Attracting Early Stage Investors: Evidence from a Randomized Field Experiment

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Abstract

Which start-up characteristics are most important to investors in early-stage firms? This paper uses a randomized field experiment involving 4,500 active, early stage investors. The experiment takes place on AngelList, an online platform that matches investors with start-ups seeking capital. The experiment randomizes investors' information sets on start-up characteristics through the use of nearly 17,000 emails. The average investor responds strongly to information about the founding team, but not to information about either firm traction or existing lead investors. This is in contrast to the least experienced investors, who respond to all categories of information. Our results suggest that information about human assets is causally important for the funding of early-stage firms.

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Early stage investors provide an important source of capital enabling the birth and growth of companies, thus contributing to innovation and growth in the economy (Solow (1957)). A large and growing literature demonstrates the impact of early stage investments (e.g., Kortum and Lerner (2000)) and the factors that affect the terms of financing (e.g., Kaplan and Stromberg (2003)). But, what factors drive the selection process of early-stage investors, that is, how do they choose which start-up to fund? While this issue is often debated among academics and practitioners (see e.g., Quindlen (2000), Gompers and Lerner (2001)), there is little systematic, non-survey 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 attempts to fill this gap.

The scarcity of evidence on the selection process of early stage investors is due to several empirical challenges. 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 that are 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-up firms contain only a small fraction of investors' information sets at the time of funding. Moreover, existing databases 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, learning about their decision process is problematic.

The ideal setting to establish causality between start-up characteristics and investor interest would compare an investor's reaction to two identical firms that differ only in the

[1] See, for example, evidence on the investment behavior of mutual funds in Falkenstein (1996), Wermers (2000), and Gompers and Metrick (2001), and for individual retail investors in Barber and Odean (2000), and Ivković and Weisbenner (2005), amongst others.

characteristic of interest. Such a setting is not feasible using observational data, but we approximate it with a randomized field experiment that builds on the correspondence testing methodology that was pioneered in labor economics.[2] The experiment takes place on AngelList, an online platform that matches start-ups and angel investors, and we observe these start-up companies at the stage at which they approach investors to raise capital. The platform includes many companies that have raised subsequent venture capital rounds, and many well-known investors that are experienced in investing in, and building, early-stage firms. These individuals are highly involved in start-up creation, taking various roles in these firms such as investors, board members, advisors and founders. Therefore, they are well suited to inform research about early-stage investor decision-making.

AngelList regularly sends out emails to investors featuring start-ups that are raising capital. The emails contain information on the start-up idea, potential market, how much money the firm aims to raise, and how much it has raised to date. In addition, AngelList provides information on three categories that "package" the company: the founding team's background (e.g., college, prior work experience, or entrepreneurial background), the start-up's traction (such as revenues and user growth), and the identity of current investors. These categories capture the key assets a firm may possess at such an early stage, and represent the types of information that investors are a priori likely to find important. A category is shown in the email only if it passes a certain threshold as defined by AngelList. These thresholds reflect AngelList's determination of

[2] In labor market applications of the correspondence testing methodology, fictitious applications are sent to job openings, and employer responses such as call-backs are recorded for analysis. The applications are constructed such that they differ only in the characteristic of interest. For example, Bertrand and Mullainathan (2004) explore racial discrimination in the labor market, Weichselbaumer (2003) studies the impact of sex stereotypes and sexual orientation, and Nisbett and Cohen (1996) study employers' response to past criminal activity. The main methodological difference with this paper is that we use real start-ups and real investors in our experiment, rather than fictitious resumes.

what information may be most useful for investors. Hence, investors believe that if an information category is not in the email, it is of no significance.

In the experiment, we randomly choose which of the categories that passed the disclosure threshold are revealed in the emails, and exploit the variation across angels' reactions *within* each start-up. In other words, conditioning on other information about the start-up's business idea, we exogenously vary the information about the start-up's team, traction, and current investors. We causally infer which factors drive investors' decisions by measuring each investor's interest in the company. Specifically, we record whether investors choose to learn more about the firm on the online platform.

We sent approximately 17,000 emails to nearly 4,500 angels, spanning 21 different start-ups, over the summer of 2013. The email recipients include many of the most prominent and active angel investors. Among these investors, 82% have made past investments, with a median of eight investments. Almost half of the investors have served as an advisor to one or more start-ups. Interestingly, 60% of the investors have an entrepreneurial background themselves, having founded at least one venture in the past.

The start-ups in the experiment are raising capital at a very early stage. The median company seeks to raise $1.3 million, and approximately half the companies have previously raised capital, with a median amount raised of $290,000. The median start-up has two founders and employs three additional workers. Only 23% of these firms have formed a board, and 57% graduated from an incubator.

The randomized experiment reveals that, on average, angels are highly responsive to information about the founding team, whereas information about the 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 when controlling for the information about the start-up's idea that is contained in the email.

One may be concerned that the above results may be due to different information content, (i.e., different signal-to-noise ratios) across categories. This is not likely to be the case, for two reasons. First, the information passes AngelList's disclosure threshold with nearly identical frequencies across categories, suggesting that AngelList does not release more salient information in one category over the other. Second, we find significant heterogeneity across investors in their responses to the same information category in a way that is inconsistent with certain information categories being uninformative: although the most highly experienced investors (as measured by a battery of metrics, including the number of prior investments, a measure of success, and a measure of reputation), react only to the team information, the least experienced investors react to all categories of information. To the extent that experienced and successful investors know better what matters most for start-up success, this means that they know that traction and current investors are simply not as important to predict future success.

Our results suggest that the founding team is important for fundraising, which is a prerequisite for success: without funding, the company will surely not succeed. 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 raise the chances of success for the start-up. Second, a founding team with attractive outside options that chooses to commit to the start-up sends a strong signal about the firm's prospects that cannot be otherwise learned by (or credibly signaled to) investors. We test the null hypothesis that investors' reaction to team information is only due to the signal it sends about the start-up's chance of success. Under the null, one would expect that investors specialized in the sector in which the start-up operates will react less strongly to team information than less knowledgeable investors. However, we find that these investors react as strongly to team information as investors that are less familiar with the start-up's sector. This provides suggestive evidence that team information also matters due to the operational abilities of founding team, not only as a signal for the prospects of the idea.

A unique feature of our setting is that it allows us to empirically confirm the importance of the randomization of information sets for establishing causality. Running the same regressions on the subset of emails with the information set that would have been sent outside of the experiment, we find that we would overestimate the importance of the various information categories, due to the positive correlation of the categories with unobserved (to the econometrician) information about the company. Start-up characteristics such as traction, and existing investors, may therefore be mistakenly identified as highly influencing investor decision-making, and this underscores the importance of randomization for establishing the causal effect of start-up characteristics on early stage investors' interest.

We mitigate external validity concerns by showing that the start-ups in the experiment are fairly representative for the more than 5,500 start-ups raising capital on AngelList that attracted a minimal level of attention by investors, across a long list of observable characteristics. Moreover, based on a comparison to the popular Crunchbase database, over 60% of the companies claiming to raise a seed round in 2013 have an AngelList profile, and more than half of these firms attempted to raise funds on the platform.

A common drawback of the correspondence testing methodology is that the use of fictitious correspondence does not allow the researcher to observe real outcomes. For example, Bertrand and Mullainathan (2004) send fictitious resumes with randomized names to employers in order to study discrimination and record employer callback, but they cannot observe actual hiring outcomes. Such limitation applies to our study as well. However, since our experiment involves real start-ups and real investors, we can observe how often investors' indication of interest in the experiment translates into investor introduction requests and investments. We find that when investors show interest, there is a 15.1 percentage point increase in introduction requests between investors and founders and an approximate 3 to 6 percentage point increase in actual investments.[3] These rates indicate that our measure of interest has a material impact on real outcomes.

This paper adds to the literature on early stage investments. There appears to be skill in venture capital investing (e.g., Ljungqvist and Richardson (2003), Kaplan and Schoar (2005), Sorensen (2007), Puri and Zarutskie (2012), Korteweg and Sorensen (2013), and Harris et al. (2014)), and many papers focus on establishing a causal impact of early stage investments on firm success (e.g., Kerr, Lerner and Schoar (2013), Kortum and Lerner (1998), Sorensen (2007), Samila and Sorenson (2010), and Bernstein, Giroud, and Townsend (2013)). Yet, little is known about how exactly early stage investors select the companies to which they provide funding. Several papers explore investors' behavior using surveys and interviews (e.g., Pence (1982), MacMillan, Siegel, and Narasimha (1986), MacMillan, Zemann, and Subbanarasimha (1987), and Fried and Hisrich (1994)), but our paper provides the first large sample systematic evidence on this issue, spanning thousands of investors and using a randomized field experiment.

Our findings suggest that the characteristics of the founding team are important for fundraising, and thus ultimately for firm success. In this regard, our study adds to the literature that relates founder characteristics and firm performance (e.g., Gompers, Lerner and Scharfstein

[3] Closed financing rounds are reported back to AngelList in approximately 50% of the cases, therefore leading to an estimated range of investments.

(2005), Ouimet and Zarutskie (2013)), and also has implications for which individuals choose to become entrepreneurs, and their likelihood of success (e.g., Moskowitz and Vissing-Jorgensen (2003), Hurst and Lusardi (2004), Puri and Robinson (2013)).

As discussed in Kaplan, Sensoy, and Stromberg (2009), existing theories of the firm yield different predictions towards the importance of key assets that the organization is built around. The property rights theory (e.g., Grossman and Hart (1986), Hart and Moore (1990), Holmstrom (1999)) places the ownership of non-human assets at the core of the firm, whereas the contrasting view puts the human assets of the firm at its core (e.g., Wernerfelt (1984), Rajan and Zingales (1998, 2001) and Rajan (2012)).[4] Our results present evidence of the importance of human capital assets at the earliest stages of the firm, around the firm's birth. However, our results do not suggest that non-human assets are not essential. Kaplan, Sensoy, and Stromberg (2009) explore the evolution of 50 venture capital backed companies from the business plan stage to initial public offering (IPO). They find that business lines remain stable from birth to IPO, while management turnover is substantial. Combined with this evidence, the evidence in our paper tells a story that is consistent with the model in Rajan (2012). Rajan argues that the entrepreneur's human capital is important early on to differentiate her enterprise. However, to raise substantial funds (for instance, when going public), the entrepreneur needs to go through a standardization phase that will make human capital in the firm replaceable, so outside financiers can obtain control rights.

The paper is structured as follows. In section 1, we give a brief overview of the AngelList platform. Section 2 describes the randomized experiment, and section 3 presents descriptive

[4] For example, Rajan and Zingales (1998, 2001) view the firm as a hierarchy of people who gain different degrees of access to critical resources in the firm. The critical resources can be a person, a business idea, or key customers. These resources are providing an incentive to specialize human capital towards the firm's goals. In newer firms, therefore, the competitive advantage comes from specific human capital rather than from non-human assets, which can be bought or sold easily (Zingales (2000)).

statistics. In section 4 we analyze investors' reactions to the emails. Section 5 addresses concerns about internal and external validity. In section 6 we dive deeper into the real effects of disclosed information on investment and introductions, and section 7 concludes.

1. The AngelList platform

The early stage financing market is dominated by search frictions and asymmetric information. AngelList is an online platform to reduce these frictions, and improve the matching between start-ups and potential angel investors. The platform was founded in 2010 by Naval Ravikant (the co-founder of Epinions) and Babak Nivi (a former Entrepreneur-in-Residence at Bessemer Ventures and Atlas Capital), and has experienced rapid growth since. The platform has attracted much attention, often argued to have the potential to reshape the venture capital landscape and early stage funding as a whole.[5]

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, BranchOut, and Leap Motion.

Individuals who are accredited according to the rules set by the U.S. Securities and Exchange Commission[6] can join the platform to search for potential investments. Investors

[5] Arguments for AngelLists transformative potential were made recently by the Economist ("From Leafy to Lofty - venture capital is adapting itself to the new startup landscape", January 18, 2014), Business Week ("AngelList - The Social Network for Startups", January 16, 2014), Forbes ("How Software is Eating Venture Capital", October 2, 2013) and Wall Street Journal ("AngelList and Beyond: What VC's Really Think of Crowdfunding", October 8, 2013)

[6] For individuals, an accredited investor is a natural person with either at least $1 million in net worth (either individually or jointly with their spouse, but excluding the value of their primary residence) or with income of at least $200,000 (or $300,000 jointly with a spouse) in each of the two most recent years and a reasonable expectation of such income in the current year.

typically list information on their background as well as their portfolio of past and current investments. The platform is host to many prominent and active angels with extensive experience investing in, building, and operating early stage companies. Examples are Marc Andreessen and Ben Horowitz (of 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 500 Startups).

Through AngelList, interested investors request an introduction to the start-up's founders. From there the parties can negotiate a final investment. 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, raising over $200 million.[7] Most of these 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. There is no exact benchmark to compare these numbers to, but to give a rough comparison, the University of New Hampshire's Center of Venture Research estimates total 2012 angel investments at $22.9 billion, of which seed rounds of start-ups totaled $731 million in 2012 and $893 million in 2013.[8] Ewens, Nanda, and Rhodes-Kropf (2014) also show statistics of seed and series A financing. As we discuss in more detail below, over 60% of

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[7] AngelList estimates that only 50% of closed financing rounds are ultimately disclosed, suggesting that number of closed rounds is potentially much higher.

[8] Data on total seed funding is from CB Insights: http://www.cbinsights.com/blog/trends/2013-seed-venture-capital, accessed February 17, 2014. The University of New Hampshire's angel market analysis reports are accessible at https://paulcollege.unh.edu/research/center-venture-research/cvr-analysis-reports.

the companies claiming to raise 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.

2. Experimental Design

The field experiment builds on correspondence testing methodology and 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 for showing promise that could appeal to a broad set of investors who have previously indicated an interest in the industry or the location of the start-up.

An example of a featured email is shown in Figure 1. The email starts with a description of the start-up and its product. Next, the email lists up to three categories of information about: i) the start-up team's background; ii) current investors; iii) traction. Outside of the experiment, a category is shown if it passes a certain threshold as defined by AngelList. The thresholds are determined by AngelList's to show information that investors might be most interested in. 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. As we discuss below, this algorithm is important for the interpretation of the experiment's results: if investors do not see a particular category, they assume that the information for that category has not passed the disclosure threshold, and is therefore not particularly interesting. To provide a sense of the information content in the featured emails, the appendix shows the information that passed the disclosure threshold for all the start-ups in the experiment. Finally, the email shows the amount of money that the company aims to raise, and how much has been raised to date.

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 3,000 angels receive a featured email about a given start-up. Outside of the experiment, all investors would receive the same email, and let's assume that this email would show information about the team and traction, while the current investors category for this company does not meet the threshold to be included in the email. In the experiment, 1,000 investors receive the original email with both team and traction shown, 1,000 receive the identical email except that it does not show the team category, and another 1,000 receive the email that shows the team information but with the traction category hidden. We do not send any emails with all categories hidden, as this would 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 (see Figure 1). If an investor is interested in the start-up, she can click on the "View" button to be taken to the AngelList website and view the detailed company profile. We record whether this happens. If the investor is particularly interested, she can click the "Get an Intro" button to request an introduction to the company straight away. However, this is a very rare event as nearly all investors take a look at the full company profile on the AngelList website before asking for an introduction. Hence, instead of clicks on the "Get an Intro" button, we record whether the angel 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 gleaned more information from the website.

Our experiment allows us to circumvent several challenges associated with studying investor decision-making. First, we observe both positive and negative investor reactions, unlike extant data sets that contain only firms that are successful in attracting funding. Thus, we can explore which start-up characteristics are more interesting or attractive to investors. Second, we know exactly what information is shown to investors, unlike the standard databases of early stage deals. Finally, we can separate the potentially endogenous link between various start-up characteristics by randomizing investors' information sets.

3. Summary statistics

A. Emails

We ran the experiment over an eight week period in the summer of 2013. Table 1 reports descriptive statistics. 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 angels that have requested at least one introduction to a start-up while they have been enrolled in AngelList. Investors come to the platform for a variety of purposes: to research, to confirm their affiliation with a start-up that is fundraising, or to invest. Restricting the sample to active investors excludes those are not on the platform to seek new investments.

For each start-up, we sent an average (median) of 2.76 (3) versions of the email, each with an exogenously different information set. This means that in total we sent 58 unique emails (2.76 emails per start-up times 21 start-ups). Each unique email was sent to 293 recipients on average (median 264). Within a start-up, the number of recipients per unique email is roughly equal, but there is some variation across start-ups in how many angels receive the featured emails, as some start-ups are in more popular industries or locations than others. On average, 809 investors receive a featured email about a given start-up, with a minimum of 202 and a maximum of 1,782 recipients per start-up. An investor in the sample receives on average 3.78 emails (median 3 emails) of different featured start-ups, and importantly, no investor receives more than one email for a given start-up.

In terms of response, recipients opened nearly half (48.3%) of their emails. Some investors open none of their emails, but 2,925 investors open at least one. Of the opened emails, 16.5% of investors clicked on the "View" button to see more information about the start-up. Of the investors who clicked on the email, Table 1 also reports the proportion that requested an introduction within three days of viewing the email, as well as the proportion that ended up investing in the company. We discuss these numbers in more detail below.

Panel B of Table 1 shows that there is no statistically significant difference in the frequency with which each information category passes the threshold set by AngelList. This means that the salience of the presence of an information category in an email is roughly equal across information categories. Outside of the experiment, categories that pass the threshold would always be shown in the email.

Within the experiment, the categories are randomly excluded. Panel B shows that, conditional on passing the threshold, the information regarding, team, current investors, and traction is shown about 73% of the time, with no material difference in frequencies across categories. 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 (we don't use the empty set to avoid raising suspicion amongst investors). In that case, if each email is shown at random then team and traction would each be shown 67% of the time.

B. Start-ups

Table 2 presents detailed descriptive statistics of the 21 start-ups in the randomized email experiment. Panel A shows the geographical distribution of firms. The most popular location is Silicon Valley with six firms, but the dispersion is quite wide, with firms spread across the United States, Canada, the United Kingdom, and Australia. Panel B shows that most firms operate in the Information Technology and the Consumers sectors. Other represented sectors are Business-to-business, Cleantech, Education, Healthcare, and Media. Note that the 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. In terms of company structure, panel C shows that the median start-up has two founders, and 17 start-ups (81% of the 21 firms) have (non-founder) employees. The median firm with employees has three workers, though there is some variation, with the largest company having as many as nine employees. Counting both founders and employees, the largest start-up consists of 11 people. Only a quarter of firms have a board of directors at this stage of fund-raising. Of those that do have a board, the median board size is two, and no board is larger than three members.[9] Almost all companies (19 out of 21) have advisors,[10] and the median number of advisors for the companies that have any, is three.

Panel D reports details on the financing of the sample firms. Twelve companies (57%) have gone through an incubator or accelerator program before fundraising on AngelList. Eleven

[9] It is not clear how much of an outside governance role the board fulfills at this stage of the firm, rather than simply fulfilling a legal requirement of incorporation.
[10] Advisors are typically high profile individuals, and are compensated with stocks and options.

companies (52%) received prior funding, and those eleven firms raised an average (median) of $581 thousand ($290 thousand). For the sixteen companies for which a pre-money valuation is available, the average (median) valuation is $5.5 million ($5 million), and ranges between a minimum of $1.2 million and a maximum of $10 million.[11] Eighteen companies explicitly state their fundraising goal, which ranges from $500 thousand 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 3 reports descriptive statistics of the 2,925 angel investors who received the featured emails in the field experiment, and who opened at least one email. This is the set of investors that is the focus of our empirical analysis in the next section. 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.

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.

In order to provide an indication of investors' past success, AngelList computes a "signal" for each investor and start-up that ranges from zero to ten. The algorithm that assigns signals works recursively, and is seeded by assigning a value of ten to high exit value companies (from

[11] 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.

Crunchbase) such as Google or Facebook, and to a set of hand-picked (by AngelList) 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. This signal construction, rather than crediting investors only for realized past successes, also gives credit for investing in very young but highly promising firms that may have great exits in the future, but are still too young to have made it to the exit stage. The average (median) investor signal is 6.4 (6.3), with a standard deviation of 2.3. The wide distribution of the signal in Figure 2 shows that there is significant heterogeneity in signal across investors.[12,13]

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, we see large heterogeneity in investors, with the 10th percentile having only 26 followers while the 90th percentile investor has 1,346 followers.

Over 90% of investors are actively involved with start-ups (as with the signal calculation, these numbers are not limited to start-ups that tried to raise money through AngelList). 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 investors invest in as many as 30 companies. Roughly 44% of angels are active as advisors to start-ups, with the median advisor advising two firms. Also, 17% of investors served as a board member on a start-up. Last,

[12] There are few signal scores below three, because we limit the set of investors to those that have requested at least one introduction through the platform.

[13] The signal calculations use all declared investments on the AngelList platform. This data represents self-declared investments by both angels and start-ups on the platform that were subsequently verified by AngelList with the party on the other end of the transaction (i.e., investments declared by start-ups are verified with the investors and vice versa). Importantly, the data are not limited to companies that (tried to) raise money through the platform. There are many thousands of companies, such as Facebook, that are on the platform but never have, or ever intend to, raise money through AngelList. Instead, they are there only because an investor declared to have invested in them (or declared to have served another role in the firm, such as founder or advisor) that was subsequently verified by AngelList. In addition, the signal calculation includes investment data available from Crunchbase.

but certainly not least, 60% of investors were at one point founders themselves.[14] The median of these founder-investors founded two companies.[15]

In our empirical analysis we explore whether investors react differently to the information categories depending on their level of experience (measured by number of investments), past success (measured by signal), or reputation (measured by the number of followers, or the weighted number of followers on the platform). Panel D of Table 3 shows the correlations between several investor characteristics such as number of past investments, investor signal, and number of followers. These will be used in the investor heterogeneity analysis section. While there is a meaningful correlation between these variables, they clearly capture non-overlapping investor sub-populations.

Taken together, the evidence presented here shows that the group of investors in our sample 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 about the assets that are most important to very early stage firms. Moreover, there is significant heterogeneity within this group that may help to distinguish between theories.

4. Analysis of investors' responses in the randomized experiment

Table 4 shows results of regressions that explore how the three randomized categories of information (team, traction, and current investors) affect angels' interest level and trigger a

[14] Declarations of advisor, board member, or founder roles are verified using the same procedure as was followed for investments.

[15] The investors in Table 3, who opened at least one email, tend to be more active and involved than the investors who received features emails but did not open any of them: they request more introductions (9.72 on average versus 4.97 for the investors who did not open any emails), have a higher signal (average 6.44 versus 5.89), more followers (average 591 versus 480), more of them are involved with start-ups (91.93% versus 85.15%), and conditional on being involved, they are involved with more start-ups (average 12.55 versus 10.56) . These differences are all statistically significant at the 1% level (results not tabulated).

response. We use the set of 8,189 opened emails, to ensure that investors see the information in the email.[16] The dependent variable equals one when an investor clicked on the "View" button 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 descriptive paragraph (which mainly describes the idea of the start-up), the amount that the company aims to raise, has already raised, or any other common knowledge about the start-up. Thus, start-up fixed effects allows the comparison of investor responses within a given start-up. All models in Table 4 have standard errors clustered at the investor level, to account for investors making correlated decisions across the emails they receive for various start-ups.[17]

In column (1) we run an ordinary least squares (OLS) regression that explores how the three information categories affect click rates.[18] Revealing information about the team raises the unconditional click rate by 2.2%, which is statistically significantly different from zero. Given a base click rate of 16.5% (Table 1), this represents a 13% increase. Recall that investors are calibrated to think that if the information is not shown, it has not crossed the threshold and is therefore of insufficient significance for AngelList to report. This is important for the interpretation of the results, as the increase in the click rate thus represents the effect of the team's background being above the importance threshold. Showing information about the current investors or traction does not significantly alter the click rate. This means that knowing whether

[16] In unreported results, we confirm that our main results hold if we use both opened and unopened emails. We also verified that the decision to open an email is not correlated with the three randomized categories of information.

[17] The results are nearly identical if we include investor fixed effects. We do not cluster standard errors at the start-up level because there are too few clusters to produce reliable estimates (see Angrist and Pischke (2009), chapters 8.2.1 and 8.2.3). The start-up fixed effects in the regressions remove unobserved heterogeneity in click rates for each start-up.

[18] The regressor indicator variables equal one when the information is shown in the email, and zero otherwise. It is not necessary to interact these indicators with dummy variables whether the disclosure threshold was passed, as the results are mechanically the same.

a notable investor is investing in the company, or if the start-up has material traction, does not make investors more likely to click.

In column (2) we introduce controls for investors' pre-existing knowledge of the start-up company, and the number of emails an investor has already received in the experiment. We will discuss these results in more detail in the next section. What is important at this stage of the analysis is that adding these controls does not change the coefficients on the randomized information categories. The final two columns show that the results are robust to using a logit model instead of OLS regressions.

A unique feature of our setting is that we can show the importance of the randomized experiment for identification, by re-running the regressions of Table 4 on the subset of 2,992 opened emails that show every piece of information that crossed the threshold. These are the only emails that would have been sent outside of the experiment, and the regressions therefore show the results from a sample of featured emails without randomization of the information. Note that with this subsample of emails we cannot include start-up fixed effects as there is by construction no variation across emails for a given start-up.

Focusing on the OLS regression with the information categories as the only explanatory variables, Table 5 shows that the coefficients on revealed information about the team, investors, and traction 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. These coefficients are uniformly higher than the coefficients of 0.022, 0.010 and 0.016 using the full set of randomized emails (replicated for ease of comparison in the four right-most columns of Table 5), and where the coefficients on both investors and traction are insignificant. This means that the randomization of information is important: without the experiment, we would overestimate the importance of traction, and to some extent, team. This is exactly what one would expect if good teams, investors, and traction are positively correlated with good ideas, which is likely to be the case. The results for the other models are similar, as seen in Table 5.

The results thus far suggest that information about human capital is very important to investors. However, an alternative interpretation is that the informational content may be different across categories depending on where the AngelList set the disclosure threshold. For example, suppose team and traction are equally important to investors, but AngelList used a higher threshold to disclose information about the team than traction. We may then find that investors react more strongly to the team. This concern is mitigated by the fact that in Panel B of Table 2 we find no significant differences between AngelList's likelihood to disclose information across categories. To address this concern further, we next explore how different types of investors react to the revealed information.

The regression results in Table 6 show the difference in response between experienced and inexperienced investors, where we use investors' total number of 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 about 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 cutoff between inexperienced and experienced investors at the 25th and 50th percentile of investors, ranked by their number of investments, respectively. The results for the experienced investors remain the same, as they respond only to information about the team, while the significance of the response to traction and current investors categories among inexperienced investors weakens somewhat as we broaden the definition of inexperience.

The results of Table 6 are consistent with the most inexperienced investors interpreting all information categories as signals of the quality of the start-up. This means that the absence of a reaction by experienced investors to the traction and current investors categories is not due the fact that there is no information content in these categories. Rather, it suggests that the experienced investors believe that these categories are simply less relevant to the success of the company. Alternatively, inexperienced investors may have a different investment strategy, or are less certain in their ability to judge the team and thus are rationally more sensitive to other outside signals. Whichever is the true explanation, the main result remains that information about human capital is truly most important to investors at this stage of the company's development.

We should be careful to point out that the fact that human capital appears to matter more to experienced investors than information about traction, does not mean 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 shown in the descriptive paragraph of the email. This description contains information on the market, technology and other aspects of the idea that may be important to investors. We do claim that, conditional on this information, the information about human capital matters to investors. In other words, our results point to the jockey being important at this stage of the firm, irrespective of whether the horse matters or not.

In Tables 7 and 8 we explore other measures of investor heterogeneity. In Table 7 we use investors' signal as an alternative measure of investor experience, which also captures past success. In Table 8 we use the weighted number of followers as a measure of an investor's importance and reputation, where the weights are followers' signal.[19]

[19] We also considered the unweighted number of followers, but the correlation with the weighted number of followers is 0.95 (Table 3 panel D). For brevity, we only report results for weighted number of followers.

Overall, the results are robust: investors in the lowest quartile of experience or importance respond to all categories of information, whereas investors in the top quartile only respond to the information in the team category. These results reinforce the conclusion that these findings are not simply an outcome of different informativeness of the categories due to the choice of disclosure threshold.

A remaining question is what is the channel through which human capital information is important for early stage companies? One explanation is that the operational or technical capabilities of the founding team raise the chances of success. An alternative explanation is that high quality teams have attractive outside options, and can therefore credibly signal the prospects of the idea, which is often difficult to evaluate. We provide suggestive evidence that human capital is important to investors not only as a signal of the prospects of the idea, but also due the operational value of the founders. Consider the null hypothesis in which team matters *only* because it provides a signal of the underlying idea. To test this null hypothesis we explore the response of investors that specialize in the sector in which the start-up operates. These investors are relatively more knowledgeable about this particular sector, and therefore more capable to evaluate start-up ideas in this area (for example, from the description of the start-up's business in the featured email), relative to investors who do not specialize in the start-up's sector. 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 investors that specialize in its market by using the information tags that investors provide about their interest and expertise. For example, investors may specify that they specialize and look for start-up companies in clean technology, mobile, or consumer-internet. We calculate the cosine similarity between the vector of investor market tags and the vector of tags that the start-up uses to describe its market.[20] We define investors as specialized if the similarity between their expertise and the start-up market is within the top 25% of the distribution for a given start-up (that is, they are among the closest start-up – investor pairs).

In column (1) of Table 9 we repeat our baseline result illustrating that investors are highly responsive to information about the team. In column (2), we add the investor specialization dummy variable, and find that specialized investors have a 3.9% higher click rate (24% higher than the baseline click rate), which is statistically highly significant. This higher unconditional click rate is not surprising given the declared interest of these investors. The addition of the specialized variable does not change the coefficient of the team variable, due to the randomization of the information categories.

In column (3) we explore whether specialized investors react differently to team information, by interacting the specialization dummy and the team disclosure dummy variables. The coefficient of the interaction term is -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 information about the team, despite their likely superior expertise in evaluating the start-up idea. This contradicts the null hypothesis, and provides suggestive 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.

5. Internal and external validity

[20] Specifically, we use the cosine similarity package in Python (part of the “scikit-learn” package). This similarity measure is highest if an investor and start-up have exactly the same set of tags, and lowest if they have no tags in common.

The experiment is run in a highly controlled information environment, where angel investors are making decisions about the same start-up company at the same time, with exogenously varying information sets. Still, we should be careful to consider any concerns about the internal and external validity of the experiment.

One potential internal validity concern is that the coefficients on the disclosed information in the regressions in Tables 4 to 8 may be affected by investors who already know the information in the emails, especially if these are “hot” and promising start-ups. As long as such information is common knowledge, this will be absorbed in the start-up fixed effect. Moreover, we add controls for investors’ pre-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. Not surprisingly, investors are more likely to click if they already follow the start-up, or have pre-existing connections. 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. Still, the fact that even the most experienced and well-connected investors react to the information in the emails suggests that this is not a first-order concern.

Another common concern with experiments that involve repeated measurements on subjects (investors, in our setting) is that subjects may learn about the existence of the experiment, contaminating the results. This concern is mitigated by three features of the experiment: First, the experiment window of eight weeks is short. Second, the randomized information categories are not always shown outside of the experiment, so a missing category is not out of the ordinary. Third, no investor received more than one email for any given featured start-up, so there is no risk of the same investor receiving and comparing emails across the same start-up and noticing different information sets. Still, to check whether investors realize that the experiment is going on, we also include the number of prior experiment emails that the investor received as a control in the regressions of Tables 4 to 8. The insignificant coefficients imply that click rates do not change as the investor receives more emails in the experiment. Unreported regression results show that including interactions of this control with the information category dummies also yields insignificant results, showing that investor responsiveness to the information categories also does not change as the experiment progresses.

AngelList chooses which companies to feature in their emails, and this could raise validity concerns. Since our inference exploits the variation *within* each start-up, internal validity is not a concern. Similarly, the choice of recipients does not violate internal validity, as information is varied randomly across the recipients. However, the endogenous choice of start-ups and investors does raise questions regarding external validity (i.e., generalization) of the results.

The experiment covers a large proportion of the active angels on the AngelList platform: of the 5,869 angels who are active on the platform,[21] 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. To get a sense of representativeness of the sample of 21 start-ups in the experiment, Table 10 compares them to a larger sample of 5,538 firms raising money on the AngelList platform. This larger sample consists of "serious" firms in the sense that these companies received at least one introduction request while raising capital on AngelList. Table 10 shows that the field experiment

[21] By active we refer to investors who requested at least a single start-up introduction.

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), funding targets for the AngelList round ($1.2 million versus $0.9 million)), are more likely to have employees (81% versus 53%), and are more likely 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 two samples do not look vastly different, which mitigates the concern about generalization of the results of the field experiment.

To assess the representativeness of AngelList for the broader start-up market, AngelList performed an internal analysis comparing the firms on the platform against Crunchbase, a popular wiki-based site that has detailed fundraising information for start-ups. They found that over 60% of the companies claiming to raise a seed round in 2013 have an AngelList profile, and more than half of these firms attempted to raise funds on the platform. However, AngelList coverage differs by geography. Close to 60% of successful seed rounds in the Silicon Valley and Texas fundraised on AngelList, while only 15%-20% in Boston or Seattle. Overall, it appears that AngelList provides a fairly representative sample of start-ups seeking seed funding, but it is tilted towards start-ups located in Silicon Valley and Texas.

6. Investments and Introduction Requests

The analysis up to this point has focused on click rates to measure investors' level of interest. Ideally, we would also use actual investments as a dependent variable. However, this setting does not allow us to infer the causal effect of randomized information sets on investment: after clicking on the emails, all start-up information is revealed, and the information environment is no longer strictly controlled. In other words, all start-up information is revealed between the stage of randomized information in the emails and the actual investment decision, even if it was excluded as part of the experiment. This contaminates the effect of the initial information randomization and prevents us from estimating the causal effect of the information categories on investments.

Despite this limitation, we argue that clicks capture real and important information about investors' interest, which affects ultimate funding decisions. First, consider the base click rate of 16.5%. This shows that investors do not ignore the information in the emails, nor do they click on every featured company that lands in their inbox. Second, if investors did not care about the information in the emails, clicks would be random and we would not see strong reactions to any information. The fact that we find economically and statistically significant results suggests that investors do care, and pay attention to the information provided at this stage. Finally, to the extent that the search process has even moderate frictions, one would expect that increased click rates would 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 base rate) implies a 13% increase in actual investments.

While we can only estimate the causal effect of information categories on investor interest (measured by clicks), rather than actual investments, we can examine how likely such interest translates into real investments. That is, we can measure the conversion rate from clicks into actual investments. This addresses a common weakness of the correspondence testing literature, where real outcomes cannot usually be observed. For example, in their study on racial discrimination in hiring, Bertrand and Mullainathan (2004) cannot measure the conversion rate of callbacks into actual hiring, since the randomized resumes that they send out are fictitious. Since our experiment involves real companies and real investors, we can observe the real outcomes.

Table 1 report that the conversion rate from clicks to ultimate investment is 2.98%. However, investors are not required to report their investment to AngelList. Based on the company's estimates, only half of investments are reported, leading to a click-to-investment rate of as high as 6%.[22] This is fairly high compared to venture capital, as venture capitalists invest in about one in every 50 to 100 deals that they look into (Metrick and Yasuda, 2010). Moreover, no investments were made without an initial click on these emails. Thus, clicks are a prerequisite for investment, capturing investor interest.

Next, we look at introductions as an alternate outcome measure that is less subjective to the underreporting issue. AngelList records whenever an investor requests an introduction with a start-up through the website, and introductions are therefore more precisely measured than investments. Table 1 shows that the conversion rate of clicks to introductions is 15.14%. This includes not only direct introductions from the email but also introductions that were made later, when investors have seen more information about the start-up. 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.

[22] We have tried to supplement the investments data using Crunchbase but did not identify any further investors in the angel round.

7. Conclusion

In this paper we shed light on the investment decision process of early stage investors. Unlike investments in publicly traded firms, we know little on the selection process and investment decision making process of early stage investors, despite of their important role in promoting innovation and growth in the economy. This due to limitation information on the selection set available of early stage investors, the lack of unsuccessful fundraising attempts, and endogeneity between start-up characteristics and other unobservables of start-ups.

This paper uses a field experiment to study early stage investors' responses to information about start-up firms. We randomly vary investors' information sets in a tightly controlled information environment that uses emails regarding featured start-ups, sent through AngelList's platform. We find that investors react most strongly to the information about the start-up's founding team. However, there is considerable heterogeneity among investors, and while experienced and successful investors react only to the team information, inexperienced investors also react to information about the firm's traction and current investors.

Our results show that information about human assets is causally important for the success of early-stage firms. We provide further suggestive evidence that investors do not only care about strong founding teams for pure signaling reasons, but also because teams matter for operational reasons.

Overall, the results present evidence of the importance of human capital assets at the earliest stages of the firm, around the firm's birth. Therefore, contributing to the debate around the importance of various key assets to organization success (e.g., Grossman and Hart 1986, Rajan and Zingales 1998, 2001). Our results, however, do not suggest that non-human assets are not essential but rather consistent with Rajan (2012). Rajan argues that the entrepreneur's human capital is important early on to differentiate her enterprise as we find. However, consistent with Kaplan, Sensoy, and Stromberg (2009), to raise substantial funds, the entrepreneur needs to go through a standardization phase that will make human capital in the firm replaceable, so outside financiers can obtain control rights.

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Appendix: Information disclosed in featured emails

For each start-up in the randomized experiment, we show the information that passed AngelList's disclosure threshold. This information would be shown in the featured emails outside of the experiment. To protect the companies' identities each column is shown in a different order, so that rows do not correspond to companies. The team, investors, and traction information passed AngelList's disclosure threshold for 19, 17, and 18 start-ups, respectively.

Team information	Investors information	Traction information
Team worked at Microsoft, Google and Ask.com.	Great Oaks and Josh Abramowitz are investing in this round.	$125K revenue in first 5 months, 15 companies, 1.7K testers.
Team worked at Starbucks and Nabisco.	500 Startups is investing. Incubated by Startmate.	$30M in transaction volume.
Team worked at Royal Bank of Canada and went to University of Toronto.	Summit Partners are investing in this round.	3.2K health providers, 15% monthly growth.
Team worked at IBM and went to the University of Waterloo.	Hadi Partovi, Keith Rabois and Tony Hsieh are investing in this round.	$1M/year revenue, 70K users, 20% monthly growth.
Team worked at Accel. Went to Cambridge and Oxford.	Quest Venture Partners are investing in this round. Incubated by Y Combinator.	$800K revenue/year, 60% annual growth, 1K customers.
Team went to Stanford and Berkeley.	Laurent Drion is investing $500K in this round.	$250K in pre-sales, 960 pre-orders.
Team worked at Microsoft, Groupon and went to Stanford GSB.	Grishin Robotics is investing $500K in this round.	40 vending machines, 3 pilot contracts.
Team members worked at Accenture.	Lightbank is investing in this round.	350 subscribing businesses, 700 active users, 125% monthly growth.
Team worked at E*TRADE and studied at Stanford.	Adventure Capital is investing in this round.	$10K/month revenue, 120K users, 7.5K courses.
Team includes the founder of SIMMS - radiology software used by 2 million patients.	Incubated by AngelPad.	$20K/month revenue, 25% monthly growth, 12K monthly active users.
Team worked at Intel and went to The University of Chicago.	SoftTech VC and Matt Mullenweg are investing in this round.	$1K revenue, 12 customers.
Team worked at JPMorgan and went to MIT.	Jeff Fluhr and Great Oaks are investing in this round.	130K users, 10% monthly growth, $6K/month revenue.

Team worked at Yahoo!, Oracle and went to Stanford.	Dave McClure is investing in this round.	80 users. Waiting list includes BHP Billiton, USGS and the WWF.
Team members went to Harvard.	Sandbox Industries are investing.	90K items for sale, 10K monthly active users, 30% monthly growth.
Team worked at Google and went to The University of Cambridge. Includes 2 Artificial Intelligence PhDs.	Golden Gate Ventures is investing in this round.	$20K revenue/month, 10K engineers.
Team worked at Microsoft, GE and went to Cornell.	Patrick Condon (co-founder of Rackspace) investing. Incubated by TechStars.	$1.4M revenue/year, 10K units sold.
Team founded well.ca ($40M/year revenue), worked at IBM and RIM.	Boris Wertz is investing in this round. Incubated by Y Combinator.	$10M/year revenue, 60% annual growth, 13 stores, 25% profit margin.
Team went to University of British Columbia.		$70K revenue/month, 500K monthly active users, 100K daily active users.
The founder's last company designed and built 12 composting facilities in the US.		

Table 1: 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 reaches a threshold as defined by AngelList (see Figure 1 for an example). For each start-up, various unique versions of each email are generated that randomly hide these pieces of information. 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. *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

	mean	st. dev.	percentile		
			10	50	90
Emails					
Total	16,981				
Unique	58				
Investors / unique email	293	149	86	264	468
Active investors emailed	4,494				
Active investors who opened at least one email	2,925				
Start-ups	21				
Investors / start-up	809	468	338	676	1,451
Start-ups / investor	3.78	2.45	1	3	7
Emails opened (%)	48.28				
Of opened emails:					
Clicked (%)	16.45				
Of clicked emails:					
Intro (%)	15.14				
Investment (%)	2.98				

Panel B: Information in emails

	Team	Investors	Traction	p-value
Information passed AngelList threshold (% of start-ups)	90.48	80.95	85.71	0.678
Information shown in experiment, if passed threshold (% of unique emails)	73.24	73.02	72.06	0.987

Table 2: Descriptive Statistics of Start-ups

This table shows descriptive statistics of the 21 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

	N	fraction (%)
Austin, TX	1	4.76
Chicago, IL	1	4.76
Kitchener, Canada	1	4.76
London, United Kingdom	1	4.76
Melbourne, Australia	1	4.76
New York City, NY	3	14.28
San Antonio, TX	1	4.76
Silicon Valley, CA	6	28.57
Singapore	1	4.76
Sydney, Australia	1	4.76
Toronto, Canada	3	14.28
Vancouver, Canada	1	4.76

Panel B: Start-up Distribution across Sectors

	N	fraction (%)
Information Technology	18	85.71
Consumers	13	61.90
Clean Technology	1	4.76
Healthcare	3	14.28
Business-to-business	8	38.10
Media	2	9.52
Education	2	9.52

Panel C: Start-up Structure

	N	mean	st. dev.	percentile		
				10	50	90
# Founders	21	2.62	0.92	2	2	4
Employees (%)	21	80.95				
If >0, # employees	17	3.35	2.21	1	3	7
Board members (%)	21	23.81				
If >0, # board members	5	1.80	0.84	1	2	3
Advisor (%)	21	90.48				
If >0, # advisors	19	4.74	6.00	1	3	7
Attorney (%)	21	71.43				

Panel D: Start-up Funding

	N	mean	st. dev.	percentile		
				10	50	90
Incubator (%)	21	57.14				
Pre-round funding (%)	21	52.38				
If > 0, pre-round funding raised ($000s)	11	580.95	855.33	50.	290	950
Pre-money valuation ($000s)	16	5,465.63	2,133.60	3,000	5,000	8,000
Fundraising goal ($000s)	18	1,183.06	462.88	570	1,250	2,000
Equity financing (%)	21	76.19				

Table 3: 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 these involvements into various roles. *Investor (%)* shows the percentage of angels who have invested in start-ups. For the subset of angels 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 variables such as number of investments, signal, and number of followers.

Panel A: Investor Stated Interest across Sectors

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

Panel B: Investor Characteristics

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

Panel C: Investor Roles in Start-up Companies

	N	mean	st. dev.	percentile		
				10	50	90
Investor (%)	2,925	82.36				
If > 0, # start-ups funded	2,409	13.10	16.81	2	8	28
Advisor (%)	2,925	43.49				
If > 0, # start-ups as advisor	1,272	3.47	4.54	1	2	7
Board member (%)	2,925	16.92				
If > 0, # start-ups as board member	495	1.93	1.82	1	1	4
Start-up founder (%)	2,925	60.00				
If > 0, # start-ups founded	1755	2.05	1.44	1	2	4

Panel D: Correlations between Investor Heterogeneity Measures

	No. of investments	Signal	# Followers
No. of investments	1		
Signal	0.51	1	
# Followers	0.63	0.41	1

Table 4: 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 angel 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 variables 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.

	(1)	(2)	(3)	(4)
Model	OLS	OLS	Logit	Logit
Team = 1	0.022**	0.023**	0.162**	0.172**
	(0.010)	(0.010)	(0.073)	(0.074)
Investors = 1	0.010	0.009	0.070	0.067
	(0.013)	(0.013)	(0.097)	(0.097)
Traction = 1	0.016	0.017	0.122	0.123
	(0.014)	(0.014)	(0.106)	(0.106)
Connections		0.010		0.064*
		(0.006)		(0.038)
Prior follow = 1		0.143***		0.835***
		(0.033)		(0.166)
Prior emails		0.001		0.006
		(0.003)		(0.022)
Start-up fixed effects	Y	Y	Y	Y
Number of observations	8, 189	8, 189	8, 189	8, 189
R2	0.001	0.005	0.028	0.033

Table 5: Investor Response to Non-randomized Emails

This table replicates the regressions in Table 4 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 4. For ease of comparison, the columns labeled "Randomized sample" show the results from Table 4 for the same set of models. The dependent variable is one when an angel investor clicked on the "View" button in the featured email, and zero otherwise. The explanatory variables are as defined in Table 4. 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.

	Full Information Subsample				Randomized sample			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	OLS	OLS	Logit	Logit	OLS	OLS	Logit	Logit
Team = 1	0.046**	0.045**	0.336**	0.337*	0.022**	0.023**	0.162**	0.172**
	(0.022)	(0.022)	(0.171)	(0.172)	(0.010)	(0.010)	(0.073)	(0.074)
Investors = 1	0.013	0.022	0.091	0.155	0.010	0.009	0.070	0.067
	(0.018)	(0.019)	(0.127)	(0.133)	(0.013)	(0.013)	(0.097)	(0.097)
Traction = 1	0.037*	0.043**	0.265*	0.311**	0.016	0.017	0.122	0.123
	(0.020)	(0.020)	(0.149)	(0.154)	(0.014)	(0.014)	(0.106)	(0.106)
Connections		0.010		0.058		0.010		0.064*
		(0.010)		(0.054)		(0.006)		(0.038)
Prior follow = 1		0.150**		0.822***		0.143***		0.835***
		(0.059)		(0.277)		(0.033)		(0.166)
Prior emails		-0.006		-0.042*		0.001		0.006
		(0.003)*		(0.025)		(0.003)		(0.022)
Start-up fixed effects	N	N	N	N	Y	Y	Y	Y
Number of observations	2,992	2,992	2,992	2,992	8,189	8,189	8,189	8,189
R2	0.001	0.006	0.002	0.008	0.001	0.005	0.028	0.033

Table 6: 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 angel 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 4. 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.

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

Table 7: 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 angel 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 4. 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.

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

Table 8: 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 angel 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 4. 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.

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

Table 9: 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 angel 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. *Market Similarity = 1* is an indicator variable that equal one if the distance between investor market interests and start-up market is at the top 25% of the distance distribution. See the main text for the algorithm used to compute distance. *Other controls* are *Connections, Prior follow,* and *Prior emails,* as defined in Table 4, but not reported for brevity. 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.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	OLS	OLS	OLS	Logit	Logit	Logit	Logit
Team shown = 1	0.023**	0.024**	0.024**	0.023**	0.172**	0.177**	0.190**	0.177**
	(0.010)	(0.010)	(0.011)	(0.011)	(0.074)	(0.074)	(0.085)	(0.087)
Investors shown = 1	0.009	0.009	0.009	0.003	0.067	0.068	0.068	0.014
	(0.013)	(0.013)	(0.013)	(0.014)	(0.097)	(0.097)	(0.097)	(0.108)
Traction shown = 1	0.017	0.016	0.016	0.011	0.123	0.119	0.120	0.090
	(0.014)	(0.014)	(0.014)	(0.016)	(0.106)	(0.106)	(0.106)	(0.117)
Market Similarity = 1		0.039***	0.041***	0.006		0.291***	0.315***	0.081
		(0.011)	(0.015)	(0.035)		(0.079)	(0.112)	(0.260)
Market Similarity = 1			-0.002	0.004			-0.041	0.002
x Team shown = 1			(0.019)	(0.020)			(0.136)	(0.143)
Market Similarity = 1				0.026				0.192
x Investors shown = 1				(0.023)				(0.167)
Market Similarity = 1				0.017				0.099
x Traction shown = 1				(0.025)				(0.182)
Start-up fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Other controls	Y	Y	Y	Y	Y	Y	Y	Y
Number of observations	8,189	8,189	8,189	8189	8,189	8,189	8,189	8189
R2	0.005	0.007	0.007	0.007	0.033	0.035	0.035	0.035

Table 10: 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 2. The rightmost column shows the p-value for a differences-in-means test between the experiment and non-experiment samples.

	Experiment firms (N = 21)				Non-experiment firms (N = 5,538)				Means test p
	N	mean	median	st. dev.	N	mean	median	st. dev.	
# Founders	21	2.62	2	0.92	5,538	2.11	2	1.06	0.028
Employees (%)	21	80.95			5,538	52.56			0.009
If > 0, # employees	17	3.35	3	2.21	2,911	2.91	2	2.45	0.453
Board members (%)	21	23.81			5,538	16.78			0.390
If > 0, # board members	5	1.80	2	0.84	929	1.96	2	1.14	0.749
Advisor (%)	21	90.48			5,538	60.74			0.005
If > 0, # advisors	19	4.74	3	6.00	3,364	2.94	2	2.18	0.000
Incubator (%)	21	57.14			5,538	29.70			0.006
Pre-round funding (%)	21	47.62			5,538	45.76			0.865
If > 0, amount raised ($000s)	10	605.05	234.00	897.66	2,534	674.27	250.00	1,874.28	0.904
Pre-money valuation ($000s)	12	5,579.17	5,000.00	2,383.22	2,616	4,857.83	3,500.00	15,747.91	0.873
Fundraising goal ($000s)	15	1,226.33	1,325.00	488.96	4,321	923.99	500.00	1,135.56	0.303
Equity financing (%)	21	76.19			4,912	69.04			0.603

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.

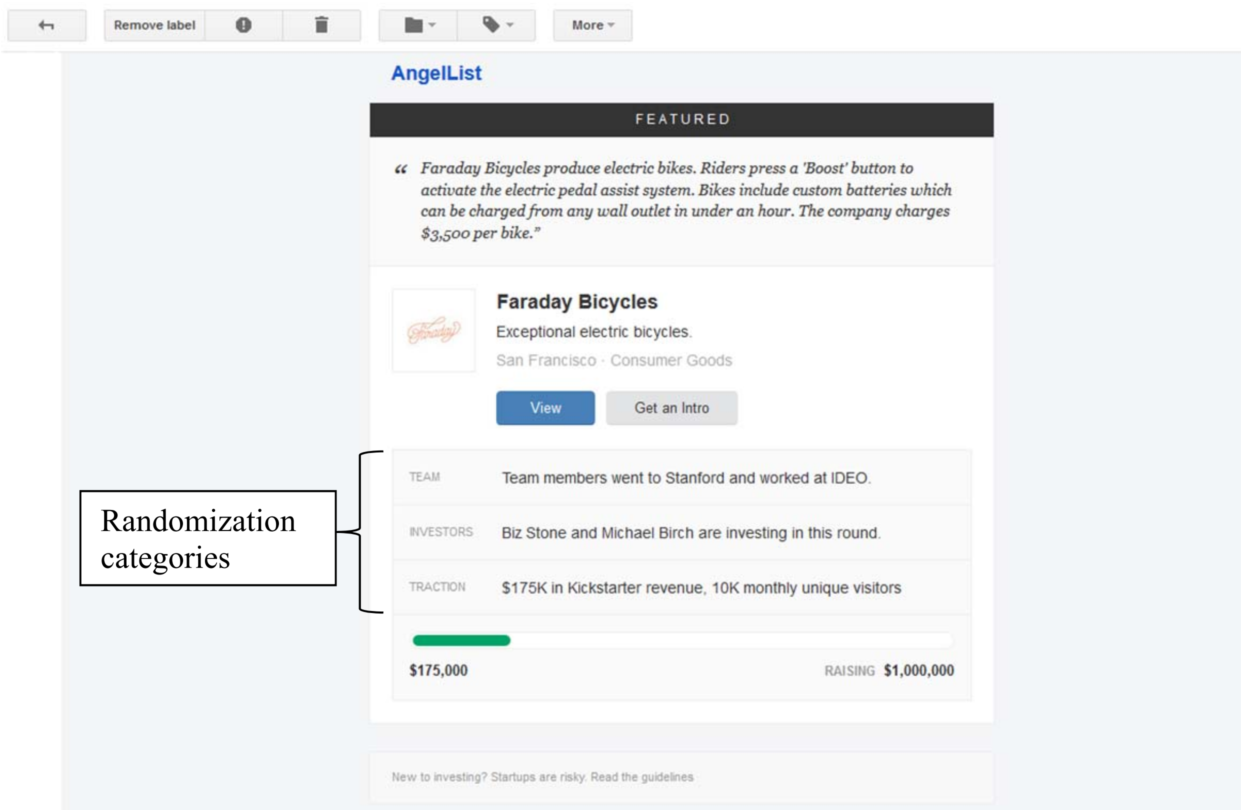

Figure 2: Distribution of investor signal measure

This figure shows the histogram of the investor signal for the 2,925 active investors that received emails about featured start-ups in the randomized field experiment, and opened at least one such email. The signal ranges from zero to ten. See the main text for a description of the algorithm used to compute the signal.