’ information sets at the time of funding. Moreover, existing data sets include only completed deals rather than the entire pool of start-ups considered by investors. Without data on the characteristics of companies that were turned down by investors, it is difficult to learn about investors’ decision-making process.

To address these problems, we conduct a randomized field experiment on AngelList, an online platform that matches start-ups with potential investors. AngelList regularly sends emails to investors featuring start-ups that are raising capital. Besides broad information about the start-up idea and funding goal, the emails show specific information on the founding team, the start-up’s traction, and the identity of current investors, but only if the specific information passes a disclosure threshold set by AngelList. Investors therefore perceive a given dimension of the firm (team, traction, or current investors) as low quality if the corresponding information category is missing from the email.

In the experiment, we randomly choose which of the categories that passed AngelList’s disclosure threshold are revealed in a given email. We thus exogenously change investors’
perception of the quality of a start-up’s team, traction, and current investors. Conditional on other information that is provided about the start-up, we exploit the variation across investors’ reactions within each start-up to infer which factors drive investors’ decisions. Specifically, we measure each investor’s level of interest in the company by recording whether the investor chooses to learn more about the firm on the platform. This allows us to explore the impact of information on investors’ initial screening process.

We sent approximately 17,000 emails to nearly 4,500 investors on the platform, spanning 21 different start-ups, during the summer of 2013. The randomized experiment reveals that the average investor is highly responsive to information about the founding team, whereas information about traction and current investors does not lead to a significantly higher response rate. This suggests that information about the human capital of the firm is uniquely important to potential investors, even after controlling for information about the start-up’s idea.

There are two non-mutually exclusive channels through which human capital information may be important to early stage investors. First, the operational capabilities of the founding team may be important at the earliest stages of a start-up, when most experimentation takes place. Second, a founding team with attractive outside options that nevertheless commits to the start-up sends a strong signal about the firm’s prospects that cannot be otherwise learned by (or credibly signaled to) investors. If team information only conveys a signal about start-up prospects, then one would expect that knowledgeable investors who are specialized in the start-up’s sector will react less strongly to team information. However, we find that such investors react as strongly to team information as investors that are less familiar with the start-up’s sector, suggesting that the operational abilities of the founding team matter.
A related question is whether an investment strategy that selects start-ups based on the team is indeed more successful. Our results suggest that team is important for fundraising, which is a prerequisite for entrepreneurial success. However, exploring this question directly by observing firm outcomes is not feasible within our experiment, as participating companies are still at a very early stage, and long-run outcomes such as acquisitions or IPOs are as of yet unknown. Moreover, the counterfactuals in our analysis are derived from the same start-up with randomly different information sets. Since more information is revealed before actual investments take place, we cannot compare the long-term outcomes of treated firms with their counterfactuals. This is a common limitation in field experiments that rely on correspondence testing methodology.²

We can, however, explore the screening behavior of successful and highly reputable investors. The empirical literature attributes successfully investing in early stage firms to skill, as is evident in the persistence of venture capital returns (e.g., Kaplan and Schoar (2005), Hochberg, Ljungqvist, and Vissing-Jorgensen (2014), Korteweg and Sorensen (2014), Harris, Jenkinson, Kaplan, and Stucke (2014)). The selection behavior of successful investors is therefore likely to be correlated with future successful outcomes. We find that the more experienced and successful investors react strongly only to the team information, which provides indirect evidence of the viability of an investment strategy based on selecting on team information.

Overall, the results in this paper present evidence for the importance of human capital assets for the success of early stage firms. Our results, however, do not suggest that non-human assets are not essential. In that regard, our paper is most closely related to Kaplan, Sensoy, and

---

² For example, Bertrand and Mullainathan (2004) send fictitious resumes with randomized names to employers in order to study discrimination while controlling for applicant resume fixed effects. Since resumes are fictitious, they can only capture the initial callback response of the employer, rather than actual hiring outcomes.
Stromberg (2009). They find that business lines remain stable from birth to IPO, while management turnover is substantial, illustrating the importance of non-human assets. Our results illustrate the importance of the founding team at the earliest stages of the firm. Together, the two papers are consistent with Rajan’s (2012) model, in which the entrepreneur’s human capital is important early on to differentiate her enterprise, but to raise substantial funds (for instance, by going public), the entrepreneur needs to go through a standardization phase that makes human capital in the firm replaceable, so outside financiers can obtain control rights.

Many papers focus on establishing the impact of early stage investments on firm success (e.g., Kerr, Lerner, and Schoar (2013), Kortum and Lerner (2000), Sorensen (2007), Samila and Sorensen (2010), Bernstein, Giroud, and Townsend (2013)). Yet, little is known about the process by which early stage investors select the companies to which they provide funding. Our paper is most closely related to several papers that explore investors’ behavior using surveys and interviews (e.g., Pence (1982), MacMillan, Siegel, and Narasimha (1986), MacMillan, Zemann, and Subbanarasimha (1987), Fried and Hisrich (1994)), but ours provides the first large sample evidence on this issue, spanning thousands of investors and using a randomized field experiment.

Our study also contributes to the literature that relates founder characteristics and firm performance (e.g., Gompers, Lerner, and Scharfstein (2005), Pukthuanthong (2006), Ouimet and Zarutskie (2013)), and has implications for the literature on the choice to become an entrepreneur, and their likelihood of success (e.g., Moskowitz and Vissing-Jorgensen (2003), Hurst and Lusardi (2004), Puri and Robinson (2013)).

The paper is structured as follows. In section I, we give a brief overview of the AngelList platform. Section II describes the randomized emails experiment, and section III presents descriptive statistics. In section IV, we analyze investors’ reactions to the emails. Section V
explores why team information is important to investors. Section VI analyzes whether investing in teams is a viable investment strategy. Section VII discusses robustness and alternative interpretations of the results, and section VIII concludes.

I. The AngelList Platform

The early stage financing market is dominated by search frictions and asymmetric information. AngelList is an online platform built to reduce these frictions and improve the matching between start-ups and potential investors. The platform was founded in 2010, and has experienced rapid growth since. The company has attracted much attention, and is often argued to have the potential to reshape the venture capital landscape and early stage funding as a whole.3

Start-up companies looking for funding may list themselves on the platform and post information about the company, its product, traction (e.g., revenues or users), current investors, the amount of money they aim to raise and at which terms, and any other information they would like to present to potential investors. Examples of well-known companies that have raised money through AngelList are Uber, Pinterest, and Leap Motion.

Accredited investors (as defined by the U.S. Securities and Exchange Commission) can join the platform to search for potential investments.4 Investors typically list information on their background, markets and industries of interest, and their portfolio of past and current investments. The platform hosts many prominent and active investors with extensive experience investing in, building, and operating early stage companies, such as Marc Andreessen and Ben

4 For individuals, an accredited investor is a natural person with either at least $1 million in net worth (individually or jointly with a spouse, but excluding their primary residence) or with income of at least $200,000 (or $300,000 jointly) in each of the two most recent years, and a reasonable expectation of such income in the current year.
Horowitz (of the venture capital firm Andreessen-Horowitz), Reid Hoffman (co-founder of LinkedIn), Yuri Milner (founder of Digital Sky Technologies), Marissa Mayer (president and CEO of Yahoo), Max Levchin (co-founder of Paypal), and Dave McClure (of the accelerator 500 Startups).

Through AngelList, interested investors request an introduction to the start-up’s founders. Usually, investors decide to invest following a phone call with the founders or - depending on geographical closeness - a face-to-face meeting. There is a strong social networking component to the platform: investors can “follow” each other as well as start-ups, they can post comments and updates, and they can “like” comments made by others.

By the fall of 2013, about 1,300 confirmed financings had been made through AngelList, totaling over $250 million, though AngelList estimates that only 50% of completed financing rounds are disclosed, suggesting that the numbers are potentially much higher. Most investments were concentrated in 2012 and 2013. The companies funded through AngelList have gone on to raise over $2.9 billion in later rounds of venture capital and exit money. Over 60% of the firms that raised a seed round in 2013 have an AngelList profile, and more than half of these firms attempted to raise funds on the platform, based on a comparison to the Crunchbase database.

II. Experimental Design

The field experiment uses “featured” emails about start-ups that AngelList regularly sends out to investors listed on its platform. The featured start-ups are real companies, chosen by AngelList based on an assessment of their appeal to a broad set of investors who have previously indicated an interest in the industry or the location of the start-up.
Figure 1 shows an example of a featured email. The email starts with a description of the start-up and its product. Next, up to three categories of information are listed, describing: i) the start-up team’s background; ii) current investors who have already invested in the start-up; iii) traction. Outside of the experiment, a category is shown if it passes a certain threshold as defined by AngelList with the aim of showing only information that investors might be interested in. The algorithm is described in detail in Internet Appendix A. For example, the team category is shown if the founders were educated at a top university such as Stanford, Harvard, or MIT, or if they worked at a top company such as Google or Paypal prior to starting the company. The final piece of information, which is always shown, is the amount the company aims to raise, and its progress towards that goal.

In the experiment, we randomly choose which of the team, current investors, or traction categories are shown in each email, from the set of categories that exceed their threshold. For example, suppose 1,500 investors qualify to receive an email about a given start-up, and only team and traction information exceed their disclosure thresholds. A random set of 500 investors will be sent the email with both team and traction shown (the original email that would have been sent to all investors outside of the experiment), 500 investors receive the identical email except that the team category is not shown, and another 500 receive the email that shows the team, but not the traction information. We do not send any emails with all categories hidden, as this does not happen outside of the experiment, and could raise suspicion among investors.

Investors respond to the emails using the “View” and “Get an Intro” buttons that are included in each email. The “View” button takes an interested investor to the AngelList website to view the full company profile. This event captures the investor’s initial screening phase, and is the primary dependent variable in our analysis. Alternatively, clicking the “Get an Intro” button
sends an immediate introduction request to the company, but this is a very rare event as nearly all investors take a look at the full company profile first. Hence, to capture introduction requests, we record whether an investor asks for an introduction within three days of viewing the email through either the email or the website. Naturally, we need to exercise caution in interpreting the results on introductions, as investors will likely have learned more information from the website.

The experiment allows us to circumvent the three main empirical challenges associated with studying investor decision-making that were mentioned in the introduction. First, we observe favorable investor reactions as well as cases in which investors choose to pass on an investment opportunity, a necessary requirement for studying which start-up characteristics are more attractive to investors. Second, we know exactly what information is shown to investors. Third, randomizing investors’ information sets allows us to separate the potentially endogenous link between various start-up characteristics.

III. Summary Statistics

A. Emails

The experiment ran over an eight-week period in the summer of 2013. Table I Panel A shows that a total of 16,981 emails were sent to 4,494 active investors, spanning 21 unique start-ups. Active investors are defined as having requested at least one introduction to a start-up since the time of their enrollment on AngelList. This excludes people who are not on the platform to seek new investments, but rather to confirm their affiliation with a start-up that is fundraising or to do research without the intent to invest.

For each start-up, we sent an average (median) of 2.76 (3) versions of the email, each with an exogenously different information set, for a total of 58 unique emails. Each unique email
was sent to 293 recipients on average (median: 264). The number of recipients per unique email is roughly equal for a given start-up, but varies across start-ups depending on the popularity of their industries and locations. Between 202 and 1,782 investors receive an email for a given start-up, with an average of 809 recipients. An investor receives on average 3.78 emails (median: 3 emails), with no investor receiving more than one email for a given start-up. Recipients opened 48.3% of their emails, and 2,925 investors opened at least one email. Of the opened emails, 16.5% of investors clicked on the “View” button to see more information about the start-up.

Panel B shows that there is no statistically significant difference in the frequency with which each information category passes AngelList’s disclosure threshold, suggesting that the information salience is roughly equal across categories (we discuss this in more detail in the section VII below). Within the experiment, categories are randomly excluded. Conditional on passing the threshold, the information regarding team, current investors, and traction is shown about 73% of the time. Note that these frequencies are different from 50% because we randomize across different versions of the emails. For example, if team and traction pass the threshold, there are three versions of the email: one that shows team only, one that shows traction only, and one that shows both. In that case, team and traction are each shown 67% of the time. As mentioned above, we do not use the empty set because this never happens outside the experiment.

B. Start-Ups

Table II presents detailed descriptive statistics of the 21 start-ups in the randomized experiment. Panel A shows that firms are located in the United States, Canada, the United Kingdom, and Australia, amongst others, with Silicon Valley being the most popular location (with six firms). Most firms operate in the Information Technology and the Consumers sectors
Panel C shows that the median start-up has two founders. Most firms (17 out of 21) have non-founder employees, and the median firm with employees has three workers. The largest start-up has eleven people, counting both founders and employees. Only a quarter of firms have a board of directors. Of those that do have a board, the median board size is two, and no board has more than three members. All but two companies have advisors (typically high-profile individuals who are compensated with stock and options), and the median number of advisors for these firms is three. Panel D reports prior financing information. Twelve companies (57%) have previously gone through an incubator or accelerator program. Eleven firms (52%) received prior funding, and raised an average (median) of $581,000 ($290,000). For the sixteen companies that report a pre-money valuation, the valuation ranges from $1.2 million to $10 million, with an average (median) of $5.5 million ($5.0 million). Eighteen companies explicitly state their fundraising goal, ranging from $500,000 to $2 million, with an average (median) of $1.2 million ($1.3 million). Most companies (76%) are selling shares, with the remaining 24% selling convertible notes.

C. Investors

Table III reports descriptive statistics of the 2,925 investors who received the featured emails in the field experiment, and who opened at least one email. This set of investors is the focus of our empirical analysis. Panel A shows that virtually all investors are interested in investing in the Information Technology and Consumers sectors. Other key sectors of interest are Business-to-business, Healthcare and Media.

---

5 Note that sector designations are not mutually exclusive. For example, a consumer internet firm such as Google would be classified as belonging to both the Information Technology and Consumers sectors.

6 At this stage, a board may simply fulfill a legal requirement of incorporation rather than a governance mechanism.

7 The pre-money valuations are based on the companies’ ex-ante proposed terms, not on ex-post negotiated terms. We do not know the negotiated valuations, but they are likely lower than the ex-ante valuations shown here.
Panel B reveals that investors are very active on the platform, with the average (median) investor requesting ten (three) introductions to start-ups from the time that they joined the platform until we harvested the data in the late summer of 2013. Note that there is considerable heterogeneity in the number of introductions requested, with the lowest decile of investors requesting only one introduction, while the top decile requested more than twenty.

To measure investors’ past success, AngelList computes a “signal” for each investor and each start-up that ranges from zero to ten. The algorithm works recursively. It is seeded by assigning a value of ten to high exit value companies (from Crunchbase) such as Google or Facebook, and to a set of hand-picked highly credible investors. The signal then spreads to start-ups and investors through past investments: any start-up that has a high signal investor gets a boost in its own signal. Likewise, an investor who invests in a high signal company gets a boost in his or her signal.\(^8\) This construction gives credit for having invested both in realized successes, and in firms that are still too young for an exit, but that show great promise for successful exits in the future. The average (median) investor signal is 6.4 (6.3), with substantial heterogeneity across investors as indicated by the standard deviation of 2.3.

The social network on the platform is extensive, and the investors in the sample are well-connected: the average (median) investor had 591 (202) followers at the time of data collection. Again, there is large heterogeneity across investors, with the 10\(^{th}\) percentile having only twenty-six followers while the 90\(^{th}\) percentile investor has 1,346 followers. We also construct a weighted number of followers measure that uses followers’ signal as weights.

---

\(^8\) The signal calculations use all investments on the AngelList platform, supplemented with data from Crunchbase. The AngelList data are self-declared investments by investors and start-ups on the platform that were subsequently verified by AngelList with the party on the other side of the transaction (i.e., investments declared by start-ups are verified with the investors and vice versa). This includes many companies that are on the platform but have never raised money through AngelList, such as Facebook. These firms appear on the platform because someone was verified to have been an investor, founder, board member or advisor.
Over 90% of investors are actively involved with start-ups. Panel B shows that most (82%) have a track record as investors. Conditional on making an investment, the average (median) number of investments is 13 (8), though some invest in as many as thirty companies. Roughly 44% of investors are active as advisors to start-ups, with the median advisor advising two firms, and 17% of investors served as a board member on a start-up. Many investors (60%) were at one point founders themselves. Of these, the median founded two companies.

Panel D of Table III shows the correlations between investor experience (measured by number of investments), past success (signal), and reputation (weighted number of followers). Though correlated, these measures clearly capture non-overlapping investor sub-populations.

To summarize the above findings, the sample group of investors are active, successful, connected, and highly experienced, not only in investing in very early stage firms, but also in building companies from the ground up. As such, these individuals form a sample that is ideally suited to inform us about the assets that are most important to very early stage firms.

IV. Main Results

Table IV shows regression results for the effect of the randomized information categories (team, current investors, and traction) on investor click rates. We use the sample of 8,189 opened emails, to ensure that investors have seen the information in the email. The dependent variable equals one when an investor clicked on the “View” button in the email, and zero otherwise. The explanatory indicator variables equal one when an information category is shown in the email, and zero otherwise. All specifications include start-up fixed effects to control for the effect on click rates of any information conveyed in the email’s descriptive paragraph, the amount that the

---

9 As in the signal calculation, these numbers are not limited to start-ups that tried to raise money through AngelList, and any roles claimed (advisor, board member, founder, or investor) are verified with the companies in question.
company aims to raise, has already raised, or any other common knowledge about the start-up. Thus, we compare investor responses within a given start-up.\textsuperscript{10} We cluster standard errors at the investor level to account for correlated decisions across emails received by the same investor.\textsuperscript{11}

The ordinary least squares (OLS) regression results in column 1 show that revealing information about the team raises the unconditional click rate by 2.2\%, which is statistically significantly different from zero. With a base click rate of 16.5\% (Table I), this represents a 13\% increase. Note that from prior featured emails before the experiment, investors are calibrated to think that if a given category is missing, then that category has not crossed the disclosure threshold. This means that the 2.2\% difference in the click rate is the difference between an average team above the threshold relative to an average below-threshold team.

Showing information about the other categories, current investors or traction, does not significantly alter the click rate. This means that knowing whether a notable investor is investing in the firm, or if the start-up has material traction, does not make investors more likely to click.

We should be careful to point out that the finding that human capital is the most important category does not imply that the business idea of the start-up is irrelevant. We explore variation about information shown on human capital conditional on the information about the company that is disclosed in the descriptive paragraph of the email. Conditional on this information, our results show that information about human capital matters to investors.

It is possible that some investors already know the information in the emails, especially if the start-up is “hot”. If such information is common knowledge, this will be absorbed in the start-up fixed effect. In column 2 we allow for heterogeneity by adding controls for investors’ pre-

\textsuperscript{10} The results are nearly identical if we include investor fixed effects.
\textsuperscript{11} Internet Appendix B shows that the results are robust to clustering by treatment (i.e., by unique featured email), and to double-clustering by both treatment and investor, using the Cameron et al. (2008) bootstrap to avoid bias due to the small number of clusters (Rothenberg (1988), Kauermann and Carroll (2001), Petersen (2009), Thompson (2011)).
existing knowledge, using an indicator variable that captures whether investors already follow the start-up on AngelList before receiving the email, and a variable that counts prior connections between the investor and the start-up. Prior connections are measured as the number of people on the profile of the start-up (in any role) that the investor already follows prior to receiving the email. Though investors are more likely to click if they already follow the start-up or have pre-existing connections, adding these controls does not change the coefficients on the randomized information categories. Internet Appendix C further shows that dropping connected investors from the regressions altogether, strengthens the effect of team on click rates while leaving the other categories’ coefficients insignificant. To the extent that these proxies are not perfect, our results are biased towards not finding an effect of the disclosed information, and our estimates should be interpreted as lower bounds on the importance of the information categories.

In experiments that involve repeated measurement, subjects may learn about the existence of the experiment, which may change their behavior. This concern is mitigated by the short (eight-week) experiment window, and the fact that no investor received more than one email for any one featured start-up. The regression in column 2 also includes as an additional control the number of prior emails that the investor received in the experiment. The insignificant coefficient implies that click rates do not change as an investor receives more emails in the experiment. Unreported regression results show that including interactions of this control with the information category dummies are also insignificant. Investor responsiveness to disclosed information thus does not change as the experiment progresses. In columns 3 and 4 we show that the results are robust to using a logit model instead of OLS.

A unique feature of our setting is that we can explore the importance of the randomized experiment for identification by re-running the regressions on the subset of 2,992 opened emails
that show every piece of information that crossed the AngelList threshold. These are the only emails that would have been sent outside of the experiment. Focusing on the OLS regression with only the information categories as explanatory variables, Table V shows that the coefficients on revealed information about the team, investors, and traction in the sample without randomization are 0.046, 0.013, and 0.037, respectively, where team is significant at the 5% level, investors is insignificant, and traction is significant at the 10% level.\(^{12}\) These coefficients are uniformly higher than the coefficients of 0.022, 0.010, and 0.016 using the full set of randomized emails (replicated in the four right-most columns of Table V), where only team is significant. Without the experiment, we would thus overestimate the importance of the information categories, which is exactly what one would expect if good teams, investors, and traction are positively correlated with good ideas. The results for the other models are similar.

V. Why do Investors React to Information on Founding Team?

Given the importance of team information, what is the channel through which human capital information is important for early stage investors? One explanation is that the operational or technical capabilities of the founding team raise the chance of success, especially in the earlier stages of a firm’s lifecycle, when experimentation is important. An alternative explanation is that high quality teams have attractive outside options, and can therefore credibly signal the quality of the idea. We find evidence that human capital is important at least in part due to the operational capabilities and expertise of the founders.

Consider the null hypothesis in which team matters only because it provides a signal of the underlying idea. To test this hypothesis we explore the response of investors that specialize in the sector in which the start-up operates. These investors are the most knowledgeable about this

\(^{12}\) Note that we cannot include start-up fixed effects here, as there is no variation in emails for a given start-up.
particular sector, and therefore more capable to evaluate start-up ideas in this area (for example, from the business description in the email). Therefore, under the null hypothesis, the specialized investors will not react as strongly to team information as the less knowledgeable investors.

For each start-up, we identify the investors that specialize in its sector by using the tags that investors provide about their interest and expertise. For example, investors may specify that they specialize in, and look for start-up companies in the clean technology and consumer internet sectors. Investors and start-ups may be associated with multiple sectors, and we calculate the cosine similarity between the vector of investor sector tags and the vector of tags that the start-up uses to describe its sector. The similarity measure is highest if an investor and start-up have identical sets of tags, and lowest if they have no tags in common. We designate investors as specialized if their similarity measure is in the top 25% of the distribution for a given start-up.

Column 1 of Table VI repeats our baseline result that investors are highly responsive to team information. In column 2, we add the specialization dummy variable. As expected given the declared interest of specialized investors, we find that they have a 3.9% higher click rate (24% higher than the baseline rate), which is statistically highly significant. The coefficient of the team information variable, however, remains unchanged.

In column 3, we add the interaction of the specialization and team disclosure dummy variables, which has a coefficient of -0.002 with a t-statistic close to zero. This result is robust to adding interactions of the specialization variable with all information categories in column (4). These regressions show that specialized investors react the same as other investors to

---

13 The sector tags provided by investors and start-ups are very specific. The average investor uses 15 tags, and there are more than a thousand unique sector tags used on the platform.

14 Internet Appendix D describes the cosine similarity measure in detail, and shows that the results are robust to alternative definitions of similarity. The appendix also shows that cosine similarity is different from experience (a potential concern if experienced investors have more sector tags), and that the results are robust to adding controls for investor experience.
information about the team, despite their superior expertise in evaluating the start-up idea. This contradicts the null hypothesis, and provides suggestive - albeit not conclusive - evidence that the importance of the team category is not entirely due to its signal value, but likely also due to the operational and execution skills of the founding team.

VI. Is it Rational to Invest Based on Founding Team?

A natural next question to ask is whether investors are right to focus on team information. In other words, are investments selected on founding team characteristics more profitable and more likely to succeed? This question relates to an ongoing debate among academics and practitioners over what constitutes a firm, and what factors predict future success of an early-stage firm - the idea or the human capital - as discussed by Kaplan et al. (2009).

It is challenging to answer this question directly, for several reasons. First, cross-sectional variation is limited, with only 21 start-ups. Second, it is still too early to observe real outcomes, since these start-ups are at a very early stage (earlier than most VC investments), and it takes years before payoffs materialize. Third, our counterfactuals are based on investors with different information sets on the same start-up. Since they rely on the same firm, we cannot compare long-term outcomes (such as future financing rounds, acquisitions, or IPOs) of treatment and control.

We can, however, take an indirect approach by exploring how successful and experienced investors react to various information categories. There is skill in investing in early stage firms, as is evident in the persistence of venture capital returns (e.g., Kaplan and Schoar (2005); Hochberg et al. (2014); Korteweg and Sorensen (2014); Harris, et al. (2014)). The selection behavior of successful investors is therefore likely to be correlated with future successful outcomes.
The regression results in Table VII show the difference in response between experienced and inexperienced investors, using investors’ total number of prior investments as a measure of experience. The first column shows that investors who have made at least one investment behave similarly to the overall sample, and react only to the team information. The inexperienced investors with no prior investments, who make up 18% of the sample, react not only to the team information, but also to the traction and current investor information. Columns 2 and 3 redefine the experience cutoff at the 25th and 50th percentile of investors, ranked by number of investments. The experienced investors still only respond to information about the team, while the significance of the response to the traction and current investors categories among inexperienced investors weakens somewhat.15

We also consider other measures of investor experience and prior success. In Table VIII, we use investors’ signal, which is a measure of both experience and past success. In Table IX, we use investors’ weighted number of followers to capture his or her importance and reputation.16 Overall, the results are robust: more experienced and successful investors only respond to the information about the team. Given that these investors are more likely to invest in ultimately successful start-ups, this suggests that selecting on founding team information is a successful and viable investment strategy.

VII. Discussion

This section discusses alternative interpretations and additional robustness tests.

15 Internet Appendix E shows that also the inexperienced investors actively request introductions, suggesting that their primary objective is to invest rather than to observe and learn from the actions of the experienced investors.
16 We also considered the unweighted number of followers, but the correlation with the weighted number of followers is 0.95 (Table III panel D). For brevity, we only report the results for the weighted number of followers.
A. Ordering of Information Categories

The experiment builds on the repeated interaction between AngelList and investors. To avoid raising suspicion amongst investors, who are accustomed to seeing emails in a certain format, the information in the randomized emails is always presented in the same order. However, since information about the team always appears first, a concern is that our results may be driven by a “primacy” effect, in which survey responses are more likely to be chosen because they are presented at the beginning of the list of options (Krosnick (1999)).

The psychology literature suggests that primacy effects are a concern when the list of alternatives is long, when the included information is difficult to comprehend (leading to respondents’ fatigue), and when respondents have limited cognitive skills (see Internet Appendix F for a detailed discussion). Our setting is quite the opposite, with sophisticated investors who were unaware that they were part of an experiment, and simple and concise information with only three categories (see Figure 1).

We can use our data to test if investor behavior is driven by primacy, as reactions to the current investors information category should be stronger when it is shown first, which happens when information about the team is missing from the email. The results in Internet Appendix F show no evidence supporting the primacy hypothesis. Appendix F also contains simulations that show that our regression results cannot be explained by primacy alone.

B. Signal-to-Noise Ratios of Information Categories

An alternative interpretation of the results is that they are due to variation in signal-to-noise ratios across the information categories. To fix ideas, it is useful to distinguish between two factors that can cause differences in signal-to-noise ratios. The first factor is “true” signal-to-noise. For example, if founders’ backgrounds are a less noisy measure of success than a start-
up’s traction, investors may pay more attention to the team information. This explains why investors’ reactions differ across information categories, and is in line with our prior interpretation of the results. The second factor is differences in AngelList’s disclosure threshold across categories. For example, knowing that a team graduated from a top 1% university could be very important. If, however, AngelList discloses that a team graduated from a top 95% college then one might conclude that the team information category is not very useful – not because educational background is useless but because the way the information is disclosed is uninformative. This channel is potentially more worrisome.

 Though it is difficult to rule out completely, it does not appear that the choice of disclosure thresholds is causing large differences in informativeness across categories. Panel B of Table I shows that there is no statistically significant difference in the likelihood to disclose information across categories in the experiment. Internet Appendix A further shows that all disclosed information is in the far right tail of their respective population distributions. For example, AngelList discloses founders’ colleges and past employers if they are in the top 3.5% of their populations (based on AngelList’s internal rankings). Similarly, AngelList discloses information about current investors if their signal is in the top 5%.

 The result in Section VI that inexperienced investors react quite strongly to the traction and current investors categories suggests that there is information content in these categories, and that they are not subject to an uninformative choice of disclosure threshold. Rather, the evidence suggests that the experienced investors believe that these categories are simply less relevant to the success of the company (i.e., that these categories have truly low signal-to-noise), and thus choose to ignore them.


C. External Validity

AngelList chooses which companies to feature in their emails and which investors to contact, raising potential external validity (i.e., generalization) concerns about the results.17

Table X compares the 21 start-ups in the experiment to a larger sample of 5,538 firms raising money on AngelList. This larger sample consists of “serious” firms who received at least one introduction request while attempting to raise capital. Table X shows that the field experiment firms are slightly larger in terms of the number of founders (2.6 versus 2.1, on average), pre-money valuation ($5.6 million versus $4.9 million), and funding targets ($1.2 million versus $0.9 million). They are also more likely to have employees (81% versus 53%), and to have attended an incubator or accelerator program (57% versus 30%). Still, for the most part the differences are small on both statistical and economic grounds, and the samples are comparable on other dimensions such as board size, the fraction of companies that get funding prior to AngelList, and the prior amount raised. Also, in both samples, about three out of four firms sell equity, while the remainder sells convertible notes. Altogether, the samples do not look vastly different, mitigating external validity concerns.

To assess its representativeness for the broader start-up market, AngelList compared the firms on their platform against Crunchbase, a popular wiki-based site with detailed fundraising information for start-ups. Over 60% of the companies raising a seed round in 2013 have an AngelList profile, and more than half of these firms attempted to raise funds on the platform. Coverage differs by geography, though. Close to 60% of successful seed rounds in Silicon Valley and Texas fundraised on AngelList, compared to only 15-20% in Boston and Seattle.

17 Note that internal validity due to the choice of featured companies is not a concern, because our inference exploits the random variation of information within each start-up. Similarly, the choice of recipients does not violate internal validity, as information is varied randomly across recipients.
Overall, AngelList appears to capture a fairly representative sample of start-ups seeking seed funding, though tilted towards Silicon Valley and Texas.

With respect to the representativeness of the investors, the experiment covers a large fraction of the 5,869 active investors on AngelList at the time of the experiment, as 4,494 (77%) received at least one featured email over the course of the experiment, and 2,925 (50%) opened at least one of these emails.

D. Combinations of Information Categories

We explore whether information categories have a differential effect when other information is disclosed at the same time. The results in Internet Appendix G reveal that, overall, we do not find any evidence of interaction effects. Specifically, we find that both traction and current investors remain insignificant when conditioning on the appearance of the other information categories. Similarly, team information remains statistically significant when interacted with the other categories. One caveat to this analysis is that, since we only have 21 start-ups in the experiment, we cannot rule out that lack of power prevents us from finding any effects when including multiple interaction terms in the regressions.

E. Detailed Information Categories

Internet Appendix H reruns the regressions in Table IV using more detailed information categories. For example, team information can be disaggregated into founders’ prior work experience, their educational background, and whether they have experience in the start-up’s industry. Only founders’ education shows up weakly statistically significant at the 10% level, though lack of power is an issue.
The education result raises the question whether investors click simply because they are curious what their entrepreneur peers are doing. To test this hypothesis, we added an indicator to the regressions in Table IV that equals one if the email reveals that the investor went to the same college as one of the founders. Its coefficient is insignificant, and the other information category coefficients are unaffected. We do not have enough power to say whether this coefficient varies across experience levels, though, as sharing an alma mater with a founder is rare (it happens for only 78 of the 2,925 investors).

**F. Interpretation of Click Rates**

Clicks on featured emails are important, because they capture real and important information about investors’ level of interest in the start-up, which affects ultimate funding decisions. The base click rate of 16.5% shows that investors do not ignore the information in the emails, nor do they click on every featured email that lands in their inbox. Moreover, if investors did not care about the information in the emails, clicks would be random and we would not see a reaction to any information. The fact that we find economically and statistically significant results suggests that investors do care and pay attention to the information in the emails.

It is not feasible to use actual investments decisions as an explanatory variable in the regressions, because investors learn more about the start-up from the AngelList website after clicking on the email. At that point all information is revealed, and investment decisions are no longer based on the randomized information (this is a common limitation in field experiments using the correspondence testing). Nevertheless, given that the search process has moderate to large frictions, higher click rates should translate into more investments. If the conversion rate
from clicks to investment remains unchanged, our finding that team information increases click rates by 13% (relative to the base rate) implies a 13% increase in actual investments.

Table I Panel A quantifies the value of a click through the conversion rate from clicks to investments. The conversion rate is 2.98%, but it may be as high as 6%, because investors are not required to report investments to AngelList, and the company estimates that only half of investments are reported. This is fairly high compared to venture capitalists, who invest in about 1 in every 50 to 100 deals that they look into (Metrick and Yasuda (2010)), although investors on AngelList may have different incentives than venture capitalists (e.g., Goldfarb et al. (2013)). Importantly, no investments are made without an initial click on an email. Thus, clicks are a prerequisite for investment.

Introduction requests are an alternative outcome variable that is less susceptible to the underreporting issue, because AngelList records whenever an investor requests an introduction with a start-up through the website. The conversion rate from clicks to introductions is 15.14% (Table I Panel A). This rate is higher than the investment rate not only due to the underreporting of investments, but also because introductions are a lower screen than investments, as only a certain proportion of introductions lead to investments. Still, the click-to-introduction conversion rate shows that clicks are meaningful for real outcomes as they lead to a significant number of introductions.

VIII. Conclusion

In this paper, we shed light on the investment decision process of early stage investors. Unlike investments in publicly traded firms, little is known about the selection process of these investors, despite their important role in promoting innovation and economic growth. This is due
to lack of data on investors’ information sets and unsuccessful fundraising attempts by start-ups, as well as endogeneity problems due to omitted unobservable start-up characteristics.

This paper uses a field experiment that randomly varies investors’ information sets in a tightly controlled information environment, using emails about featured start-ups on AngelList. Investors react most strongly to the information about the start-up’s founding team. We provide further suggestive evidence that investors care about strong founding teams not only for pure signaling reasons, but also because teams matter for operational reasons. The most experienced and successful investors only react to team information, suggesting that selecting on founding team information is a successful and viable investment strategy.

Overall, the results in this paper present evidence for the causal importance of human capital assets for the success of early stage firms, and contribute to the debate around the importance of various key assets to organization success. Our results, however, do not suggest that non-human assets are not essential. Rather, the results are consistent with the model by Rajan (2012), in which human capital is initially important for differentiation, but needs to be replaceable in later stages so that outside investors can obtain control rights, thus allowing the firm to raise large amounts of external funding.

References


Table I: Descriptive Statistics of Emails in Randomized Field Experiment

This table reports summary statistics for the sample of emails about featured start-ups in the randomized field experiment. Each featured start-up has up to three information categories (team, traction, and current investors) that would normally be shown in the email if the information for that category passes the threshold as defined by AngelList (see Figure 1 for an example). For each start-up in the experiment, various unique versions of each email are generated that randomly hide these pieces of information, and these emails are sent to investors registered on the AngelList platform. The sample is limited to active investors who have in the past requested at least one introduction to a start-up on AngelList. Panel A shows basic descriptive statistics regarding the emails, the investors who received the emails, and the start-ups covered by the experiment. Each email contains a button that, when clicked, takes the investor to the AngelList platform where more information about the company is shown, and introductions to the company’s founders can be requested. Clicked measures the frequency of this occurrence. Intro means an investor requested an introduction to the start-up’s founders within three days of viewing the email. Investment means the investor invested in the company at some time after receipt of the email. Panel B shows the frequency with which each information category passed the threshold where it would normally be shown, and how often this information was actually shown in the experiment emails conditional on the threshold being passed. The rightmost column shows the p-value for Pearson’s chi-squared test with null hypothesis that the proportions in the first three columns are all equal.

Panel A: Experiment Descriptive Statistics

<table>
<thead>
<tr>
<th></th>
<th>mean</th>
<th>st. dev.</th>
<th>10</th>
<th>50</th>
<th>90</th>
</tr>
</thead>
<tbody>
<tr>
<td>Emails</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>16,981</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Unique</td>
<td>58</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Investors / unique email</td>
<td>293</td>
<td>149</td>
<td>86</td>
<td>264</td>
<td>468</td>
</tr>
<tr>
<td>Active investors emailed</td>
<td>4,494</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Active investors who opened at least one email</td>
<td>2,925</td>
<td>21</td>
<td>809</td>
<td>468</td>
<td>338</td>
</tr>
<tr>
<td>Start-ups</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Investors / start-up</td>
<td>3.78</td>
<td>2.45</td>
<td>1</td>
<td>3</td>
<td>7</td>
</tr>
<tr>
<td>Start-ups / investor</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Emails opened (%)</td>
<td>48.28</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Of opened emails:</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Clicked (%)</td>
<td>16.45</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Of clicked emails:</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intro (%)</td>
<td>15.14</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Investment (%)</td>
<td>2.98</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Panel B: Information in Emails

<table>
<thead>
<tr>
<th></th>
<th>team</th>
<th>investors</th>
<th>traction</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Information passed AngelList threshold (% of start-ups)</td>
<td>90.48</td>
<td>80.95</td>
<td>85.71</td>
<td>0.678</td>
</tr>
<tr>
<td>Information shown in experiment, if passed threshold (% of unique emails)</td>
<td>73.24</td>
<td>73.02</td>
<td>72.06</td>
<td>0.987</td>
</tr>
</tbody>
</table>
Table II: Descriptive Statistics of Start-ups

This table shows descriptive statistics of the twenty-one start-ups in the randomized field experiment at the time of fundraising. Panel A shows the distribution across cities and countries. Panel B reports the distribution across sectors, where sectors are not mutually exclusive. Panel C shows the structure of the start-up in terms of number of founders, employees, board size, advisors, and whether or not the company has an attorney. *Employees (%)* is the fraction of start-ups that has non-founder employees. The *If > 0, # employees* variable shows how many employees are working for those start-up that have employees. The variables for board members, advisors, and attorney follow a similar pattern. Panel D reports the percentage of start-ups that had funding prior to the current round (*Pre-round funding (%)*) and, if any prior money was raised, the amount raised (*If > 0, pre-round funding raised*). *Incubator (%)* is the fraction of start-ups that have been part of an incubator or accelerator program in the past, and *Equity financing (%)* is the percentage of firms selling stock, with the remainder selling convertible notes.

Panel A: Start-up Distribution across Cities

<table>
<thead>
<tr>
<th>N</th>
<th>fraction (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Austin, TX</td>
<td>1</td>
</tr>
<tr>
<td>Chicago, IL</td>
<td>1</td>
</tr>
<tr>
<td>Kitchener, Canada</td>
<td>1</td>
</tr>
<tr>
<td>London, United Kingdom</td>
<td>1</td>
</tr>
<tr>
<td>Melbourne, Australia</td>
<td>1</td>
</tr>
<tr>
<td>New York City, NY</td>
<td>3</td>
</tr>
<tr>
<td>San Antonio, TX</td>
<td>1</td>
</tr>
<tr>
<td>Silicon Valley, CA</td>
<td>6</td>
</tr>
<tr>
<td>Singapore</td>
<td>1</td>
</tr>
<tr>
<td>Sydney, Australia</td>
<td>1</td>
</tr>
<tr>
<td>Toronto, Canada</td>
<td>3</td>
</tr>
<tr>
<td>Vancouver, Canada</td>
<td>1</td>
</tr>
</tbody>
</table>

Panel B: Start-up Distribution across Sectors

<table>
<thead>
<tr>
<th>N</th>
<th>fraction (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Information Technology</td>
<td>18</td>
</tr>
<tr>
<td>Consumers</td>
<td>13</td>
</tr>
<tr>
<td>Clean Technology</td>
<td>1</td>
</tr>
<tr>
<td>Healthcare</td>
<td>3</td>
</tr>
<tr>
<td>Business-to-business</td>
<td>8</td>
</tr>
<tr>
<td>Media</td>
<td>2</td>
</tr>
<tr>
<td>Education</td>
<td>2</td>
</tr>
</tbody>
</table>
### Panel C: Start-up Structure

<table>
<thead>
<tr>
<th></th>
<th>N</th>
<th>mean</th>
<th>st. dev.</th>
<th>percentile</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td># Founders</td>
<td>21</td>
<td>2.62</td>
<td>0.92</td>
<td>10  50  90</td>
</tr>
<tr>
<td>Employees (%)</td>
<td>21</td>
<td>80.95</td>
<td></td>
<td></td>
</tr>
<tr>
<td>If &gt;0, # employees</td>
<td>17</td>
<td>3.35</td>
<td>2.21</td>
<td>1   3   7</td>
</tr>
<tr>
<td>Board members (%)</td>
<td>21</td>
<td>23.81</td>
<td></td>
<td></td>
</tr>
<tr>
<td>If &gt;0, # board members</td>
<td>5</td>
<td>1.80</td>
<td>0.84</td>
<td>1   2   3</td>
</tr>
<tr>
<td>Advisor (%)</td>
<td>21</td>
<td>90.48</td>
<td></td>
<td></td>
</tr>
<tr>
<td>If &gt;0, # advisors</td>
<td>19</td>
<td>4.74</td>
<td>6.00</td>
<td>1   3   7</td>
</tr>
<tr>
<td>Attorney (%)</td>
<td>21</td>
<td>71.43</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

### Panel D: Start-up Funding

<table>
<thead>
<tr>
<th></th>
<th>N</th>
<th>mean</th>
<th>st. dev.</th>
<th>percentile</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Incubator (%)</td>
<td>21</td>
<td>57.14</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pre-round funding (%)</td>
<td>21</td>
<td>52.38</td>
<td></td>
<td></td>
</tr>
<tr>
<td>If &gt; 0, pre-round funding raised ($000s)</td>
<td>11</td>
<td>580.95</td>
<td>855.33</td>
<td>50. 290 950</td>
</tr>
<tr>
<td>Pre-money valuation ($000s)</td>
<td>16</td>
<td>5,465.63</td>
<td>2,133.60</td>
<td>3,000 5,000 8,000</td>
</tr>
<tr>
<td>Fundraising goal ($000s)</td>
<td>18</td>
<td>1,183.06</td>
<td>462.88</td>
<td>570 1,250 2,000</td>
</tr>
<tr>
<td>Equity financing (%)</td>
<td>21</td>
<td>76.19</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Table III: Descriptive Statistics of Investors

This table reports descriptive statistics of the active investors (defined as having requested at least one introduction through the AngelList platform) who received featured emails about the start-ups in the randomized field experiment, and opened at least one such email. Panel A shows in which sectors investors have stated they are interested in investing. A single investor can indicate multiple sectors of interest. Panel B shows the number of introductions requested by investors, the signal of an investors’ success as computed by AngelList (see the main text for a description of the algorithm), the number of followers that investors have on the platform, both the raw number and weighted by the followers’ signals, the percentage of investors that were involved with start-ups in the past, and for those involved with start-ups, the number of start-ups the investor was involved with. Panel C breaks down involvement into various roles. Investor (%) shows the percentage of investors who have invested in start-ups. For the subset of investors who invested in start-ups, If > 0, # start-ups funded reports the number of start-ups that they invested in. The variable definitions for advisor, board member, and founder follow a similar pattern. Panel D shows the correlations between the number of investments, signal, and number of followers.

Panel A: Investor Stated Interest across Sectors

<table>
<thead>
<tr>
<th>Sector</th>
<th>N</th>
<th>fraction (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Information Technology</td>
<td>2,884</td>
<td>98.59</td>
</tr>
<tr>
<td>Consumers</td>
<td>2,769</td>
<td>94.66</td>
</tr>
<tr>
<td>Clean Technology</td>
<td>861</td>
<td>29.43</td>
</tr>
<tr>
<td>Healthcare</td>
<td>1,239</td>
<td>42.35</td>
</tr>
<tr>
<td>Business-to-business</td>
<td>2,328</td>
<td>79.58</td>
</tr>
<tr>
<td>Finance</td>
<td>949</td>
<td>32.44</td>
</tr>
<tr>
<td>Media</td>
<td>1,420</td>
<td>48.54</td>
</tr>
<tr>
<td>Energy</td>
<td>165</td>
<td>5.64</td>
</tr>
<tr>
<td>Education</td>
<td>685</td>
<td>23.41</td>
</tr>
<tr>
<td>Life Sciences</td>
<td>414</td>
<td>14.15</td>
</tr>
<tr>
<td>Transportation</td>
<td>307</td>
<td>10.49</td>
</tr>
<tr>
<td>Other</td>
<td>26</td>
<td>0.8</td>
</tr>
</tbody>
</table>

Panel B: Investor Characteristics

<table>
<thead>
<tr>
<th></th>
<th>N</th>
<th>mean</th>
<th>st. dev.</th>
<th>10</th>
<th>50</th>
<th>90</th>
</tr>
</thead>
<tbody>
<tr>
<td># Introductions requested</td>
<td>2,925</td>
<td>9.72</td>
<td>31.09</td>
<td>1</td>
<td>3</td>
<td>21</td>
</tr>
<tr>
<td>Signal</td>
<td>2,925</td>
<td>6.44</td>
<td>2.26</td>
<td>3.28</td>
<td>6.30</td>
<td>9.87</td>
</tr>
<tr>
<td># Followers</td>
<td>2,925</td>
<td>591.12</td>
<td>1,493.10</td>
<td>26</td>
<td>202</td>
<td>1346</td>
</tr>
<tr>
<td>Weighted # followers</td>
<td>2,925</td>
<td>2,527.30</td>
<td>5,763.70</td>
<td>108.97</td>
<td>915.70</td>
<td>5,896.90</td>
</tr>
<tr>
<td>Involved in start-ups (%)</td>
<td>2,925</td>
<td>91.93</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>If &gt; 0, # start-ups involved with</td>
<td>2,689</td>
<td>12.55</td>
<td>17.18</td>
<td>2</td>
<td>8</td>
<td>27</td>
</tr>
</tbody>
</table>


Panel C: Investor Roles in Start-up Companies

<table>
<thead>
<tr>
<th>Role</th>
<th>N</th>
<th>mean</th>
<th>st. dev.</th>
<th>percentile 10</th>
<th>percentile 50</th>
<th>percentile 90</th>
</tr>
</thead>
<tbody>
<tr>
<td>Investor (%)</td>
<td>2,925</td>
<td>82.36</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>If &gt; 0, # start-ups funded</td>
<td>2,409</td>
<td>13.10</td>
<td>16.81</td>
<td>2</td>
<td>8</td>
<td>28</td>
</tr>
<tr>
<td>Advisor (%)</td>
<td>2,925</td>
<td>43.49</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>If &gt; 0, # start-ups as advisor</td>
<td>1,272</td>
<td>3.47</td>
<td>4.54</td>
<td>1</td>
<td>2</td>
<td>7</td>
</tr>
<tr>
<td>Board member (%)</td>
<td>2,925</td>
<td>16.92</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>If &gt; 0, # start-ups as board member</td>
<td>495</td>
<td>1.93</td>
<td>1.82</td>
<td>1</td>
<td>1</td>
<td>4</td>
</tr>
<tr>
<td>Start-up founder (%)</td>
<td>2,925</td>
<td>60.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>If &gt; 0, # start-ups founded</td>
<td>1,755</td>
<td>2.05</td>
<td>1.44</td>
<td>1</td>
<td>2</td>
<td>4</td>
</tr>
</tbody>
</table>

Panel D: Correlations between Investor Heterogeneity Measures

<table>
<thead>
<tr>
<th></th>
<th>Number of investments</th>
<th>Signal</th>
<th># Followers</th>
<th>Weighted # followers</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of investments</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Signal</td>
<td>0.51</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td># Followers</td>
<td>0.63</td>
<td>0.41</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Weighted # followers</td>
<td>0.68</td>
<td>0.44</td>
<td>0.95</td>
<td>1</td>
</tr>
</tbody>
</table>
Table IV: Investor Response to Randomized Emails

This table reports regression results of investor responses to the featured emails in the randomized field experiment. The dependent variable is one when an investor clicked on the “View” button in the featured email, and zero otherwise. Only opened emails are included in the sample. Team = 1 is an indicator variable that equals one if the team information is shown in the email, and zero otherwise. Similarly, Investors = 1 and Traction = 1 are indicator variables for the current investors, and traction information, respectively. Connections counts the number of people on the start-up’s profile (in any role) that the investor already follows prior to receiving the email. Prior follow = 1 is an indicator variable that equals one if the investor was already following the start-up on AngelList prior to receiving the featured email. Prior emails is the number of emails that the investor has received in the experiment prior to the present email. R2 is the adjusted $R^2$ for OLS regressions, and pseudo $R^2$ for logit models. Standard errors are in parentheses, and are clustered at the investor level. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent level, respectively.

<table>
<thead>
<tr>
<th>Model</th>
<th>(1) OLS</th>
<th>(2) OLS</th>
<th>(3) Logit</th>
<th>(4) Logit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Team = 1</td>
<td>0.022**</td>
<td>0.023**</td>
<td>0.162**</td>
<td>0.172**</td>
</tr>
<tr>
<td></td>
<td>(0.010)</td>
<td>(0.010)</td>
<td>(0.073)</td>
<td>(0.074)</td>
</tr>
<tr>
<td>Investors = 1</td>
<td>0.010</td>
<td>0.009</td>
<td>0.070</td>
<td>0.067</td>
</tr>
<tr>
<td></td>
<td>(0.013)</td>
<td>(0.013)</td>
<td>(0.097)</td>
<td>(0.097)</td>
</tr>
<tr>
<td>Traction = 1</td>
<td>0.016</td>
<td>0.017</td>
<td>0.122</td>
<td>0.123</td>
</tr>
<tr>
<td></td>
<td>(0.014)</td>
<td>(0.014)</td>
<td>(0.106)</td>
<td>(0.106)</td>
</tr>
<tr>
<td>Connections</td>
<td>0.010</td>
<td></td>
<td>0.064*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td></td>
<td>(0.038)</td>
<td></td>
</tr>
<tr>
<td>Prior follow = 1</td>
<td>0.143***</td>
<td></td>
<td>0.835***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.033)</td>
<td></td>
<td>(0.166)</td>
<td></td>
</tr>
<tr>
<td>Prior emails</td>
<td>0.001</td>
<td></td>
<td>0.006</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td></td>
<td>(0.022)</td>
<td></td>
</tr>
<tr>
<td>Start-up fixed effects</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Number of observations</td>
<td>8,189</td>
<td>8,189</td>
<td>8,189</td>
<td>8,189</td>
</tr>
<tr>
<td>R2</td>
<td>0.001</td>
<td>0.005</td>
<td>0.028</td>
<td>0.033</td>
</tr>
</tbody>
</table>
**Table V: Investor Response to Non-randomized Emails**

This table replicates the regressions in Table IV for the subset of featured emails that show all information that has crossed the disclosure threshold, in the columns labeled “Full Information Subsample.” The model numbers in the second row correspond to the model numbers in Table IV. For ease of comparison, the columns labeled “Randomized Sample” show the results from Table IV for the same set of models. The dependent variable is one when an investor clicked on the “View” button in the featured email, and zero otherwise. The explanatory variables are as defined in Table IV. R2 is the adjusted R² for OLS regressions, and pseudo R² for logit models. Standard errors are in parentheses, and are clustered at the investor level. ***, **, and * to indicate statistical significance at the 1, 5, and 10 percent level, respectively.

<table>
<thead>
<tr>
<th></th>
<th>Full Information Subsample</th>
<th>Randomized Sample</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>Team = 1</td>
<td>0.046**</td>
<td>0.045**</td>
</tr>
<tr>
<td></td>
<td>(0.022)</td>
<td>(0.022)</td>
</tr>
<tr>
<td>Investors = 1</td>
<td>0.013</td>
<td>0.022</td>
</tr>
<tr>
<td></td>
<td>(0.018)</td>
<td>(0.019)</td>
</tr>
<tr>
<td>Traction = 1</td>
<td>0.037*</td>
<td>0.043**</td>
</tr>
<tr>
<td></td>
<td>(0.020)</td>
<td>(0.020)</td>
</tr>
<tr>
<td>Connections</td>
<td>0.010</td>
<td>0.058</td>
</tr>
<tr>
<td></td>
<td>(0.010)</td>
<td>(0.054)</td>
</tr>
<tr>
<td>Prior follow = 1</td>
<td>0.150**</td>
<td>0.822***</td>
</tr>
<tr>
<td></td>
<td>(0.059)</td>
<td>(0.277)</td>
</tr>
<tr>
<td>Prior emails</td>
<td>-0.006</td>
<td>-0.042*</td>
</tr>
<tr>
<td></td>
<td>(0.003)*</td>
<td>(0.025)</td>
</tr>
<tr>
<td>Start-up fixed effects</td>
<td>N</td>
<td>N</td>
</tr>
<tr>
<td>Number of observations</td>
<td>2,992</td>
<td>2,992</td>
</tr>
<tr>
<td>R²</td>
<td>0.001</td>
<td>0.006</td>
</tr>
</tbody>
</table>
Table VI: Response of Specialized Investors

This table reports regression results of investor responses to the featured emails in the randomized field experiment. The dependent variable is one when an investor clicked on the “View” button in the featured email, and zero otherwise. Only opened emails are included in the sample. Team = 1, Investors = 1, and Traction = 1 are indicator variables that equal one if the team, current investors, or traction information, respectively, are shown in the email. Sector similarity = 1 is an indicator variable that equals one if the distance between the vectors capturing investor sector interests and the start-up’s sectors is at the top 25% of the distance distribution. See the main text for the algorithm used to compute the distance metric. Other controls are Connections, Prior follow, and Prior emails, as defined in Table IV, but not reported for brevity. R² is the adjusted R² for OLS regressions, and pseudo R² for logit models. Standard errors are in parentheses, and are clustered at the investor level. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent level, respectively.

<table>
<thead>
<tr>
<th></th>
<th>(1) OLS</th>
<th>(2) OLS</th>
<th>(3) OLS</th>
<th>(4) OLS</th>
<th>(5) Logit</th>
<th>(6) Logit</th>
<th>(7) Logit</th>
<th>(8) Logit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Team shown = 1</td>
<td>0.023**</td>
<td>0.024**</td>
<td>0.024**</td>
<td>0.023**</td>
<td>0.172**</td>
<td>0.177**</td>
<td>0.190**</td>
<td>0.177**</td>
</tr>
<tr>
<td></td>
<td>(0.010)</td>
<td>(0.010)</td>
<td>(0.011)</td>
<td>(0.011)</td>
<td>(0.074)</td>
<td>(0.074)</td>
<td>(0.085)</td>
<td>(0.087)</td>
</tr>
<tr>
<td>Investors shown = 1</td>
<td>0.009</td>
<td>0.009</td>
<td>0.009</td>
<td>0.003</td>
<td>0.067</td>
<td>0.068</td>
<td>0.068</td>
<td>0.014</td>
</tr>
<tr>
<td></td>
<td>(0.013)</td>
<td>(0.013)</td>
<td>(0.013)</td>
<td>(0.014)</td>
<td>(0.097)</td>
<td>(0.097)</td>
<td>(0.097)</td>
<td>(0.108)</td>
</tr>
<tr>
<td>Traction shown = 1</td>
<td>0.017</td>
<td>0.016</td>
<td>0.016</td>
<td>0.011</td>
<td>0.123</td>
<td>0.119</td>
<td>0.120</td>
<td>0.090</td>
</tr>
<tr>
<td></td>
<td>(0.014)</td>
<td>(0.014)</td>
<td>(0.014)</td>
<td>(0.016)</td>
<td>(0.106)</td>
<td>(0.106)</td>
<td>(0.106)</td>
<td>(0.117)</td>
</tr>
<tr>
<td>Sector similarity = 1</td>
<td>0.039***</td>
<td>0.041***</td>
<td>0.006</td>
<td>0.291***</td>
<td>0.315***</td>
<td>0.081</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.011)</td>
<td>(0.015)</td>
<td>(0.035)</td>
<td>(0.079)</td>
<td>(0.112)</td>
<td>(0.260)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sector similarity = 1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>x Team shown = 1</td>
<td>-0.002</td>
<td>0.004</td>
<td></td>
<td>-0.041</td>
<td>0.002</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.019)</td>
<td>(0.020)</td>
<td></td>
<td>(0.136)</td>
<td>(0.143)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sector similarity = 1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>x Investors shown = 1</td>
<td>0.026</td>
<td></td>
<td></td>
<td>0.192</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.023)</td>
<td></td>
<td></td>
<td>(0.167)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sector similarity = 1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>x Traction shown = 1</td>
<td>0.017</td>
<td></td>
<td></td>
<td>0.099</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.025)</td>
<td></td>
<td></td>
<td>(0.182)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Start-up fixed effects</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Other controls</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Number of observations</td>
<td>8,189</td>
<td>8,189</td>
<td>8,189</td>
<td>8,189</td>
<td>8,189</td>
<td>8,189</td>
<td>8,189</td>
<td>8,189</td>
</tr>
<tr>
<td>R²</td>
<td>0.005</td>
<td>0.007</td>
<td>0.007</td>
<td>0.007</td>
<td>0.033</td>
<td>0.035</td>
<td>0.035</td>
<td>0.035</td>
</tr>
</tbody>
</table>
**Table VII: Investor Response by Number of Investments**

This table reports regression results of investor responses to the featured emails in the randomized field experiment. The dependent variable is one when an investor clicked on the “View” button in the featured email, and zero otherwise. Only opened emails are included in the sample. *Team = 1, Investors = 1,* and *Traction = 1* are indicator variables that equal one if the team, current investors, or traction information, respectively, are shown in the email. *# Investments <= cutoff* is an indicator variable that equals one if number of investments by a given investor is less than or equal to the percentile of the investments count distribution shown in the row labeled *Cutoff*. The other variables are as defined in Table IV. *R2* is the adjusted *R2* for OLS regressions, and *pseudo R2* for logit models. Standard errors are in parentheses, and are clustered at the investor level. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent level, respectively.

<table>
<thead>
<tr>
<th></th>
<th>(1) OLS</th>
<th>(2) OLS</th>
<th>(3) OLS</th>
<th>(4) Logit</th>
<th>(5) Logit</th>
<th>(6) Logit</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Team shown = 1</strong></td>
<td>0.017*</td>
<td>0.021*</td>
<td>0.026**</td>
<td>0.130*</td>
<td>0.162*</td>
<td>0.203**</td>
</tr>
<tr>
<td></td>
<td>(0.010)</td>
<td>(0.011)</td>
<td>(0.013)</td>
<td>(0.079)</td>
<td>(0.087)</td>
<td>(0.099)</td>
</tr>
<tr>
<td><strong>Investors shown = 1</strong></td>
<td>-0.001</td>
<td>0.004</td>
<td>0.003</td>
<td>-0.012</td>
<td>0.025</td>
<td>0.016</td>
</tr>
<tr>
<td></td>
<td>(0.013)</td>
<td>(0.014)</td>
<td>(0.016)</td>
<td>(0.104)</td>
<td>(0.115)</td>
<td>(0.125)</td>
</tr>
<tr>
<td><strong>Traction shown = 1</strong></td>
<td>0.009</td>
<td>0.003</td>
<td>0.010</td>
<td>0.066</td>
<td>0.024</td>
<td>0.076</td>
</tr>
<tr>
<td></td>
<td>(0.014)</td>
<td>(0.016)</td>
<td>(0.017)</td>
<td>(0.108)</td>
<td>(0.117)</td>
<td>(0.129)</td>
</tr>
<tr>
<td><strong># Investments &lt;= cutoff</strong></td>
<td>0.037</td>
<td>0.007</td>
<td>-0.007</td>
<td>0.235</td>
<td>0.029</td>
<td>-0.061</td>
</tr>
<tr>
<td><strong>x Team shown = 1</strong></td>
<td>(0.025)</td>
<td>(0.018)</td>
<td>(0.017)</td>
<td>(0.176)</td>
<td>(0.137)</td>
<td>(0.131)</td>
</tr>
<tr>
<td><strong># Investments &lt;= cutoff</strong></td>
<td>0.070**</td>
<td>0.021</td>
<td>0.014</td>
<td>0.476**</td>
<td>0.146</td>
<td>0.103</td>
</tr>
<tr>
<td><strong>x Investors shown = 1</strong></td>
<td>(0.028)</td>
<td>(0.021)</td>
<td>(0.020)</td>
<td>(0.189)</td>
<td>(0.151)</td>
<td>(0.149)</td>
</tr>
<tr>
<td><strong># Investments &lt;= cutoff</strong></td>
<td>0.063**</td>
<td>0.047**</td>
<td>0.015</td>
<td>0.427*</td>
<td>0.351**</td>
<td>0.116</td>
</tr>
<tr>
<td><strong>x Traction shown = 1</strong></td>
<td>(0.031)</td>
<td>(0.021)</td>
<td>(0.020)</td>
<td>(0.220)</td>
<td>(0.163)</td>
<td>(0.154)</td>
</tr>
<tr>
<td><strong># Investments &lt;= cutoff</strong></td>
<td>-0.080*</td>
<td>-0.028</td>
<td>-0.001</td>
<td>-0.530*</td>
<td>-0.193</td>
<td>0.001</td>
</tr>
<tr>
<td></td>
<td>(0.043)</td>
<td>(0.031)</td>
<td>(0.030)</td>
<td>(0.320)</td>
<td>(0.241)</td>
<td>(0.231)</td>
</tr>
<tr>
<td><strong>Connections</strong></td>
<td>0.010</td>
<td>0.010</td>
<td>0.010</td>
<td>0.066*</td>
<td>0.068*</td>
<td>0.067*</td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td>(0.006)</td>
<td>(0.006)</td>
<td>(0.038)</td>
<td>(0.038)</td>
<td>(0.038)</td>
</tr>
<tr>
<td><strong>Prior follow</strong></td>
<td>0.145***</td>
<td>0.144***</td>
<td>0.145***</td>
<td>0.847***</td>
<td>0.849***</td>
<td>0.852***</td>
</tr>
<tr>
<td></td>
<td>(0.033)</td>
<td>(0.033)</td>
<td>(0.033)</td>
<td>(0.166)</td>
<td>(0.166)</td>
<td>(0.166)</td>
</tr>
<tr>
<td><strong>Prior emails</strong></td>
<td>0.002</td>
<td>0.002</td>
<td>0.001</td>
<td>0.013</td>
<td>0.014</td>
<td>0.010</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.022)</td>
<td>(0.022)</td>
<td>(0.022)</td>
</tr>
<tr>
<td><strong>Start-up fixed effects</strong></td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td><strong>Cutoff</strong></td>
<td>Zero</td>
<td>25%</td>
<td>50%</td>
<td>Zero</td>
<td>25%</td>
<td>50%</td>
</tr>
<tr>
<td><strong>Number of observations</strong></td>
<td>8,189</td>
<td>8,189</td>
<td>8,189</td>
<td>8,189</td>
<td>8,189</td>
<td>8,189</td>
</tr>
<tr>
<td><strong>R2</strong></td>
<td>0.007</td>
<td>0.006</td>
<td>0.005</td>
<td>0.035</td>
<td>0.035</td>
<td>0.034</td>
</tr>
</tbody>
</table>
Table VIII: Investor Response by Signal

This table reports regression results of investor responses to the featured emails in the randomized field experiment. The dependent variable is one when an investor clicked on the “View” button in the featured email, and zero otherwise. Only opened emails are included in the sample. Team = 1, Investors = 1, and Traction = 1 are indicator variables that equal one if the team, current investors, or traction information, respectively, are shown in the email. Signal < cutoff is an indicator variable that equals one if the investor signal is below the percentile of the signal distribution shown in the row labeled Signal cutoff. See the main text for the algorithm used to compute the signals. The other variables are as defined in Table IV. R² is the adjusted R² for OLS regressions, and pseudo R² for logit models. Standard errors are in parentheses, and are clustered at the investor level. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent level, respectively.

<table>
<thead>
<tr>
<th></th>
<th>(1) OLS</th>
<th>(2) OLS</th>
<th>(3) OLS</th>
<th>(4) Logit</th>
<th>(5) Logit</th>
<th>(6) Logit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Team shown = 1</td>
<td>0.019*</td>
<td>0.024*</td>
<td>0.035*</td>
<td>0.147*</td>
<td>0.184*</td>
<td>0.265*</td>
</tr>
<tr>
<td></td>
<td>(0.011)</td>
<td>(0.013)</td>
<td>(0.019)</td>
<td>(0.085)</td>
<td>(0.097)</td>
<td>(0.139)</td>
</tr>
<tr>
<td>Investors shown = 1</td>
<td>-0.003</td>
<td>0.01</td>
<td>-0.005</td>
<td>-0.036</td>
<td>0.005</td>
<td>-0.045</td>
</tr>
<tr>
<td></td>
<td>(0.014)</td>
<td>(0.016)</td>
<td>(0.022)</td>
<td>(0.112)</td>
<td>(0.127)</td>
<td>(0.170)</td>
</tr>
<tr>
<td>Traction shown = 1</td>
<td>0.005</td>
<td>0.010</td>
<td>0.009</td>
<td>0.037</td>
<td>0.077</td>
<td>0.067</td>
</tr>
<tr>
<td></td>
<td>(0.015)</td>
<td>(0.017)</td>
<td>(0.022)</td>
<td>(0.112)</td>
<td>(0.123)</td>
<td>(0.156)</td>
</tr>
<tr>
<td>Signal &lt; cutoff</td>
<td>0.013</td>
<td>-0.003</td>
<td>-0.016</td>
<td>0.067</td>
<td>-0.027</td>
<td>-0.127</td>
</tr>
<tr>
<td>x Team shown = 1</td>
<td>(0.020)</td>
<td>(0.017)</td>
<td>(0.020)</td>
<td>(0.145)</td>
<td>(0.131)</td>
<td>(0.154)</td>
</tr>
<tr>
<td>Signal &lt; cutoff</td>
<td>0.055**</td>
<td>0.016</td>
<td>0.019</td>
<td>0.385**</td>
<td>0.121</td>
<td>0.141</td>
</tr>
<tr>
<td>x Investors shown = 1</td>
<td>0.022</td>
<td>0.020</td>
<td>0.024</td>
<td>0.159</td>
<td>0.151</td>
<td>0.184</td>
</tr>
<tr>
<td>Signal &lt; cutoff</td>
<td>0.063**</td>
<td>0.015</td>
<td>0.012</td>
<td>0.440**</td>
<td>0.122</td>
<td>0.093</td>
</tr>
<tr>
<td>x Traction shown = 1</td>
<td>0.024</td>
<td>(0.020)</td>
<td>0.023</td>
<td>0.180</td>
<td>0.155</td>
<td>0.171</td>
</tr>
<tr>
<td>Signal &lt; cutoff</td>
<td>-0.049</td>
<td>-0.013</td>
<td>0.001</td>
<td>-0.320</td>
<td>-0.102</td>
<td>0.010</td>
</tr>
<tr>
<td></td>
<td>(0.034)</td>
<td>(0.030)</td>
<td>(0.036)</td>
<td>(0.261)</td>
<td>(0.231)</td>
<td>(0.276)</td>
</tr>
<tr>
<td>Connections</td>
<td>0.011*</td>
<td>0.01</td>
<td>0.010</td>
<td>0.075*</td>
<td>0.066*</td>
<td>0.067*</td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td>(0.006)</td>
<td>(0.006)</td>
<td>(0.038)</td>
<td>(0.038)</td>
<td>(0.038)</td>
</tr>
<tr>
<td>Prior follow</td>
<td>0.144***</td>
<td>0.144***</td>
<td>0.145***</td>
<td>0.843***</td>
<td>0.841***</td>
<td>0.846***</td>
</tr>
<tr>
<td></td>
<td>(0.033)</td>
<td>(0.033)</td>
<td>(0.033)</td>
<td>(0.166)</td>
<td>(0.166)</td>
<td>(0.166)</td>
</tr>
<tr>
<td>Prior emails</td>
<td>0.003</td>
<td>0.001</td>
<td>0.001</td>
<td>0.020</td>
<td>0.008</td>
<td>0.006</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.022)</td>
<td>(0.022)</td>
<td>(0.022)</td>
</tr>
<tr>
<td>Start-up fixed effects</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Signal cutoff</td>
<td>25%</td>
<td>50%</td>
<td>75%</td>
<td>25%</td>
<td>50%</td>
<td>75%</td>
</tr>
<tr>
<td>Number of observations</td>
<td>8,189</td>
<td>8,189</td>
<td>8,189</td>
<td>8,189</td>
<td>8,189</td>
<td>8,189</td>
</tr>
<tr>
<td>R²</td>
<td>0.007</td>
<td>0.005</td>
<td>0.005</td>
<td>0.036</td>
<td>0.033</td>
<td>0.034</td>
</tr>
</tbody>
</table>
Table IX: Investor Response by Weighted Number of Followers

This table reports regression results of investor responses to the featured emails in the randomized field experiment. The dependent variable is one when an investor clicked on the “View” button in the featured email, and zero otherwise. Only opened emails are included in the sample. Team = 1, Investors = 1, and Traction = 1 are indicator variables that equal one if the team, current investors, or traction information, respectively, are shown in the email. Weighted # followers < cutoff is an indicator variable that equals one if number of followers of a given investor, weighted by their signal, is less than the percentile of the weighted followers count distribution shown in the row labeled Cutoff. The other variables are as defined in Table IV. R2 is the adjusted R² for OLS regressions, and pseudo R² for logit models. Standard errors are in parentheses, and are clustered at the investor level. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent level, respectively.

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>OLS</td>
<td>OLS</td>
<td>OLS</td>
<td>Logit</td>
<td>Logit</td>
<td>Logit</td>
</tr>
<tr>
<td>Team shown = 1</td>
<td>0.020*</td>
<td>0.026**</td>
<td>0.033*</td>
<td>0.158*</td>
<td>0.207**</td>
<td>0.268*</td>
</tr>
<tr>
<td></td>
<td>(0.011)</td>
<td>(0.013)</td>
<td>(0.017)</td>
<td>(0.085)</td>
<td>(0.104)</td>
<td>(0.140)</td>
</tr>
<tr>
<td>Investors shown = 1</td>
<td>-0.003</td>
<td>-0.017</td>
<td>-0.013</td>
<td>-0.036</td>
<td>-0.156</td>
<td>-0.111</td>
</tr>
<tr>
<td></td>
<td>(0.013)</td>
<td>(0.016)</td>
<td>(0.020)</td>
<td>(0.109)</td>
<td>(0.127)</td>
<td>(0.164)</td>
</tr>
<tr>
<td>Traction shown = 1</td>
<td>0.006</td>
<td>0.003</td>
<td>0.014</td>
<td>0.048</td>
<td>0.023</td>
<td>0.112</td>
</tr>
<tr>
<td></td>
<td>(0.015)</td>
<td>(0.017)</td>
<td>(0.021)</td>
<td>(0.113)</td>
<td>(0.126)</td>
<td>(0.158)</td>
</tr>
<tr>
<td>Weighted # followers &lt; cutoff x Team shown = 1</td>
<td>0.009</td>
<td>-0.008</td>
<td>-0.014</td>
<td>0.035</td>
<td>-0.082</td>
<td>-0.129</td>
</tr>
<tr>
<td></td>
<td>(0.020)</td>
<td>(0.017)</td>
<td>(0.020)</td>
<td>(0.144)</td>
<td>(0.132)</td>
<td>(0.157)</td>
</tr>
<tr>
<td>Weighted # followers &lt; cutoff x Investors shown = 1</td>
<td>0.051**</td>
<td>0.051***</td>
<td>0.028</td>
<td>0.354**</td>
<td>0.399***</td>
<td>0.221</td>
</tr>
<tr>
<td></td>
<td>(0.024)</td>
<td>(0.020)</td>
<td>(0.022)</td>
<td>(0.165)</td>
<td>(0.152)</td>
<td>(0.176)</td>
</tr>
<tr>
<td>Weighted # followers &lt; cutoff x Traction shown = 1</td>
<td>0.049**</td>
<td>0.030</td>
<td>0.003</td>
<td>0.338*</td>
<td>0.229</td>
<td>0.023</td>
</tr>
<tr>
<td></td>
<td>(0.024)</td>
<td>(0.020)</td>
<td>(0.022)</td>
<td>(0.177)</td>
<td>(0.157)</td>
<td>(0.176)</td>
</tr>
<tr>
<td>Weighted # followers &lt; cutoff</td>
<td>-0.035</td>
<td>-0.018</td>
<td>0.021</td>
<td>-0.216</td>
<td>-0.117</td>
<td>0.183</td>
</tr>
<tr>
<td></td>
<td>(0.034)</td>
<td>(0.029)</td>
<td>(0.034)</td>
<td>(0.254)</td>
<td>(0.231)</td>
<td>(0.276)</td>
</tr>
<tr>
<td>Connections</td>
<td>0.013**</td>
<td>0.013**</td>
<td>0.013**</td>
<td>0.083**</td>
<td>0.090**</td>
<td>0.084**</td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td>(0.006)</td>
<td>(0.006)</td>
<td>(0.039)</td>
<td>(0.040)</td>
<td>(0.039)</td>
</tr>
<tr>
<td>Prior follow</td>
<td>0.145***</td>
<td>0.146***</td>
<td>0.145***</td>
<td>0.855***</td>
<td>0.861***</td>
<td>0.854***</td>
</tr>
<tr>
<td></td>
<td>(0.033)</td>
<td>(0.033)</td>
<td>(0.033)</td>
<td>(0.166)</td>
<td>(0.166)</td>
<td>(0.166)</td>
</tr>
<tr>
<td>Prior emails</td>
<td>0.002</td>
<td>0.001</td>
<td>0.001</td>
<td>0.018</td>
<td>0.008</td>
<td>0.005</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.022)</td>
<td>(0.022)</td>
<td>(0.021)</td>
</tr>
<tr>
<td>Start-up fixed effects</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Cutoff</td>
<td>25%</td>
<td>50%</td>
<td>75%</td>
<td>25%</td>
<td>50%</td>
<td>75%</td>
</tr>
<tr>
<td>Number of observations</td>
<td>8,189</td>
<td>8,189</td>
<td>8,189</td>
<td>8,189</td>
<td>8,189</td>
<td>8,189</td>
</tr>
<tr>
<td>R2</td>
<td>0.007</td>
<td>0.008</td>
<td>0.006</td>
<td>0.036</td>
<td>0.037</td>
<td>0.035</td>
</tr>
</tbody>
</table>
Table X: Start-ups in Field Experiment Sample versus Broad Sample

This table compares the sample of 21 start-ups in the randomized field experiment (the “experiment firms”) with a broad sample of 5,538 firms raising funding on AngelList (the “non-experiment firms”). The non-experiment firms are those firms that attempted to raise money through AngelList and received at least one introduction request. The variables are as defined in Table II. The rightmost column shows the p-value for a differences-in-means test between the experiment and non-experiment samples.

<table>
<thead>
<tr>
<th></th>
<th>Experiment Firms (N = 21)</th>
<th>Non-Experiment Firms (N = 5,538)</th>
<th>Means test p</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>N</td>
<td>mean</td>
<td>median</td>
</tr>
<tr>
<td># Founders</td>
<td>21</td>
<td>2.62</td>
<td>2</td>
</tr>
<tr>
<td>Employees (%)</td>
<td>21</td>
<td>80.95</td>
<td></td>
</tr>
<tr>
<td>If &gt; 0, # employees</td>
<td>17</td>
<td>3.35</td>
<td>3</td>
</tr>
<tr>
<td>Board members (%)</td>
<td>21</td>
<td>23.81</td>
<td></td>
</tr>
<tr>
<td>If &gt; 0, # board members</td>
<td>5</td>
<td>1.80</td>
<td>2</td>
</tr>
<tr>
<td>Advisor (%)</td>
<td>21</td>
<td>90.48</td>
<td></td>
</tr>
<tr>
<td>If &gt; 0, # advisors</td>
<td>19</td>
<td>4.74</td>
<td>3</td>
</tr>
<tr>
<td>Incubator (%)</td>
<td>21</td>
<td>57.14</td>
<td></td>
</tr>
<tr>
<td>Pre-round funding (%)</td>
<td>21</td>
<td>47.62</td>
<td></td>
</tr>
<tr>
<td>If &gt; 0, amount raised ($000s)</td>
<td>10</td>
<td>605.05</td>
<td>234.00</td>
</tr>
<tr>
<td>Pre-money valuation ($000s)</td>
<td>12</td>
<td>5,579.17</td>
<td>5,000.00</td>
</tr>
<tr>
<td>Fundraising goal ($000s)</td>
<td>15</td>
<td>1,226.33</td>
<td>1,325.00</td>
</tr>
<tr>
<td>Equity financing (%)</td>
<td>21</td>
<td>76.19</td>
<td></td>
</tr>
</tbody>
</table>
Figure 1: Sample Featured Start-up Email to Investors
This figure shows an example of a featured start-up email that is sent to investors. Each featured start-up has up to three information categories (team, traction, and current investors) that would normally be shown in the email if the information for that category reaches a threshold as defined by AngelList. For each start-up, various unique versions of each email are generated that randomly hide these pieces of information (the Randomization categories). Each email contains a “View” button that, when clicked, takes the investor to the AngelList platform where more information about the company is shown, and introductions to the company’s founders can be requested. The “Get an Intro” button requests such an introduction straight from the email.