# Is it Just the Idea that Matters? A Randomized Field Experiment on Early Stage Investments

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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, high-profile, early stage investors, implemented through AngelList, an online platform that matches investors with start-ups that are seeking capital. The experiment randomizes investors' information sets on "featured" start-ups through the use of nearly 17,000 emails. Investors respond strongly to information about the founding team, whereas they do not respond to information about either firm traction or existing lead investors. This result is driven by the most experienced and successful investors. The least experienced investors respond to all categories of information. The results suggest that, conditional on the quality of the idea, information about human assets is highly important for the success of early stage firms.

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Early stage investors provide an important source of capital enabling the birth and growth of start-up companies, which play a key role in promoting innovation and growth in the economy (Solow (1957)). A large and growing literature analyzes the implications 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)). There is, however, much less understanding of the investment decision-making of early stage investors, that is, how do they choose which start-up to fund? What leads investors to pick one company over the other? This stands in sharp contrast to the wealth of evidence on the behavior of retail and institutional investors who target investments in publicly traded firms.

Studying the investment decision-making of early stage investors is challenging for several reasons. First, existing databases consist of completed deals, rather than the pool of start-ups considered by the investor, thus preventing assessment of the investor selection process. Second, researchers possess far less data than investors do. Two early stage ventures may seem similar to a researcher, but may look completely different to an investor. Third, even if such data were available, how can one separate the causal effect of different start-up characteristics? For example, if we observe that a serial entrepreneur is more likely to attract financing, is it because of the importance of her past experience, or because serial entrepreneurs are just more likely to generate high-quality ideas in the first place. This endogenous relationship between ideas and start-up characteristics is even more problematic given that the quality of ideas is subjective, highly uncertain, and unobserved to the researcher, leading to omitted variable bias.

We study which start-up characteristics early-stage investors causally respond to using a randomized field experiment that builds on the correspondence testing methodology that has

been successfully used in labor economics.[1] The experiment takes place on AngelList, an online platform that matches start-ups and angel investors. Therefore, we observe the start-up companies at the stage in which they approach investors and seek capital. The platform also includes many well-known investors that are experienced in investing in, and building, early-stage firms. These individuals are highly involved in startup creation, taking various roles in these firms such as investors, board members, advisors and founders, and are therefore not only suited to inform research about early-stage investor decision-making but also about which start-up characteristics are most important for early-stage firm success.

AngelList regularly sends out emails to investors to feature start-ups who are attempting to raise capital. We randomize the information shown in these emails, and measure investors' responses and level of interest to causally infer what factors drive investors' decisions. Investors' interest is gauged by measuring whether they choose to learn more about the firm on the platform. While all investors see similar information on the startup idea and potential market, we randomly expose investors to information in 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 (e.g., revenues and user growth), and the identity of current investors. Broadly speaking, the team and traction categories correspond to information about human and non-human assets, respectively. Kaplan, Sensoy, and Stromberg (2009) show the differential importance of these two types of capital as the firm grows. The current investors category can be interpreted as "social proof", or a different type of human assets, as prominent

[1] The correspondence testing methodology has been used, for example, by Bertrand and Mullainathan (2004) to explore racial discrimination in the labor market, by Weichselbaumer (2003) to study the impact of sex stereotypes and sexual orientation, and by Nisbett and Cohen (1996) to study employers' response to past criminal activity.

investors may apply their expertise or network to the firm.[2] These categories are randomly revealed to each investor, and we exploit the variation across angels' reactions *within* each start-up. In other words, conditioning on the start-up's "idea", we exogenously vary the aforementioned categories of information.

We sent about 17,000 emails to nearly 4,500 angels, spanning 21 different capital-seeking start-ups, over the summer of 2013. Our target investors include many of the most prominent angel investors, who are very active in the startup scene. Among these investors, 82% have past investments, with a median of eight companies in their portfolio. Almost half of the investors serve as an advisor to one or more start-up companies. Interestingly, 60% of the investors have an entrepreneurial background themselves, as they formed at least a single venture in the past.

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

The randomized experiment reveals that 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 shows that the information about human capital of the firm is very important to potential investors. Interestingly, we find significant heterogeneity among angels. On one hand, the most highly experienced investors, as measured by a battery of metrics (including the number of prior investments, a success metric, and their

[2] The investor category does not, however, reveal information about the level of funding, as this is separately disclosed in the email.

network centrality), react only to the team information. On the other hand, the least experienced investors react to all categories of information. This suggests that the significance of team information is not simply due to a better signal-to-noise ratio.

A unique feature of our setting is that it allows us to empirically confirm that absent the randomization of information revelation, we would overestimate the importance of the various categories. This is consistent with the notion that good teams, current investors, and traction are all positively correlated with good ideas, and underscores the importance of randomization for establishing causality.

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.

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 (Grossman and Hart (1986), Hart and Moore (1990), Holmstrom (1999), amongst others) 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)).[3]

Our results present suggestive evidence of the importance of human capital assets at the earliest stages of the firm, around the firm's birth. Our results, however, 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).

[3] 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)).

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. Our results indeed suggest the importance of human assets at the earliest stages of a firms' life. Kaplan, Sensoy and Stromberg (2009) show that at the later stages, human capital is frequently replaced, as different human capital skills are needed to run a larger, more mature firm, and to ready the firm for the injection of significant outside capital.

This paper adds to the literature on early stage investments. While some papers attempt to illustrate causality by linking early stage investors' actions to 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)), there is little disagreement that early stage investors are skilled pickers of successful companies (e.g., Kaplan and Schoar (2005), Sorensen (2007), Puri and Zarutskie (2012), Korteweg and Sorensen (2013)). Yet, little is known about how exactly this class of investors selects 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.

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

statistics. In section 4 we analyze investors' reactions to the emails. Section 5 discusses issues of internal and external validity. In section 6 we dive deeper into the impact of disclosed information on investment, and Section 7 concludes.

## 1. The AngelList platform

AngelList is a platform that connects start-ups with 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. 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.

On the angel side, investors that are accredited following the rules set by the U.S. Securities and Exchange Commission[4] can join the platform to look for potential investments. Investors 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

[4] 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 thousand (or $300 thousand jointly with a spouse) in each of the two most recent years and a reasonable expectation of such income in the current year.

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).

Using AngelList, interested investors request an introduction to the start-up's founders. From there the parties can negotiate their way to 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 have been made through AngelList, raising over $200 million. These companies have gone on to raise over $2.9 billion in later rounds of venture capital and exit money.

## 2. Randomized field experiment

The field experiment builds on correspondence testing methodology[5] and uses so-called "featured" emails about start-ups that AngelList regularly sends out to investors listed on its platform. These start-ups are chosen by AngelList for being promising companies that could be appealing to a broad set of investors that 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 shows up to three categories of information about:

[5] This approach has been used in the context of job application recruiting in various studies. Written applications are sent to job openings and applications are constructed such that they differ only in the aspect of interest. These studies explore the employer reactions to the fictitious job applications. A few recent examples include Bertrand and Mullainathan (2004), Weichselbaumer (2003), and Nisbett and Cohen (1996). Our study does not rely on fictitious subjects, but rather uses real investors and real early stage ventures seeking for capital.

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 AngelList's determination of what information 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. Finally, the email shows information about 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 if 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.

## 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 startup 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, allowing us to explore repeated observations for each investor. 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, 16.45% of investors clicked on the "View" button to see more information about the start-up. This click rate provides the first hint that investors pay attention to the emails: they do not click on every company, but they also do not ignore the emails and the information therein altogether. Of the investors who clicked on the email, we see that 15.1% requested an introduction within three days of viewing the email. However, 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. Finally, 11.2% of investors who clicked on one of the email buttons ended up following the start-up on the AngelList platform. Following a start-up means that the investor receives automatic updates whenever a material event occurs on the platform that involves the start-up, such as anybody joining the startup, investing in that round, or news updates from the startup.

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, these categories are randomly

excluded. 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). 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%) 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.[6] Almost all companies (19 out of 21) have advisors,[7] 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%) had previously gone through an incubator or accelerator program. Eleven companies (52%) received funding prior to coming to AngelList for further financing, and had 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. Eighteen companies explicitly state their fundraising goal, which ranges from $500 thousand to $2 million (not tabulated), 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, while 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. However, there is considerable heterogeneity

[6] 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.
[7] Advisors are typically high profile individuals, and are compensated with stocks and options.

in the number of introductions requested, with the lowest decile of investors requesting only one introduction, while the top decile requested over twenty.

In order to provide an indication of the past success of investors, 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 with high exit value companies (from Crunchbase) such as Google or Facebook getting assigned a value of ten, as well as 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.[8,9]

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 10$^{th}$ percentile having only 26 followers while the 90$^{th}$ percentile investor has 1,346 followers.

[8] 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.

[9] 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.

Over 90% of investors are actively involved with start-ups (as with the signal calculation, these numbers are not limited to companies 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, but certainly not least, 60% of investors were at one point founders themselves.[10] The median of these founder-investors founded two companies.

The investors in Table 3 tend to be more active and involved than the investors that 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).

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.

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

## 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' click rates. The dependent variable equals one when an investor clicked on the "View" button in the email, and zero otherwise. 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. In column (1) we run a simple ordinary least squares (OLS) regression that explores how the three information categories affect click rates.[11] Revealing information about the team significantly changes the click rate, raising the unconditional click rate by 2.6%. Given a base click rate of 16.5% (Table 1), this represents a 16% 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 helps the experiment, as the increase in the click rate is thus 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 a notable investor (by AngelList's definition) 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, which is likely to affect the click rate. Not surprisingly, if the investor was already following the start-up prior to receiving the email, she is considerably more likely to click. Also, the click rate is positively correlated with the number of pre-existing connections between the investor and the start-up, measured as the number of people on the profile of the startup (in any

[11] 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.

role) that the investor already follows prior to receiving the email. Most importantly, these controls do not change the coefficients on the randomized information categories.

Columns (3) and (4) replicate the regressions of the first two columns with the addition of start-up fixed effects. These fixed effects control for the effect on click rates of any information conveyed in the descriptive paragraph, the amount that the company aims to raise, has already raised, or any other common knowledge about the specific start-up. The coefficients on the information categories are slightly lower, but remain significant at the 5% level. The final four 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. 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 0.026, 0.011 and 0.010 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. Clearly, the randomization of information is important: without the experiment, we would overestimate the importance of traction, and to some extent, team. In fact, one would *expect* to overestimate the importance of good teams, investors, and traction if they 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. 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.

A key question at this point is whether team matters because it is a measure of quality of the business idea, or whether there is something special about the team as a human asset that is critical to the firm? For example, if a team was trained at MIT, does this signal high human capital, or does it serve as a signal of the quality of the technology or the business plan separate from management? However, if investors care only about observing signals of idea quality, then one would expect team and current investor information to also correlate with click rates. This is not what we observe, suggesting that there is something special about team information. Still, it is possible in theory that the team information carries a higher signal-to-noise ratio then the other information categories. We exploit the rich heterogeneity in angel investors in the sample, and in particular heterogeneity in investment experience, in order to disentangle these stories.

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 relatively inexperienced investors with no prior investments, who make up about 18% of the sample, not only react 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 $25^{th}$ and $50^{th}$ percentile of investors, ranked by their number of investments, respectively. The results for the experienced investors remains the same, whereas the significance of traction and current investors categories 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 has important implications for the interpretation of the reaction of the experienced investors. In particular, it means that the absence of a reaction to the traction and current investors categories is not due the fact that the quality signal contained in this information is too low relative to the noise. Rather, it suggests that the experienced investors believe these categories are simply less relevant to the success of the company, and that there something special about the information regarding the team.

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 to 9 we explore other measures of experience as well as measures of an investor's importance in the network. In Table 7 we use investors' signal as an alternative measure of investor experience and importance. In Table 8 we use the number of followers as a measure of an investor's importance, and in Table 9 we use the weighted number of followers. All these measures are as defined in Table 3. Overall, the results are very 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.

## 5. Internal and external validity

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.

A potential internal validity concern is that investors may already know the information in the emails, especially if these are "hot" and promising start-ups. As discussed above, we control for this in the regressions through the indicator variable that captures if investors already follow the start-up before receiving the email, and the variable that counts prior connections between the investor and start-up. To the extent that these proxies are not perfect and we cannot control for pre-existing knowledge of the information categories, our results are biased towards not finding an effect of the categories, 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 probably not a first-order concern.

Another common concern with experiments that involve repeated measurements on subjects (here: investors) 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.

AngelList chooses which companies to feature through email, and this could raise validity concerns. Since our inference exploits the variation *within* each start-up, internal validity is not an issue. 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, 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 randomized field 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 while listed on AngelList. Table 10 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), 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 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.

## 6. Investment

The analysis up to this point has focused on the click rates. It is reasonable to ask how meaningful these clicks really are. We address this concern in three ways. First, consider the base click rate of 16.45%. 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 certain pieces of 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. Third, consider the conversion rates from clicks to introductions, and ultimately to investments. To the extent that these conversion rates are fixed, increasing the click rate by 16% (the effect of revealing the team information in Table 4 column 1) also increases the number of investments by 16%.

We can put some number on the conversion rate from clicks to ultimate investment through AngelList's platform, even though the information environment is no longer strictly controlled outside of the emails. Table 1 shows that of the investors who click on the email, 15.1% end up requesting an introduction within three days of viewing the email. The conversion from introduction to investment is more difficult to nail down, because AngelList does not record actual investments made but relies on investors reporting back to the platform whether they invested or not. The best estimate of the introduction-to-investment conversion rate is 7.3%. Thus, the click-to-investment conversion rate is 7.3% of 15%, or 1.1%. For comparison, venture

capitalist conversion rates are of the same order of magnitude: they invest in about one in every 50 to 100 deals that they look into.

## 7. Conclusion

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 suggest that, conditional on the quality of the idea, human assets are very important to the success of the early stage firm. This is important in light of the debate in the literature about which assets are central to the firm at an early stage. However, we cannot say that non-human assets are not essential.

Finally, this paper opens up a set of new questions for future work. In particular, the question of long-run outcomes for the companies that obtain funding is an important avenue for future work.

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**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. *Follow* means the investor started following the company through AngelList's platform within three days of viewing 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 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 |
| Unique emails / start-up | 2.76 | 0.62 | 2 | 3 | 4 |
| 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 | | | | |
| Follow (%) | 11.15 | | | | |

Panel B: Information in emails

| | Team | Investors | Traction | p-value |
|---|---|---|---|---|
| Information passed threshold (% of start-ups) | 90.48 | 80.95 | 85.71 | 0.678 |
| Information shown 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 | 50.00 | 290.00 | 950.00 |
| Pre-money valuation ($000s) | 16 | 5,465.63 | 2,133.60 | 3,000.00 | 5,000.00 | 8,000.00 |
| Fundraising goal ($000s) | 18 | 1,183.06 | 462.88 | 570.00 | 1,250.00 | 2,000.00 |
| 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 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 |

**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. 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) |
|---|---|---|---|---|---|---|---|---|
| Model | OLS | OLS | OLS | OLS | Logit | Logit | Logit | Logit |
| Team = 1 | 0.026*** | 0.027*** | 0.022** | 0.023** | 0.193*** | 0.202*** | 0.162** | 0.172** |
| | (0.009) | (0.009) | (0.010) | (0.010) | (0.064) | (0.064) | (0.073) | (0.074) |
| Investors = 1 | 0.011 | 0.010 | 0.010 | 0.009 | 0.077 | 0.075 | 0.070 | 0.067 |
| | (0.010) | (0.010) | (0.013) | (0.013) | (0.072) | (0.072) | (0.097) | (0.097) |
| Traction = 1 | 0.010 | 0.010 | 0.016 | 0.017 | 0.073 | 0.072 | 0.122 | 0.123 |
| | (0.010) | (0.010) | (0.014) | (0.014) | (0.075) | (0.075) | (0.106) | (0.106) |
| Connections | | 0.014** | | 0.010 | | 0.082** | | 0.064* |
| | | (0.006) | | (0.006) | | (0.034) | | (0.038) |
| Prior follow = 1 | | 0.129*** | | 0.143*** | | 0.732*** | | 0.833*** |
| | | (0.033) | | (0.033) | | (0.163) | | (0.166) |
| Start-up fixed effects | N | N | Y | Y | N | N | Y | Y |
| Number of observations | 8,189 | 8, 189 | 8, 189 | 8, 189 | 8, 189 | 8, 189 | 8, 189 | 8, 189 |
| R2 | 0.001 | 0.006 | 0.001 | 0.005 | 0.001 | 0.006 | 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 emails only". 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 emails only | | | | Randomized sample | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (5) | (6) | (1) | (2) | (5) | (6) |
| | OLS | OLS | Logit | Logit | OLS | OLS | Logit | Logit |
| Team = 1 | 0.046** | 0.047** | 0.336** | 0.353** | 0.026*** | 0.027*** | 0.193*** | 0.202*** |
| | (0.022) | (0.022) | (0.171) | (0.172) | (0.009) | (0.009) | (0.064) | (0.064) |
| Investors = 1 | 0.013 | 0.013 | 0.091 | 0.092 | 0.011 | 0.010 | 0.077 | 0.075 |
| | (0.018) | (0.019) | (0.127) | (0.128) | (0.010) | (0.010) | (0.072) | (0.072) |
| Traction = 1 | 0.037* | 0.036* | 0.265* | 0.262* | 0.010 | 0.010 | 0.073 | 0.072 |
| | (0.020) | (0.020) | (0.149) | (0.149) | (0.010) | (0.010) | (0.075) | (0.075) |
| Connections | | 0.008 | | 0.049 | | 0.014** | | 0.082** |
| | | (0.010) | | (0.055) | | (0.006) | | (0.034) |
| Prior follow = 1 | | 0.149** | | 0.813*** | | 0.129*** | | 0.732*** |
| | | (0.059) | | (0.279) | | (0.033) | | (0.163) |
| Start-up fixed effects | N | N | N | N | N | N | N | N |
| Number of observations | 2,992 | 2,992 | 2,992 | 2,992 | 8,189 | 8,189 | 8,189 | 8,189 |
| R2 | 0.001 | 0.005 | 0.002 | 0.006 | 0.001 | 0.006 | 0.001 | 0.006 |

**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 variables *Connections* and *Prior follow = 1* 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 | 0.017* | 0.021* | 0.026** | 0.130* | 0.161* | 0.202** |
| | (0.010) | (0.011) | (0.013) | (0.079) | (0.087) | (0.099) |
| Investors shown = 1 | -0.001 | 0.004 | 0.002 | -0.011 | 0.025 | 0.015 |
| | (0.013) | (0.014) | (0.016) | (0.104) | (0.115) | (0.125) |
| Traction shown = 1 | 0.009 | 0.003 | 0.010 | 0.067 | 0.025 | 0.077 |
| | (0.014) | (0.016) | (0.017) | (0.109) | (0.118) | (0.129) |
| # Investments <= cutoff | 0.037 | 0.007 | -0.007 | 0.234 | 0.030 | -0.059 |
| 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** | 0.147 | 0.105 |
| x Investors shown = 1 | (0.028) | (0.021) | (0.020) | (0.189) | (0.151) | (0.148) |
| # Investments <= cutoff | 0.063** | 0.047** | 0.015 | 0.426* | 0.350** | 0.115 |
| x Traction shown = 1 | (0.031) | (0.021) | (0.020) | (0.220) | (0.163) | (0.155) |
| # Investments <= cutoff | -0.081* | -0.029 | -0.002 | -0.203 | -0.006 | -0.194 |
| | (0.043) | (0.031) | (0.030) | (0.239) | (0.230) | (0.277) |
| 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 | 0.144*** | 0.144*** | 0.145*** | 0.843*** | 0.844*** | 0.848*** |
| | (0.033) | (0.033) | (0.033) | (0.166) | (0.166) | (0.166) |
| Startup 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. *Connections* and *Prior follow = 1* 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 | 0.019* | 0.024* | 0.035* | 0.147* | 0.183* | 0.265* |
| | (0.011) | (0.013) | (0.019) | (0.085) | (0.097) | (0.139) |
| Investors shown = 1 | -0.003 | 0.001 | -0.006 | -0.036 | 0.004 | -0.046 |
| | (0.014) | (0.016) | (0.022) | (0.112) | (0.127) | (0.170) |
| Traction shown = 1 | 0.005 | 0.010 | 0.009 | 0.038 | 0.077 | 0.067 |
| | (0.015) | (0.017) | (0.022) | (0.112) | (0.123) | (0.156) |
| Signal < cutoff | 0.013 | -0.003 | -0.016 | 0.068 | -0.026 | -0.126 |
| x Team shown = 1 | (0.020) | (0.017) | (0.020) | (0.145) | (0.131) | (0.154) |
| Signal < cutoff | 0.055** | 0.016 | 0.019 | 0.383** | 0.122 | 0.143 |
| x Investors shown = 1 | (0.023) | (0.020) | (0.024) | (0.159) | (0.151) | (0.184) |
| Signal < cutoff | 0.063** | 0.015 | 0.012 | 0.439** | 0.121 | 0.093 |
| x Traction shown = 1 | (0.024) | (0.020) | (0.023) | (0.180) | (0.155) | (0.171) |
| Signal < cutoff | -0.051 | -0.014 | 0.001 | -0.338 | -0.106 | 0.008 |
| | (0.034) | (0.030) | (0.036) | (0.257) | (0.230) | (0.276) |
| Connections | 0.011* | 0.010 | 0.010 | 0.074* | 0.066* | 0.067* |
| | (0.006) | (0.006) | (0.006) | (0.038) | (0.038) | (0.038) |
| Prior follow | 0.143*** | 0.144*** | 0.145*** | 0.835*** | 0.838*** | 0.845*** |
| | (0.033) | (0.033) | (0.033) | (0.166) | (0.166) | (0.166) |
| Startup 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 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. *# Followers < cutoff* is an indicator variable that equals one if number of followers of a given investor is less than the percentile of the followers count distribution shown in the row labeled *Cutoff*. The variables *Connections* and *Prior follow = 1* 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 | 0.023* | 0.036** | 0.135 | 0.182* | 0.293** |
| | (0.011) | (0.013) | (0.017) | (0.085) | (0.104) | (0.141) |
| Investors shown = 1 | -0.007 | -0.018 | -0.018 | -0.064 | -0.164 | -0.157 |
| | (0.013) | (0.016) | (0.020) | (0.109) | (0.127) | (0.164) |
| Traction shown = 1 | 0.006 | 0.003 | 0.010 | 0.047 | 0.022 | 0.078 |
| | (0.015) | (0.017) | (0.021) | (0.114) | (0.127) | (0.158) |
| # Followers < cutoff | 0.021 | -0.001 | -0.018 | 0.115 | -0.030 | -0.162 |
| x Team shown = 1 | (0.020) | (0.017) | (0.020) | (0.144) | (0.132) | (0.158) |
| # Followers < cutoff | 0.064*** | 0.053*** | 0.036 | 0.446*** | 0.415*** | 0.280 |
| x Investors shown = 1 | (0.024) | (0.020) | (0.023) | (0.164) | (0.150) | (0.177) |
| # Followers < cutoff | 0.048** | 0.030 | 0.011 | 0.320* | 0.232 | 0.082 |
| x Traction shown = 1 | (0.025) | (0.020) | (0.022) | (0.174) | (0.156) | (0.177) |
| # Followers < cutoff | -0.043 | -0.024 | 0.014 | -0.167 | 0.129 | 0.372 |
| | (0.034) | (0.029) | (0.034) | (0.228) | (0.277) | (0.392) |
| Connections | 0.013** | 0.013** | 0.013** | 0.087** | 0.089** | 0.085** |
| | (0.006) | (0.006) | (0.006) | (0.039) | (0.040) | (0.039) |
| Prior follow | 0.144*** | 0.145*** | 0.145*** | 0.847*** | 0.857*** | 0.853*** |
| | (0.033) | (0.033) | (0.033) | (0.165) | (0.166) | (0.166) |
| Startup 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 | 0.008 | 0.008 | 0.007 | 0.037 | 0.036 | 0.036 |

**Table 9: 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 variables *Connections* and *Prior follow = 1* 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 | 0.020* | 0.026** | 0.033* | 0.158* | 0.207** | 0.267* |
| | (0.011) | (0.013) | (0.017) | (0.085) | (0.104) | (0.140) |
| Investors shown = 1 | -0.003 | -0.017 | -0.013 | -0.037 | -0.158 | -0.113 |
| | (0.014) | (0.016) | (0.020) | (0.109) | (0.127) | (0.163) |
| Traction shown = 1 | 0.006 | 0.003 | 0.014 | 0.050 | 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 | -0.081 | -0.127 |
| x Team shown = 1 | (0.020) | (0.017) | (0.020) | (0.144) | (0.132) | (0.157) |
| Weighted # followers < cutoff | 0.051** | 0.051*** | 0.029 | 0.356** | 0.402*** | 0.224 |
| x Investors shown = 1 | (0.024) | (0.020) | (0.023) | (0.165) | (0.151) | (0.177) |
| Weighted # followers < cutoff | 0.049** | 0.030 | 0.003 | 0.334* | 0.229 | 0.024 |
| x Traction shown = 1 | (0.024) | (0.020) | (0.022) | (0.177) | (0.157) | (0.176) |
| Weighted # followers < cutoff | -0.037 | -0.018 | 0.020 | -0.229 | -0.122 | 0.180 |
| | (0.034) | (0.029) | (0.034) | (0.253) | (0.229) | (0.277) |
| Connections | 0.012** | 0.013** | 0.013** | 0.082** | 0.090** | 0.084** |
| | (0.006) | (0.006) | (0.006) | (0.039) | (0.040) | (0.039) |
| Prior follow | 0.144*** | 0.145*** | 0.145*** | 0.848*** | 0.858*** | 0.853*** |
| | (0.033) | (0.033) | (0.033) | (0.165) | (0.166) | (0.166) |
| Startup 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 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 |
|---|---|---|---|---|---|---|---|---|---|
| | N | mean | median | st. dev. | N | mean | median | st. dev. | test p |
| # 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, pre-round funding 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.

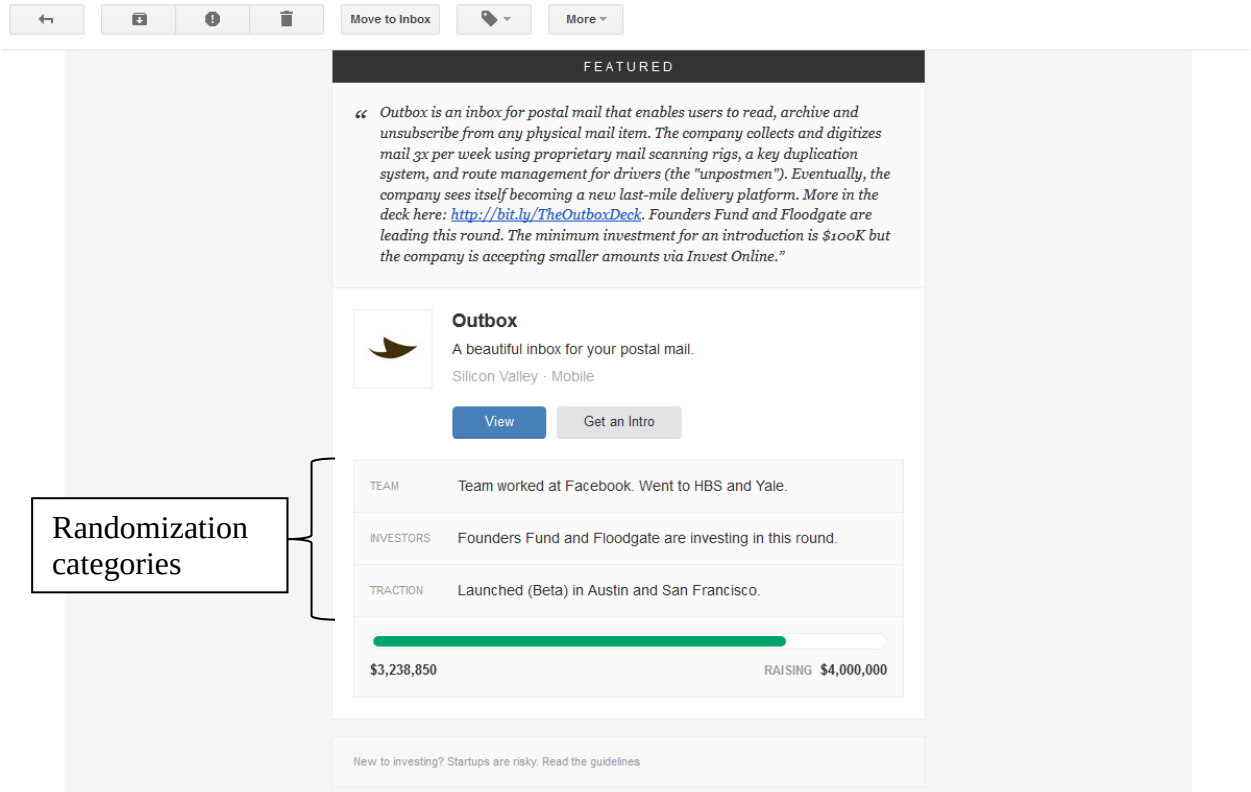

**Figure 2: Distribution of investor signal measure**

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. The signal ranges from zero to ten. See the main text for a description of the algorithm used to compute the signal.