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Abstract

We analyze a field experiment conducted on AngelList Talent, a large online search platform for startup jobs. In the experiment, AngelList randomly informed job seekers of whether a startup was funded by a top-tier investor and/or was funded recently. We find that the same startup receives significantly more interest when information about top-tier investors is provided. Information about recent funding has no effect. The effect of top-tier investors is not driven by low-quality candidates and is stronger for earlier-stage startups. The results show that venture capitalists can add value passively, simply by attaching their names to startups.

JEL Classification: G24, L26, J22, J24, C93
Keywords: Venture Capital, Startup Labor Market, Human Capital, Job Search, Randomized Field Experiment, Certification Effect

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1 Introduction

It is widely believed that venture capitalists (VCs) actively add value to startups beyond the funding they provide. For example, VCs may provide advice, connect startups with individuals in their networks, or make changes to management when necessary. A large and growing literature documents these activities, shows that they have real effects, and provides evidence that startups are willing to give up equity in exchange for them (Lerner, 1995; Kortum and Lerner, 2001; Hellmann and Puri, 2002; Hsu, 2004; Sørensen, 2007; Bernstein et al., 2016). However, it is also possible that VCs add value passively as well, simply by attaching their names to startups. Reputable VCs may attract important resources to their portfolio companies, like high-quality employees, customers, suppliers, or strategic partners. In this way, investors may help startups to overcome the "cold start" challenge they face, namely convincing various stakeholders to work with a firm that has little to no track record. While the potential for such passive value adding by VCs has long been discussed, there remains scant empirical evidence on whether it actually occurs or is important in practice. In this paper, we fill this gap by using a field experiment to study whether reputable VCs passively attract talented employees to their portfolio companies.

Whether employees are drawn to startups backed by reputable VCs is theoretically ambiguous. On the one hand, potential employees may believe that startups funded by reputable VCs are more likely to succeed, or else, that their experience working at such startups will be more valued by the labor market, regardless of startup success. On the other hand, it is also possible that potential employees do not understand the nuances of the venture capital industry and thus ignore it when deciding where to work, or that they do not believe that venture funding provides much information on top of what they already know. Finally, even if potential employees are drawn to startups backed by reputable VCs, there is a question of whether these are the employees that matter. If reputable VCs only attract low-quality job candidates that are unlikely to be hired, this may not meaningfully help the startups these VCs invest in.

Anecdotally, practitioners are split. Some claim that VC funding matters a lot for startup recruiting. For example, in a case study of Nerdwallet's talent reboot, First Round Capital claims that, "because Nerdwallet had never raised money, it never got the buzz or the coverage that usually comes with a check. Without being able to point to prestigious investors...it lacked the cache that, for better or worse, most technical talent looks for in a startup."[1] In contrast, Costanao Ventures claims that it is a myth that the "cool factor" associated with being a "hot, venture-backed startup" brings a lot of candidates. Rather, in their view, "a great product, team, culture, and category do more than [a] VC's brand."[2]

The question of whether reputable VCs matter for startup recruiting is difficult to answer empirically due to both data limitations and identification issues. In terms of data limitations, it is typically hard to observe talent flows to startups. It is usually only possible to obtain data on a startup's founders and management but not the rest of its employees. Moreover, even with data on non-founder employees, it would still only be possible to observe those who were actually hired, not all those who applied or indicated interest. This makes it difficult to estimate how the talent available to startups relates to their investors.

In terms of identification, there are also many potential endogeneity issues involved in

[1]https://firstround.com/review/the-total-talent-reboot-how-this-startup-overhauled-its-workforce/

[2]https://medium.com/costanoa-ventures/busting-myths-about-startup-success-in-attracting-talent-198deee1d399

estimating the effect of VCs on recruiting. Most obviously, firms with better prospects for success may attract both reputable VCs and talent, leading to a positive correlation between the two without a causal relationship necessarily being present. In addition, startups with worse funding could be equally attractive to employees but may choose to hire fewer employees, or lower-quality employees, due to financial constraints. In other words, venture capital may affect startups' human capital through a labor demand channel rather than a labor supply channel.

In this paper, we address these data and identification challenges by analyzing a field experiment conducted by AngelList Talent. AngelList Talent is a major online search platform for startup jobs. Startups with job openings can post them on the site, and those interested in working for a startup can search these postings and apply. Beginning in February 2020, AngelList Talent began adding "badges" to their job search results. One badge highlighted whether a job was associated with a startup that was funded by a top-tier VC. A separate badge highlighted whether a job was associated with a startup that recently closed on a round of VC funding. The visibility of each type of badge was randomly enabled at the user level. Thus, a user with the top investor (recently funded) badge feature enabled would see the badge for all startups that merited it, while a user with the feature disabled would never see it.

This experiment allows us to assess how the attractiveness of a startup to potential employees depends on each dimension of VC funding information. It overcomes the aforementioned data limitations by allowing us to actually observe the interest of potential employees in a startup. In the AngelList data, we can observe clicks for further information, clicks to begin the application process, and clicks to submit an application. The experiment also overcomes identification issues by allowing us to observe how potential employee interest *in the same startup* changes when positive funding information about that startup is randomly provided.

While it would be difficult to experimentally manipulate the actual funding histories of startups, the experiment we analyze instead manipulates the accessibility of this information. This design allows us to assess the importance of the information to job seekers. For example, if potential employees do not care about whether a startup is funded by a top-tier VC, highlighting this fact with a badge should have no effect. However, if they do care, making this information more accessible should influence their level of interest. Of course, it is possible that some users already know the information encoded in the badges. However, this would simply mean that we would underestimate the effect of this information on employee interest in startup job postings.

Our main finding is that reputable VCs do passively attract employees to their portfolio companies. Specifically, we find that the same startup receives significantly more interest from potential employees when it is represented with the top investor badge than when it is not. The magnitudes are economically large. The top investor badge causes a 30% increase in the probability of a user clicking on a job posting, relative to base rates. This is driven by a 26% increase in the probability of a click for further information about a job, a 35% increase in the probability of a click to begin the application process, and a 67% increase in the probability of actually submitting an application, when compared to base rates. These results show that employees prefer to work at startups funded by top-tier investors. Interestingly, we find no significant effect of the recently-funded badge on employee interest, nor any significant interaction between the effect of the recently-funded badge and the effect of the top-investor badge. These findings suggest that employees care much less about whether a startup was recently funded than who it was funded by. The lack of an effect of the recently-funded badge also shows that badges do not mechanically increase interest simply by drawing visual attention. Rather, the top-investor badge seems to have an effect due to the specific information that it encodes.

These baseline results are robust to a variety of sample restrictions and specifications. Notably, since the experiment spanned the start of the COVID-19 pandemic, one concern may be that the results we find are specific to crisis times. However, we show that the results are similar prior to March 13, 2020, when a state of national emergency was first announced in the U.S. due to COVID-19. We further show that our estimated coefficients are highly stable when we add additional fixed effects or user- and job-level controls, as would be expected given the randomized nature of the treatment.

We then explore whether the effect of the top investor badge varies across startups with different characteristics. One might expect that potential employees would find the presence of top investors most informative for less-developed startups that are harder to evaluate. Consistent with this idea, we find that job seekers react more strongly to the top investor badge with it is associated with an early-stage startup (pre-Series-B) than with a later-stage one (post-Series-B).

We also explore whether the effect of the top investor badge varies across different types of job seekers. It seems plausible that those who are located in innovation hubs may be more familiar with venture capital and therefore may react more strongly to the presence of top investors. Moreover, in these regions, the supply of startups is significantly larger, which may lead job seekers to rely on additional information to screen startups in their job search. We therefore partition users in our sample into those who are located in innovation hubs (San Francisco Bay Area, New York, and Boston) and those who are not. Consistent with what one might expect, we find significantly stronger effects among candidates located closer to the bulk of venture capitalists.

One potential concern is that reputable VCs may primarily draw the interest of low-quality candidates. This could occur, for example, if low-quality candidates tend to chase past success while high-quality candidates try to independently assess a startup's prospects. In that case, the actual recruiting benefit associated with being funded by a top investor might be smaller than what our baseline results would at first suggest. However, we find that responsiveness to the top investor badge does not differ by candidate quality, measured in a variety of ways. Thus, top-tier investors seem to increase the size of the candidate pool, without changing the quality distribution of the pool.

Our paper provides insight into what drives talent flows to startups. Attracting talent is widely believed to be critical to a startup's success. Indeed, it is often claimed that people are a startup's most valuable asset, and that there is currently a skill shortage hindering startups from building products on time, and being able to market and sell those products.[3] Thus, a key challenge that startups face is how to convince talented individuals to work for them rather than pursuing other, potentially more stable, career opportunities. Yet, despite the apparent importance for startups of attracting talent, there has been very little research on what drives talent flows to these firms. We begin to shed light on this question by examining the role of venture funding.

[3]https://www.entrepreneur.com/article/244826
https://www.forentrepreneurs.com/recruiting/
https://medium.com/swlh/talent-wars-silicon-valleys-hiring-secret-450632dd4ca6
https://www.inc.com/tess-townsend/how-thumbtack-is-hacking-recruitment.html

This paper relates to a large literature investigating the extent to which VCs add value beyond the funding they provide (Lerner (1995); Kortum and Lerner (2001); Hellmann and Puri (2002); Hsu (2004); Sørensen (2007); Bernstein et al. (2016)). Our paper differs in that we focus on the question of whether VCs add value *passively*, by simply attaching their names to startups. While the possibility that VCs add value passively has long been discussed, this is the first paper, as far as we are aware, to provide direct causal evidence of passive value adding. Specifically, we show that top-tier VCs aid in recruiting, not only by actively convincing talented individuals in their network to join their portfolio companies, but also by passively attracting talented individuals from outside of their network. It seems plausible that similar effects extend to other outcomes as well such as attracting valuable customers, suppliers, or strategic partners.

This paper also relates to a line of research on VC "certification effects," which focuses on whether VCs help to mitigate informational asymmetries in IPOs (Megginson and Weiss (1991)). Our paper differs in that we consider whether such effects extend to potential employees of early-stage startups, who could play an important role in determining whether firms succeed or fail. We are also able to address the endogeneity of VC investment by analyzing a field experiment. Finally, our notion of passive value adding is also broader than that of certification. Under a certification story, potential employees would be attracted to startups funded by a top investor because they believe these investors are skilled at picking investments (i.e., "screening"). However, it is also possible that employees are attracted to these startups because they believe that top investors are skilled at actively adding value (i.e., "monitoring"). In the former case, passive value adding would occur independently from active value adding. In the latter case, passive value adding would serve as an amplifier of active value adding. The main goal of our paper is not to differentiate between these two possibilities but rather to show that passive value adding occurs.

This paper also relates to a literature investigating what attracts investors to startups (Pence (1982); MacMillan et al. (1985, 1987); Fried and Hisrich (1994); Kaplan et al. (2009); Bernstein et al. (2017)). We instead investigate what attracts employees to startups. It is possible that many of the same factors are important for both parties. For example, both investors and employees may look for startups with a strong founding team, a good product, or demonstrated traction. Instead of examining the effect of such attributes, we instead examine whether top-tier investors themselves attract employees, independent of startup attributes. Our results suggest the possibility of a positive feedback loop. For example, startups with strong founding teams may attract talent directly, but this effect may be amplified by the fact that they also attract top investors.

Finally, this paper relates to a literature on performance persistence among venture investment firms (Kaplan and Schoar (2005); Phalippou and Gottschalg (2009); Robinson and Sensoy (2013); Harris et al. (2014); Hochberg et al. (2014); Ewens and Rhodes-Kropf (2015); Braun et al. (2017); Korteweg and Sorensen (2017); Nanda et al. (2020)). In light of the fact that past performance does predict future performance among VCs, it may be rational for job seekers to be attracted to startups funded by VCs with good past performance. On the flip side, VCs with good past performance may be aided by reputation spillovers to their portfolio companies in achieving good future performance, even without superior skills or access to deals. Our results thus provide a new potential channel for performance persistence among VC firms.

The rest of the paper proceeds as follows. Section 2 provides background on the AngelList

Talent platform, Section 3 discusses the design of the field experiment that we study, along with our empirical approach, Section 4 discusses the data, Section 5 presents the results, Section 6 discusses potential mechanisms, and Section 7 concludes.

2 The AngelList Talent Platform

AngelList was originally founded in 2010 as a platform to connect startups with potential investors. In 2012, it expanded into startup recruiting. The original investment portion of the site, now called AngelList Venture, was separate from the recruiting portion of the site, AngelList Talent. Since its launch, AngelList Talent has rapidly grown in popularity, becoming an important part of the startup ecosystem. Over its lifetime, more than 10M job seekers have joined the platform, more than 100,000 startups have posted a job there, and more than 5M connections have been made between job seekers and startups.

The way that AngelList Talent works is fairly straightforward. Startups can post job openings, specifying their jobs' location, role, description, type (i.e., full-time/part-time), salary range, equity range, and other details. Job postings are also linked to AngelList startup profiles that provide further firm-level information, including funding status, size, industry, and team members. After job postings are reviewed for spam, they become live for search. Users can search live job postings, potentially specifying a variety of filters based on the job and startup characteristics above. Importantly for our purposes, a user must register on the site and provide basic resume information before s/he can perform a search. Thus, all searches can be linked to a user by AngelList—although user searches are not publicly visible to startups or other users.

After a user performs a search, the results are displayed. The results can be sorted by "Recommended" (i.e., jobs that AngelList thinks are best suited to the user's profile) or "Newest" (i.e., most recently posted). If there are multiple matching jobs for a given startup, they are displayed together in a group, even if the jobs rank very differently in terms of the sorting variable. The display rank of the startup's jobs is based on the highest-ranking matching job of the startup.

Users can engage with search results in multiple ways. First, they can click on the name/logo of the startup to get further information about the firm. Second, they can click on the job title to get further information about the position. Third, they can click on the "apply" button to begin the application process. The apply button is embedded in each search result and also appears on the startup profile and job profile pages just described. After clicking the apply button, users are taken to an application page, which may ask for further resume information and/or provide space for a cover letter. To complete the application process, users must fill out the required fields and click on the "send application" button. Approximately 70% of users who click on the apply button end up sending an application.

After a user sends an application to a startup, the startup can "request an introduction" to the user, "reject" the user's application, or do nothing—in which case the user's application is automatically rejected in 14 days. Requesting an introduction to a user allows the two parties to communicate directly. After this connection is made, the rest of the hiring process occurs outside of the platform. Thus, AngelList does not directly observe if a given candidate ends up being hired.

3 Experimental Design and Empirical Strategy

3.1 Randomized Badges

From February 5, 2020 to April 7, 2020, AngelList experimentally attached “badges” to some of their search results. These badges are small graphics meant to highlight certain types of positive information, if applicable, about the startup that posted the job. Two of the initial badges involved information about VC funding.[4]

The first badge highlighted startups funded by top-tier investors, with these investors identified to users through well-know previous portfolio companies. For example, startups funded by Kleiner Perkins received a badge with the text “Same Investor as Amazon” and startups funded by Accel Partners received a badge with the text “Same Investor as Facebook.” When a user’s mouse hovered over one of these badges, additional text would also appear providing the actual name of the investor. In the examples above, the additional text would read, “Kleiner Perkins invested in both [this startup] and Amazon” or “Accel Partners invested in both [this startup] and Facebook.” Table 1 provides the full list of top investors highlighted by AngelList during our sample period as well as their associated badge text.[5]

AngelList’s decision to communicate investor quality through successful previous investments follows a common practice in the VC industry. Indeed, most top-tier VC firms list their successful previous investments prominently on their websites, and most GPs do likewise in their bios. Figure 1 shows the homepages of Kleiner Perkins and Accel Partners as examples. Notably, the Amazon logo is larger than the Kleiner Perkins logo on the front page

[4]Several additional badges were introduced later in 2020 but were not part of the experiment studied in this paper.

[5]If a startup had multiple top investors, the badge corresponded to the one that invested in the earliest round of the startup.

of their website and the Amazon logo also appears multiple times. Table 1 provides a more comprehensive look at how prominently the investors highlighted by AngelList display their former portfolio companies on their own websites. Approximately 70% of these VCs provide this information on the front page of their website and all but one provide this information within one click—with the one exception being Benchmark Capital, which does not have a website.[6]

The second badge introduced by AngelList highlighted startups that had raised funding in the past six months. This badge had the text "Recently Funded" and when a user's mouse hovered over it, additional text appeared saying, "Raised funding in the past six months." Figure 2 provides an example showing both badges.

Each badge was initially introduced in a randomized fashion, with randomization occurring at the user level. The two badges were considered two independent "features," and each feature was randomly enabled for a user with a probability of 50%. Thus, a user with the top-tier investor (recently-funded) badge feature enabled, would see the badge for all startups that merited it, while a user with the feature disabled would never see it. To be clear, the randomization never led false badges to be shown. It only led true badges not to be shown. Badge visibility for a user remained consistent across different searches and sessions. This was possible due to the fact that searches can only be performed by logged-in users as discussed previously.

[6]As another example, the most famous annual ranking of VC investors—Forbes' Midas List—ranks investors by their portfolio companies that achieved a successful exit or a large increase in private valuation. Each investor on the list is mentioned with a notable deal he/she is known for. See https://www.forbes.com/midas/.

3.2 Did Users Understand the Meaning of the Badges?

One potential concern is that users may not have fully understood the meaning of the badges. If they wanted further information they could have hovered over them to get a more detailed description. However, we cannot observe whether a user hovered over a badge, as AngelList did not track this. There is likely more scope for misunderstanding with respect to the top investor badge than the recently funded badge. As discussed above, top investors were identified to users through well-known previous portfolio companies. This raises the possibility that users may have misunderstood the relationship between the startup offering the job and the former portfolio company referenced in the badge. For example, they may have taken the "Same Investor as Amazon" badge to mean that Amazon was an investor in the startup, or else that the startup was a part of Amazon.

Feedback from users suggests that they understood the meaning of the badges. A feedback link was placed next to the badges to allowed users to express their thoughts about the usefulness of the badges. In free-form comments, no one complained of not understanding the meaning of either badge. Overall, 138/175(=79%) of respondents said they found the top-investor badge helpful and 82/93(=93%) of respondents said they found the recently-funded badge helpful. Of course, there is likely selection bias in terms of who chose to provide feedback and users may also have misunderstood the badges without realizing it.

To further explore the possibility that users may have misunderstood the top investor badge, we conducted a separate survey using Amazon Mechanical Turk (MTurk).[7] Although the MTurk respondents are different from the AngelList users in our sample, if anything,

[7]We filtered participants to include only those residing in the U.S. We also required participants to have a track record of high-quality work on MTurk (>50 Approved HITs with HIT approval rate > 90%).

they are likely to be more prone to misunderstanding the top investor badge. This is true for at least three reasons. First, MTurk respondents are likely to be less sophisticated or familiar with startups/VCs than users on AngelList Talent. As shown in Panel A of Appendix Table A.1, MTurk respondents are much less educated and less concentrated in innovation hub states (CA, NY, MA) than AngelList users. Second, in the survey, respondents do not have the option to hover over the badge for further information. Third, responding to an MTurk survey is a much lower-stakes task than searching for a job. Hence, the survey results plausibly provide an upper bound on the degree to which the badge was misunderstood among those in our AngelList sample.

Appendix Figure A.1 provides a screenshot of the survey. We showed respondents an example job listing by the startup Modern Health and asked them what they thought the badge "Same Investor as Amazon" meant. Respondents could choose from one of the following four options, the first three of which were presented in randomized order: (1) "Amazon is an investor in the startup Modern Health"; (2) "The startup Modern Health has the same investor that Amazon had when it was a startup"; (3) "The startup Modern Health is a subsidiary of Amazon"; (4) "Other." We ran the survey until we reached 300 responses. Panel B of Appendix Table A.1 shows the results. Overall, 92% of respondents correctly understood the meaning of the badge, choosing the interpretation that Modern Health has the same investor that Amazon had (column 1). This number was slightly higher for more educated respondents (columns 2-3), women (columns 4-5), and younger respondents (columns 6-7). The percentage answering correctly was also much higher for respondents in innovation hub states (i.e., CA, NY, MA) than for those in non-hub states (98.2% vs. 90.7%, columns 8-9). These results suggest that misunderstanding of the badge is relatively rare, and should be even rarer among the job seekers in our AngelList sample.

3.3 Empirical Specification

Without an experiment, making comparisons across startups with and without each badge would be problematic. It may be that startups funded by top-tier investors and/or startups funded more recently draw more interest due to being higher quality rather than anything to do with the badges. In other words, firms with better prospects for success may both attract venture capital and talent, leading to a positive correlation between the two without a causal relationship necessarily being present. The above experimental design is powerful in that it allows us to make within-startup comparisons. In particular, we can compare how potential employee interest in the *same startup* changes when the startup is displayed with and without each badge. We do this by including startup fixed-effects in all regressions. Specifically, at the user-search-startup level, we estimate equations of the form:

$$Interest_{ijs} = \alpha \times TopInvestorBadge_{ijs} + \beta \times RecentlyFundedBadge_{ijs} + \eta_j + \epsilon_{ijs}, \quad (1)$$

where s indexes searches, $Interest_{ijs}$ is a measure of user i's interest in startup j following search s, $TopInvestorBadge_{ijs}$ is an indicator equal to one if user i saw startup j represented with a top investor badge following search s, $RecentlyFundedBadge_{ijs}$ is defined analogously for the recently-funded badge, and η_j is a startup fixed effect. We cluster standard errors at the startup level.

3.4 Interpretation of Estimated Effects

To interpret the estimated effects, it is useful to compare our experiment with a hypothetical experiment where some startups are randomly funded by top-tier VCs and others by average VCs—with this information highlighted in job postings and search results. By comparing the treatment and control groups in this hypothetical experiment, it would be possible to estimate how much additional employee interest the startups funded by top-tier VCs garnered due to reputation spillovers from their investors. However, such a hypothetical experiment would likely be infeasible, as top-tier VCs would not be willing to invest randomly. Therefore, in our experiment, AngelList instead randomly manipulated the *accessibility* of startup funding histories rather than the funding histories themselves. Nonetheless, the effects that we estimate in our experiment should be closely related to those that we would estimate from the hypothetical experiment. In the hypothetical experiment, we would be comparing startups that are known to be funded by top-tier VCs with similar startups that are known to be funded by average VCs. In our experiment, we instead compare startups that are known to be funded by top-tier VCs (due to the inclusion of a badge) with the same startups funded, in expectation, by an average VC (due to the omission of a badge).[8]

One caveat to the above interpretation of our estimates is that it is possible that some users already knew the funding histories of some of the startups in their search results. In the extreme case, if all users already knew the funding histories of all the startups in their search results, we would estimate no effect in our experiment, even though we might still

[8]The omission of a badge should not suggest to users that the startup was funded by a non-top-tier VC because users who did not see this badge for one startup also did not see it for any startup. Therefore, the omission of a badge should instead suggest to users that the startup was funded by an average VC in expectation.

have estimated a positive effect in the hypothetical experiment. While information about startup funding histories is by and large publicly available, it seems plausible that many job seekers would not know this information in advance of their searches. There are a large number of startups on AngelList and many are not particularly well-known. In addition, even for well-known startups, many job seekers are still likely not informed about their funding histories. Most importantly, the fact that some users may already have known the information encoded by the badges simply means that we may underestimate the effect of this information on employee interest in startups. Thus, our estimates could be argued to represent a lower bound.

4 Data

The data we use in this paper were provided directly by AngelList and were collected by their backend system. In these data, we can observe all user searches and clicks along with their corresponding time stamps. We can also observe all jobs that were live at the time of each search, the badges associated with each job, and whether each type of badge was visible to the user performing the search.

As shown in equation 1, our baseline analysis is at the user-search-startup level. An alternative level of observation would be the user-search-job level. However, for many types of user clicks following a search, we can only observe the startup that was clicked on rather than the job. In addition, AngelList displays search results for the same startup grouped together, and the badges only vary at the startup level rather than the job level. Therefore, we consolidate all jobs from the same startup into a single observation.[9]

AngelList does not directly track the search results that a given search yielded. Instead, we reconstruct these results based on the jobs that were live when the search occurred. That is, for a given search, we find all matching jobs that were live at the time of the search and use these as the basis of the search results. We then reconstruct the order of the search results based on the time that the job was posted on AngelList, with the most recently-posted job first. This sort order should precisely match what the user saw for searches sorted by "Newest." It should also roughly match searches sorted by "Recommended," as recency is the most heavily weighted factor in the recommendation algorithm.[10]

AngelList also does not track the number of search results a user viewed following a search, as the results are not paginated but rather keep appearing continuously as a user scrolls down. In our baseline analysis, we limit the sample to the top 50 search results according to our inferred sort order. We also show that our results are robust to instead limiting the sample to the top 25 or top 100 inferred search results.

We apply several restrictions on the searches that we include in our analysis. First, we limit the sample to searches by users located in the United States in order to ensure that our findings do not reflect a mix of countries with very different startup ecosystems. Second, we exclude the top 1% of users in terms of their maximum number of searches in a single day during the sample period. This is done to limit the influence of fake users (i.e., bots) that might be scraping the AngelList website. Third, we only include basic searches in which a user specifies a location and a role without other filters.

[9]When we control for job characteristics in some specifications, we use average job characteristics collapsed to the user-search-startup level.

[10]AngelList could not provide the precise algorithm used for the recommended ordering.

AngelList's data record many extraneous searches because there is no search button that launches a search. Rather, search results are updated in real time as users update their filters and as they scroll through the results. Therefore, we exclude from the analysis searches that are followed by a different search in less than one minute, as these likely reflect intermediate searches that occurred as a user was assembling their desired combination of filters. We also consolidate repeat searches occurring consecutively, as these likely reflect reloads that occurred as a user was scrolling through the results. Overall, we are left with a sample of 8,187 users who performed 15,221 searches that yielded 17,069 startups (in the top 50 results) during our sample period.

5 Results

5.1 Summary Statistics

We begin by presenting various summary statistics for our sample. Table 2 shows summary statistics at the user level. Panel A shows that the average candidate in our sample has approximately 4.2 years of experience in her current field. About 29% of the users graduated from a U.S. top 50 university (based on U.S. World News and Report 2020 ranking), and 23% of them have a graduate degree.

Panel B shows the geographic distribution of the users in our sample across the 20 most common cities. New York and San Francisco have the highest percentage of users—each approximately 20%—followed by Los Angeles, Boston, and Seattle. Together, users in these five cities account for approximately 57% of the users in the sample (for whom a location is known). Users in the top 20 cities account for 76% of the users in our sample. Panel C shows the distribution of users across different roles. The most common role is Developer followed by Marketing, Operations, Product Manager, and Designer.

Table 3 shows summary statistics at the startup level. The sample consists of all startups that showed up in top 100 search results. Panel A shows the distribution of startups by market, across the top 20 most common markets. The most common areas that startups in the sample operate in are Mobile, E-Commerce, Enterprise Software, SaaS, and Health Care. Together, startups in these five markets account for approximately 32% of the startups in our sample (for which market is known). Startups in the top 20 markets account for 59% of the startups in our sample. Panel B shows that most of the startups in our sample are fairly small. Approximately 48% of the startups in our sample have 1-10 employees, and 77% have 1-50 employees.

Next, Table 4 shows summary statistics at the search result level (i.e., the user-search-startup level), which is the level of most of our analysis. Here we show descriptives limiting the sample to the top 25, top 50, and top 100 search results. Panel A shows summary statistics for the two dimensions of VC funding we study. The variable in the first three rows is an indicator equal to one if the startup in the search result was funded by a top-tier investor (hence meriting the top investor badge). The variable in the second three rows is an indicator equal to one if the startup in the search result had the top investor badge displayed. The variables in the next six rows are analogous but for recently-funded status and the recently-funded badge. Column 2 shows that approximately 14% of the search results were associated with startups funded by a top-tier investor, and approximately 7% of the results actually displayed the top investor badge. Approximately 4% of the search results were associated with startups that had been recently funded, and 2% of the results actually displayed the recently-funded badge. Columns 3–4 repeat the same analysis on the subsample of search results that were associated with startups funded by a top-tier investor. Columns 5-6 limit the sample to search results that were associated with startups that were recently funded. Approximately 12% of the top-tier investor search results were also recently funded. Approximately 41% of the recently-funded search results also had a top-tier investor. Consistent with the randomization described above, startups with a top investor (that were recently funded) display such a badge about 50% of the time in search results.

Panel B of Table 4 shows summary statistics for the various type of clicks that we study. The variable in the first three rows is an indicator for any click, in the next three rows it is an indicator for a click for further information, in the next three rows it is an indicator for a click to start the application process, and in the final three rows it is an indicator for a click to submit an application. As we would expect, the second column shows that click rates of all types are lower the more search results we include in the sample. For example, within the top 25 search results, there is a 2% probability of a result getting a click (of any type), but within the top 50 search results, there is a 1.6% probability of a result getting a click, and within the top 100 search results the click rate drops to 1.2%. These decreasing click rates likely reflect both a preference among users toward more recently posted jobs, and the fact that some users may not have even scrolled down to the lower-ranking results to consider clicking on them. In columns 3–4 and 5–6, we limit the sample to results that displayed the top investor badge or that did not display the top investor badge, respectively. Comparing columns 4 and 6, we see that within the top 50 results, the probability of a click (of any type) is 2.1% for results that displayed the top investor badge and 1.6% for results that did not display the badge. Similarly, in columns 7–8 and 9–10, we limit the sample to results that displayed the recently-funded badge or that did not display the recently-funded badge, respectively. Comparing columns 8 and 10, we see that within the top 50 results, the probability of a click (of any type) is 2.2% for results that displayed the recently-funded badge and 1.6% for results that did not display the badge.[11]

While the descriptive results from Panel B are suggestive of the badges attracting interest from potential employees, they are subject to endogeneity concerns. In particular, a search result has to be associated with a top-tier investor in order for it to display the top investor badge, and top-tier investors likely invest in higher-quality startups. Therefore users may tend to click on search results with the top investor badge not because of the badge but because of the quality of the underlying startup. Similar concerns may hold in comparing click rates across startups with and without the recently funded badge. To address this concern, we turn to within-startup comparisons in the next section.

Last, to verify the validity of our randomization, we test for sample balance across search results that enabled and disabled badge visibility. Table 5 shows the results. The top panel compares user-level characteristics and the bottom panel compares startup-level characteristics. As shown in columns 2 and 4, all user and startup characteristics are highly similar across search results that enabled and disabled the visibility of the top investor badge, with T-tests in column 5 showing insignificant differences in means. The same pattern holds for the recently funded badge in columns 6–10.

[11] Appendix Table A.2 shows the click rates by whether startups actually had a top investor or were recently funded.

5.2 Baseline Results

To address potential endogeneity concerns involved in making comparisons across startups, we estimate equations along the lines of Equation 1. Because equation 1 includes startup fixed effects, the coefficients on the two badge indicators are identified only from within-startup variation in the visibility of the badges. Table 6 shows our baseline findings from estimating this regression specification within the sample of top 50 search results. Column 1 shows that the visibility of the top investor badge increases the probability of a click by 0.54 ppt, with the estimated coefficient statistically significant at the 1% level. The estimated effect is also economically significant. The probability of a click on startups with a top investor in this sample is 1.82% (see Appendix Table A.2), therefore the coefficient on the top investor badge indicator implies a 30% increase in the probability of the click. Interestingly, we find no significant effect of the recently-funded badge on clicks. This finding suggests that employees care much less about whether a startup was recently funded than who it was funded by. The lack of an effect of the recently funded badge also shows that badges do not mechanically increase interest simply by drawing visual attention. Rather, the top investor badge seems to have an effect due to the specific information that it encodes. In column 2, we also include the interaction between the two badges in the specification. We do not estimate a significant coefficient on the interaction term. Therefore, it does not appear that being funded by a top-tier investor matters more if the funding was recent, nor that being funded recently matters more if it was by a top-tier investor.

Columns 3–6 decompose clicks into clicks for further information (i.e., clicks on either the startup or one of its jobs) and clicks to begin the application process. We find that both measures of potential employee interest increase in response to the top investor badge but not the recently-funded badge. In particular, clicks for further information increase by 0.28 ppt, or 26% relative to the mean, and clicks to begin the application process increase by 0.26 ppt, or 35% relative to the mean. In columns 4 and 6 we again find no evidence of interaction effects for these outcomes.

Finally, in columns 7–8, we examine application submissions. Again, we find that the top investor badge significantly increases application submissions, that the recently-funded badge has no effect, and that there is no interaction effect between the two badges. In terms of magnitudes, the estimates imply that the top investor badge increases application submissions by 0.29 ppt or 67% relative to the mean. This shows that our results do not simply reflect an increase in inconsequential clicks that are not followed up by more consequential actions.

Overall, these results show that the same startup receives significantly more interest from potential employees when it is represented with the top investor badge than when it is not. This evidence strongly suggests that the attractiveness of a startup to potential employees is affected by who has invested in it.

5.3 Robustness

We conduct a variety of robustness tests. In Panel A of Table 7, we first show that our baseline results are similar when we cluster standard errors by both startups and users. Because our results are based on a randomized experiment, they are likely to be internally valid. Confirming this internal validity, we show that our estimated coefficients are highly similar when we include additional fixed effects and controls. Specifically, Panel B of Table 7 additionally controls for search date fixed effects, result rank, user characteristics, and job characteristics (averaged to the search-startup level). The estimated coefficients are highly similar to those estimated in Table 6, lending support to the validity of our randomization.

One may still worry, however, about the external validity of our results. In particular, one concern is that, since the experiment spanned the start of the COVID-19 pandemic, the results we find may be specific to crisis times. In other words, it could be that employees do not care about a startup's investors during normal times, but they do during a crisis. To help address this concern, in Panel C of Table 7, we repeat our baseline analysis limiting the sample to dates prior to March 13, 2020—when a state of national emergency due to COVID-19 was first announced in the U.S. As can be seen, the results remain similar during the pre-COVID period, suggesting that potential employees care about who a startup's investors are, regardless of economic conditions.

Another potential concern is that AngelList does not track the number of search results a user viewed following a search, as the results are not paginated but rather keep appearing continuously as a user scrolls down. In our baseline analysis, we limit the sample to the top 50 search results according to our inferred sort order. In other words, we assume that users' choice sets following a search consisted of the 50 startups that most recently posted a job matching their search criterion. If users actually viewed fewer search results, this would not bias us toward finding an effect of the badges. In this case, many search results would not have been clicked because they were never seen, but this would be just as likely to happen for the search results with and without each badge. In Panel D of Table 7, we show that our baseline results are robust to instead limiting the sample to the top 25 or top

100 inferred search results. As we would expect, as we include more (fewer) search results, we estimate lower (higher) coefficients on the badge variables. However, these coefficients should be interpreted relative to lower (higher) baseline click rates.

5.4 Heterogeneity

5.4.1 Startup Financing Stage

Next, we examine how the effect of the top investor badge varies with a startup's financing stage. If a startup's investors provide a signal to job seekers about its prospects, then such a signal should be most valuable when the prospects of the startup are most uncertain—for example, when it is an early-stage startup. Hence, we should expect job seekers to react more strongly to the top investor badge when the badge is associated with an early-stage as opposed to a late-stage startup. Table 8 explores such heterogeneity. We partition our sample into early-stage and late-stage startups and repeat our baseline analysis in each subsample. We define early-stage (late-stage) startups as those that had not yet raised a Series B financing round (already raised a Series B financing round) at the time of the search. We find that job candidates indeed respond more strongly to the top investor badge when the associated startup is early-stage than when it is late-stage. For example, based on columns 1–2, candidates are 0.94 ppt more likely to click on an early-stage startup when it displays a top investor badge, but are only 0.33 ppt more likely to do so when the startup is late stage. This difference is statistically significant at the 1% level, as indicated by the p-value at the bottom of the table. We find similar results when looking at each type of click. These results suggest that reputable VCs add more value passively to earlier-stage startups than to later-stage ones. This finding is consistent with the idea that earlier-stage startups face greater uncertainty, or have shorter track records to convince job seekers to join.

5.4.2 Candidate Geography

We also examine whether the effect of the top investor badge varies across candidates in different types of geographies. It seems plausible that users who are located in innovation hubs may be more familiar with venture capital and therefore react more strongly to the presence of top investors. Moreover, in such regions, the supply of startups is significantly larger, allowing job seekers to be more selective, and therefore, more responsive to investor information. Therefore, we partition users in our sample into those who are located in innovation hubs (San Francisco Bay Area, New York, and Boston) and those who are not. The results are presented in Table 9. Consistent with what one might expect, we find significantly stronger reactions among candidates located closer to the bulk of venture capitalists.

5.4.3 Candidate Quality

Finally, we examine how the effect of the top investor badge varies with candidate quality. It is possible that being funded by a top-tier investor primarily draws the interest of low-quality candidates. For example, low-quality candidates may tend to chase past success, while high-quality candidates may believe that they can make their own assessment of a startup's prospects without considering VC funding. If that were the case, it would suggest that the actual recruiting benefit associated with being funded by a top-tier investor might be smaller than what our baseline results would at first suggest. On the other hand, it is also possible that being funded by a top-tier investor primarily draws the interest of high-quality candidates. For example, high-quality candidates may care about predicting the success of a startup, while low-quality candidates prioritize other considerations. Alternatively, high-quality candidates may be more knowledgeable about the performance persistence of top-tier VCs, while low-quality candidates may not understand VC funding and therefore ignore it.

In Table 10, we partition our sample into high- and low-quality candidates based on three proxies for candidate quality: whether the candidate is above the median in terms of years of experience in her current field, whether the candidate graduated from a top school, and whether the candidate holds a graduate degree. We repeat our baseline analysis in each subsample. Across all three measures, we find similar reactions to the top investor badge by high- versus low-quality candidates, with the difference in coefficients being statistically insignificant.

Lastly, we examine how startups respond to job applications. As mentioned in Section 2, startups can respond positively to an application by requesting an introduction to the candidate, which would lead to further interactions. Although we do not observe eventual hiring, intro requests are a necessary precursor to hiring, and can be viewed as another measure of candidate quality revealed by startups' preferences. In Table 11, we examine how badge display affects the likelihood of an applicant receiving an intro request from a startup. If the top investor badge mainly draws low-quality candidates that startups would not hire, then we should observe a lower intro request rate among applicants who saw the badge prior to applying relative to those who did not. Table 11 shows that this is not the case: the top investor badge did not lead to a significant decrease in the likelihood of receiving an intro request. This suggests that the marginal applicants drawn by the top investor badge are just as likely to be hired by the startup as other applicants.

Overall, these results confirm that being funded by a top-tier investor does not merely increase interest among low-quality candidates who would have been unlikely to have been hired anyway. Instead, top-tier investors seem to increase the size of the candidate pool without changing the quality distribution of the pool. These results also help to rule out the possibility that candidates do not understand what the top investor badge means, or else incorrectly react to it, as we would expect a stronger response from low-quality candidates in that case.

5.4.4 Investors

Finally, we also examine whether job seekers respond differentially to different top investors. Here, our goal is not to produce a ranking of the 23 VCs highlighted by AngelList, which we likely lack the power to do reliably. Rather, our goal is simply to test whether there is heterogeneity in the response to different investors, as one would expect if job seekers actually care about their identities. In other words, we test whether there is sufficient evidence to reject the null hypothesis of a homogeneous response to different investors.

The design of the experiment also allows us to perform a particularly strong test by looking at whether there are differential responses to *different investors that were represented with the same badge.* For example, four different VCs were represented with the "Same Investor as Facebook" badge, so we can examine whether some of these VCs drew more interest from job seekers than others. Such heterogeneity would provide particularly strong evidence that (1) users hover over the badges to learn the identity of the associated VC and (2) users care not only about the firm referenced in the badge (e.g., Facebook) but the actual VC identified in the text (e.g., Accel Partners).

We therefore estimate investor-specific effects of the top investor badge and test whether these effects differ systematically across investors. Appendix Table A.3 shows the p-values associated with these joint equality tests. Column 1 tests the joint equality of the badge effect across all 23 investors. Columns 2–3 test the joint equality across the 12 investors that had overlapping badge firms, controlling for badge-firm-specific effects (the effects of the remaining 11 investors are absorbed by badge-firm-specific effects). Across all specifications, we observe p-values well below 0.1, suggesting significant heterogeneity across investors, even within the same badge firm. These results provide evidence that users care about the identity of a startup's investors, not only the firm referenced in the badge.

6 Discussion of Potential Mechanisms

The main contribution of this paper is to show that reputable VCs significantly increase the ability of startups to attract talent, particularly at the earlier stages, before a startup has formed its own reputation or generated any observable success. Moreover, we find that such reputation spillovers are particularly helpful in innovation hubs, where competition for human capital may be particularly intense.

The question of what it is about these investors that workers find appealing is beyond the scope of our analysis. However, two potential mechanisms seem most likely. First, potential employees may be drawn to firms with top investors because they believe these firms are more likely to ultimately succeed. Second, potential employees may also believe that their experience at such firms will be more valued by the labor market, regardless of firm success. These two explanations are not mutually exclusive. We note that anecdotal evidence from the free-form feedback provided by users about the badges points more toward the first explanation. In particular, no users explicitly mentioned the second explanation, but several mentioned the first. For example, one user who was interviewed by AngelList stated, "I kind of judge a startup by who their investors are...there are really good VCs and some less well known ones...when I see people or funds investing in companies that I like and I've heard of and seen become successful it gives me a little bit more context of maybe how this startup in particular will perform in the future."

One could also further decompose the first mechanism. In particular, potential employees who are trying to predict the success of a startup may be attracted to startups funded by top investors because they believe these investors are skilled at picking investments (i.e., "screening"), or because they believe that top investors are skilled at actively adding value (i.e., "monitoring"). In the former case, passive value adding would occur independently from active value adding (this is commonly known as a "certification effect" in the literature). In the latter case, passive value adding would serve as an amplifier of active value adding. The main goal of this paper is not to differentiate these two possibilities, but rather to show that passive value adding occurs. Moreover, in practice, employees who are drawn to firms with top investors due to increased odds of success may not really think deeply about the reason for these increased odds (i.e., screening vs monitoring).

7 Conclusion

Attracting talent is widely believed to be critical to the success of a startup. However, this process can be hindered by the significant uncertainty surrounding early-stage businesses, making job seekers hesitant to supply their human capital to these firms. In this paper, we investigate whether VC investors' reputation can mitigate such uncertainty and facilitate startups' recruiting. We do so by analyzing a field experiment conducted by AngelList Talent, a large online search platform for startup jobs. In the experiment, whether a startup was funded by top-tier VCs and/or whether it was funded recently is randomly highlighted in search results. We find that the same startup receives significantly more interest from potential employees when the fact that it was funded by a top-tier VC is highlighted. In contrast, highlighting the fact that a startup was funded recently has no effect. The effect of top-tier investors is not driven by low-quality candidates, and is stronger for earlier-stage startups who face greater uncertainty. The results provide the first direct causal evidence of passive value adding by VCs and their impact on the labor market.

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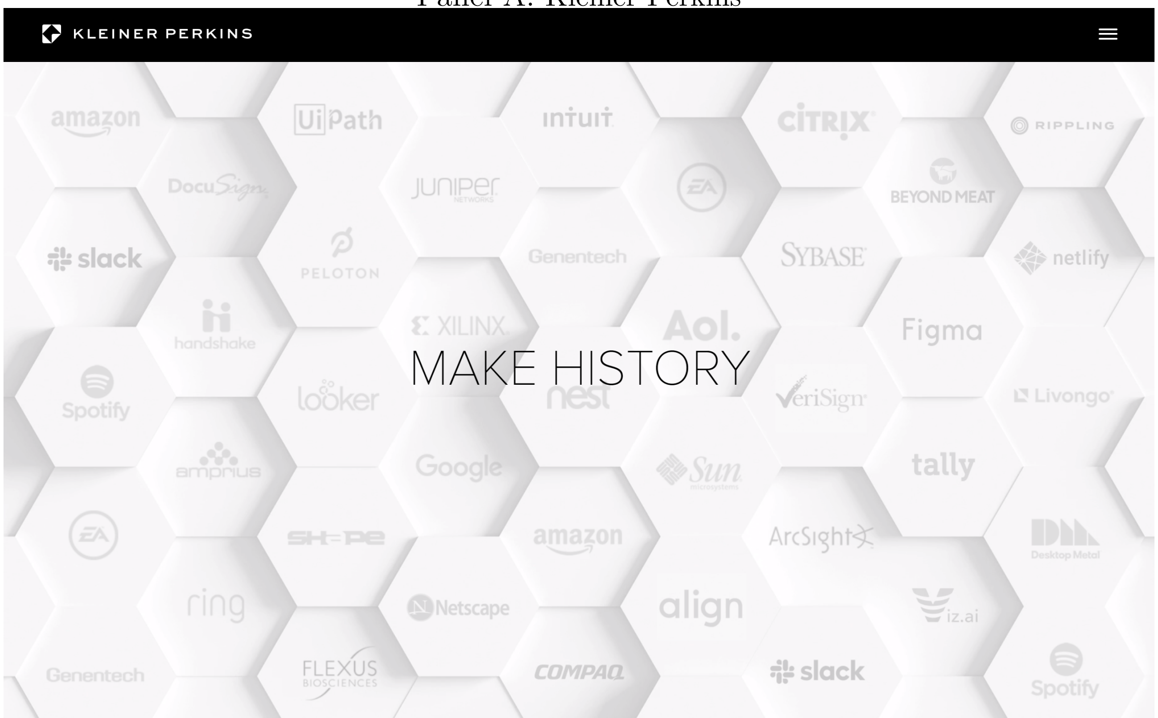
Figure 1
Examples of Top VCs' Homepage

Panel A shows the homepage of Kleiner Perkins (https://www.kleinerperkins.com/). Panel B shows the homepage of Accel Partners (https://www.accel.com/). Both websites were accessed on December 13, 2021.

Panel A: Kleiner Perkins



Panel A: Accel Partners

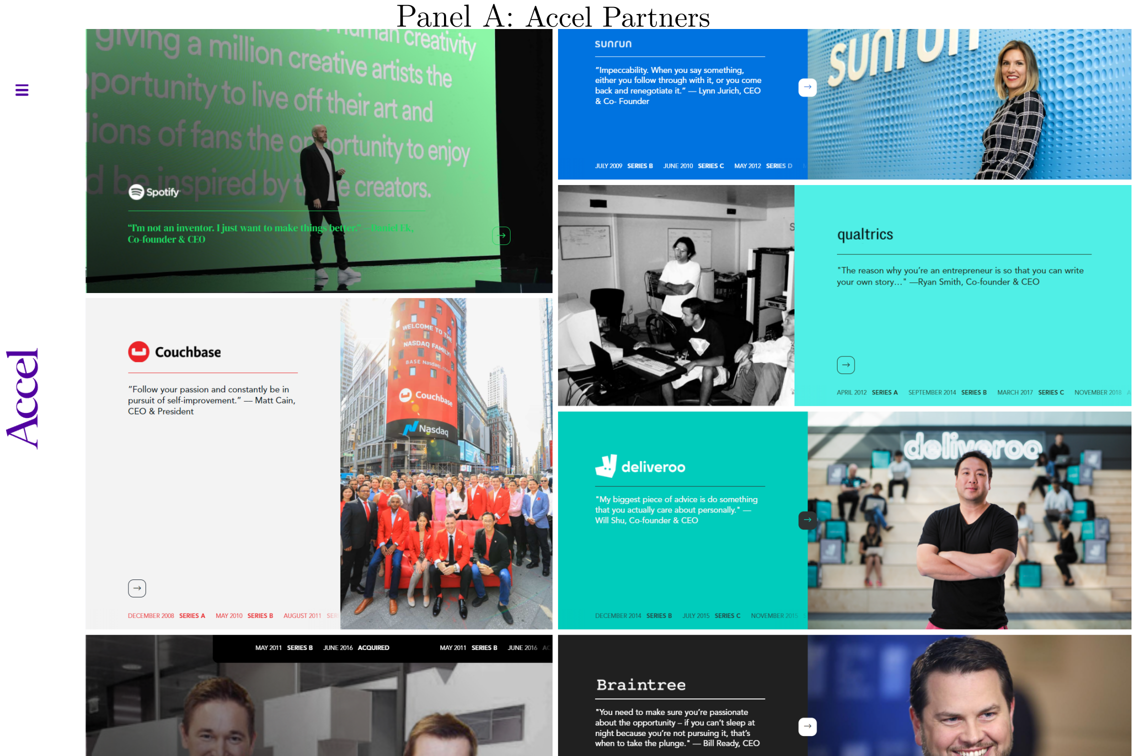


Figure 2
Example Job Listing with Badges

This figure shows an example job listing with a recently-funded badge and a top investor badge. The black bubbles show the additional text displayed when users hover their mouse on the badges.

Table 1
Top Investor List and the Display of Their Investments

This table shows the list of the 23 top investors and their well-known investments referenced in the top investor badge. The last two columns show where past investments are displayed on each investor's website and whether their general partners's profile pages mention the person's past successful investments. Note that Benchmark Capital does not have a functioning website (see https://www.businessinsider.com/benchmark-website-2012-11).

Badge Text (1)	Investor name (2)	Display of past investments (3)	Partner bio mentions past investments (4)
Same Investor as Airbnb	Andreessen Horowitz	Within one click	Yes (but not always)
Same Investor as Airbnb	Founders Fund	Within one click	Yes
Same Investor as Airbnb	Y Combinator	Front page	No
Same Investor as Amazon	Kleiner Perkins	Front page	Yes
Same Investor as Apple	Index Ventures	Front page	Yes
Same Investor as Facebook	Accel Partners	Front page	Yes
Same Investor as Facebook	First Round Capital	Within one click	No
Same Investor as Facebook	Greylock	Front page	Yes
Same Investor as Facebook	SV Angel	Front page	Yes
Same Investor as Flexport	8VC	Front page	Yes (but not always)
Same Investor as Groupon	Battery Ventures	Front page	Yes
Same Investor as Kayak	Norwest Venture Partners	Front page	Yes
Same Investor as Netflix	IVP	Front page	Yes
Same Investor as Paypal	Sequoia Capital	Front page	Yes
Same Investor as Snapchat	General Catalyst	Front page	Yes
Same Investor as Stripe	Khosla Ventures	Within one click	Yes (but not always)
Same Investor as Twitter	Slow Ventures	Within one click	No
Same Investor as Twitter	Union Square Ventures	Front page	Yes
Same Investor as Uber	Benchmark Capital	No website	No
Same Investor as Uber	Google Ventures	Front page	Yes
Same Investor as Uber	New Enterprise Associates	Front page	Yes
Same Investor as Warby Parker	Felicis Ventures	Front page	Yes
Same Investor as Yelp	Bessemer Venture Partners	Within one click	Yes

Table 2
User Summary Statistics

This table shows summary statistics for the AngelList Talent users in our sample at the user level. Panel A shows summary statistics for various measures of user quality. *Experience* is the number of years of experience a candiate has in her current field, *Top School* indicates that the candidate graduated from a U.S. top 50 university based on U.S. World News and Report 2020 ranking, and *Has Grad Degree* indicates that a candidate holds a graduate degree. Panel B shows the geographic distribution of users across the 20 most common cities. Panel C shows the distribution of users across the top 20 most common roles.

Panel A: User Experience and Quality

	Obs	Mean	Std. Dev.
Experience	8,187	4.178	3.333
Top School	8,187	0.290	0.454
Has Grad Degree	8,187	0.229	0.420

Panel B: Distribution of Users Across Geographies (Top-20)

	Freq	Percent
New York	1,579	20.31
San Francisco	1,504	19.34
Los Angeles	698	8.98
Boston	412	5.30
Seattle	252	3.24
Chicago	226	2.91
Austin	182	2.34
Atlanta	151	1.94
San Diego	135	1.74
Denver	116	1.49
Washington DC	116	1.49
Dallas	96	1.23
Philadelphia	94	1.21
Portland	87	1.12
Houston	79	1.02
Miami	51	0.66
Minneapolis	47	0.60
Boulder	46	0.59
Phoenix	42	0.54
Pittsburgh	38	0.49
Total	5,951	76.53

Table 2
(Continued)

Panel C: Distribution of Users Across Roles (Top-20)

	Freq	Percent
Developer	1,125	14.03
Marketing	714	8.90
Operations	518	6.46
Product Manager	462	5.76
Designer	396	4.94
Sales	382	4.76
UI/UX Designer	353	4.40
Data Scientist	331	4.13
Customer Service	299	3.73
Finance	288	3.59
Business Development	270	3.37
Business Analyst	266	3.32
Full Stack Developer	235	2.93
Project Manager	213	2.66
Frontend Developer	162	2.02
Content Creator	160	2.00
CEO	141	1.76
Operations Manager	137	1.71
Recruiter	120	1.50
Human Resources	116	1.45
Total	6,688	83.39

Table 3
Startup Summary Statistics

This table shows summary statistics at the startup level. The sample consists of all startups that show up in top 100 search results. Panel A shows the distribution of startups across the top 20 most common markets. Panel B shows the distribution of startups across different size categories, where size is measured in terms of the number of employees.

Panel A: Distribution of Startups Across Markets (Top-20)

	Freq	Percent
Mobile	1,019	9.21
E-Commerce	775	7.00
Enterprise Software	767	6.93
SaaS	534	4.83
Health Care	465	4.20
Financial Services	331	2.99
Software	285	2.58
Education	282	2.55
Technology	234	2.11
Marketplaces	223	2.02
Social Media	206	1.86
Big Data	186	1.68
Digital Media	184	1.66
Web Development	184	1.66
Real Estate	173	1.56
Health and Wellness	172	1.55
Advertising	147	1.33
Sales and Marketing	141	1.27
Food and Beverages	107	0.97
Internet of Things	104	0.94
Total	6,519	58.91

Panel B: Distribution of Startups Across Number of Employees

	Freq	Percent
1-10	8,873	47.65
11-50	5,715	30.69
51-200	2,564	13.77
201-500	746	4.01
501-1000	332	1.78
1001-5000	247	1.33
5000+	146	0.78
Total	18,623	100.00

Table 4
Search Result Summary Statistics

This table shows summary statistics at the search result level (i.e., the user-search-startup level). Descriptives are shown limiting the sample to the top 25, top 50, and top 100 search results. Panel A shows summary statistics for the two dimensions of VC funding we study. The variable in the first three rows is an indicator equal to one if the startup in the search result was funded by a top-tier investor. The variable in the second three rows is an indicator equal to one if the startup in the search result had the top investor badge displayed. The variables in the next six rows are analogous but for recently-funded status and the recently-funded badge. Columns 3–4 limit the sample to search results that were associated with startups funded by a top-tier investor. Columns 5–6 limit the sample to search results that were associated with startups that were recently funded.

Panel A: Badges

	All		Top Investor		Recently Funded	
	Obs	Mean	Obs	Mean	Obs	Mean
	(1)	(2)	(3)	(4)	(5)	(6)
Top Investor						
Top 25 Results	287,059	0.139	39,995	1.000	11,364	0.409
Top 50 Results	477,639	0.138	66,086	1.000	18,979	0.409
Top 100 Results	755,799	0.137	103,607	1.000	30,359	0.440
Top Investor Badge						
Top 25 Results	287,059	0.070	39,995	0.504	11,364	0.207
Top 50 Results	477,639	0.069	66,086	0.502	18,979	0.205
Top 100 Results	755,799	0.069	103,607	0.501	30,359	0.222
Recently Funded						
Top 25 Results	287,059	0.040	39,995	0.116	11,364	1.000
Top 50 Results	477,639	0.040	66,086	0.117	18,979	1.000
Top 100 Results	755,799	0.040	103,607	0.129	30,359	1.000
Recently Funded Badge						
Top 25 Results	287,059	0.020	39,995	0.061	11,364	0.512
Top 50 Results	477,639	0.020	66,086	0.061	18,979	0.511
Top 100 Results	755,799	0.021	103,607	0.066	30,359	0.512

Table 4
(Continued)

Panel B shows summary statistics for the various type of clicks that we study. The variable in the first three rows is an indicator for any click, in the next three rows it is an indicator for a click for further information, in the next three rows it is an indicator for a click to start the application process, and in the final three rows it is an indicator for a click to submit an application. In columns 3–4 and 5–6 we limit the sample to results that displayed the top investor badge or that did not display the top investor badge, respectively. Columns 7-10 are defined analogously for recently funded badge. *Any Click* is an indicator for whether the search result was clicked, *Info Click* is an indicator for whether the search result was clicked for further information, *App. Click* is an indicator for whether the search result was clicked to begin the application process, *Applied* is an indicator for whether the user submitted an application, *Top Inv. Badge* is an indicator for whether the search result displayed the top investor badge, *Rec. Funded Badge* is an indicator for whether the search result displayed the recently-funded badge.

Panel B: Clicks

	All		Top Inv. Badge		No Top Inv. Badge		Rec. Funded Badge		No Rec. Funded Badge	
	Obs	Mean	Obs	Mean	Obs	Mean	Obs	Mean	Obs	Mean
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Any Click										
Top 25 Results	287,059	0.0205	20,154	0.0250	266,905	0.0202	5,821	0.0289	281,238	0.0204
Top 50 Results	477,639	0.0162	33,178	0.0208	444,461	0.0158	9,703	0.0220	467,936	0.0161
Top 100 Results	755,799	0.0124	51,909	0.0166	703,890	0.0121	15,551	0.0167	740,248	0.0123
Info Click										
Top 25 Results	287,059	0.0128	20,154	0.0155	266,905	0.0126	5,821	0.0179	281,238	0.0127
Top 50 Results	477,639	0.0098	33,178	0.0120	444,461	0.0096	9,703	0.0126	467,936	0.0097
Top 100 Results	755,799	0.0074	51,909	0.0093	703,890	0.0073	15,551	0.0093	740,248	0.0074
App. Click										
Top 25 Results	287,059	0.0078	20,154	0.0094	266,905	0.0076	5,821	0.0110	281,238	0.0077
Top 50 Results	477,639	0.0064	33,178	0.0087	444,461	0.0062	9,703	0.0094	467,936	0.0063
Top 100 Results	755,799	0.0050	51,909	0.0072	703,890	0.0049	15,551	0.0074	740,248	0.0050
Applied										
Top 25 Results	287,059	0.0050	20,154	0.0053	266,905	0.0050	5,821	0.0076	281,238	0.0049
Top 50 Results	477,639	0.0042	33,178	0.0050	444,461	0.0041	9,703	0.0066	467,936	0.0041
Top 100 Results	755,799	0.0034	51,909	0.0044	703,890	0.0033	15,551	0.0053	740,248	0.0033

Table 5
Sample Balance Test

This table tests sample balance across randomized enabling of badge visibility. The top panel compares user characteristics at the user level and the bottom panel compares characteristics of startups that showed up in top 50 search results at the startup level. Columns 1-5 focus on the top investor badge and columns 6-10 focus on the recently-funded badge. Columns 5 and 10 show the p-values associated with mean difference tests. *Top Inv. Badge Disabled* (*Rec. Funded Badge Disabled*) indicates that a user would not see a top investor badge (a recently-funded badge) even if the startup was funded by a top-tier investor (was recently funded). *Top Inv. Badge Enabled* (*Rec. Funded Badge Enabled*) indicates that a user would see a top investor badge (a recently-funded badge) if the startup was funded by a top-tier investor (was recently funded).

	Top Inv. Badge Disabled		Top Inv. Badge Enabled		P-val of	Rec. Funded Badge Disabled		Rec. Funded Badge Enabled		P-val of
	Obs	Mean	Obs	Mean	T-test	Obs	Mean	Obs	Mean	T-test
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
					User characteristics					
Experience	4,129	4.176	4,066	4.191	0.417	4,092	4.144	4,104	4.223	0.141
Top School	4,129	0.291	4,066	0.290	0.454	4,092	0.287	4,104	0.294	0.236
Grad Degree	4,129	0.224	4,066	0.235	0.111	4,092	0.222	4,104	0.236	0.063
Hub Cities	4,129	0.426	4,066	0.428	0.421	4,092	0.427	4,104	0.427	0.481
Developer	4,129	0.244	4,066	0.248	0.336	4,092	0.251	4,104	0.241	0.153
Marketing	4,129	0.102	4,066	0.102	0.494	4,092	0.103	4,104	0.101	0.424
Operation	4,129	0.079	4,066	0.081	0.372	4,092	0.081	4,104	0.080	0.420
Product manager	4,129	0.079	4,066	0.087	0.098	4,092	0.080	4,104	0.086	0.178
Designer	4,129	0.133	4,066	0.126	0.172	4,092	0.130	4,104	0.130	0.466
Sales	4,129	0.086	4,066	0.093	0.134	4,092	0.090	4,104	0.088	0.377
					Startup characteristics					
Employment	13,215	211.491	13,897	209.209	0.438	13,592	213.730	13,509	198.728	0.146
Post-B	13,910	0.102	14,654	0.099	0.178	14,329	0.100	14,246	0.100	0.458
Enterprise Software	13,910	0.046	14,654	0.044	0.207	14,329	0.045	14,246	0.045	0.429
Mobile	13,910	0.049	14,654	0.052	0.190	14,329	0.051	14,246	0.050	0.417
E-Commerce	13,910	0.045	14,654	0.046	0.306	14,329	0.046	14,246	0.046	0.479
Health Care	13,910	0.029	14,654	0.029	0.437	14,329	0.029	14,246	0.028	0.328
SaaS	13,910	0.053	14,654	0.051	0.184	14,329	0.052	14,246	0.052	0.475

Table 6
Baseline Results

This table shows our baseline results from estimating equation 1 within the sample of top 50 search results. Variables are defined in Table 4. Standard errors are clustered by startup. ***, **, and * indicate significance at the 1%, 5% and 10% level, respectively.

	(1) Any Click	(2) Any Click	(3) Info Click	(4) Info Click	(5) App. Click	(6) App. Click	(7) Applied	(8) Applied
Top Investor Badge	0.0054***	0.0055***	0.0028***	0.0029***	0.0026***	0.0026***	0.0029***	0.0029***
	(0.0011)	(0.0012)	(0.0008)	(0.0009)	(0.0008)	(0.0009)	(0.0008)	(0.0008)
Recently Funded Badge	0.0018	0.0020	0.0006	0.0009	0.0012	0.0011	0.0007	0.0008
	(0.0020)	(0.0022)	(0.0015)	(0.0016)	(0.0013)	(0.0014)	(0.0014)	(0.0015)
Top Investor Badge × Recently Funded Badge		-0.0009		-0.0015		0.0006		-0.0004
		(0.0035)		(0.0026)		(0.0027)		(0.0025)
Startup FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.059	0.059	0.059	0.059	0.040	0.040	0.041	0.041
Observations	477,639	477,639	477,639	477,639	477,639	477,639	477,639	477,639

Table 7
Robustness

This table shows the robustness of our baseline results in Table 6. Panel A clusters standard errors by both startup and user. Panel B additionally controls for user and job characteristics (averaged to the search-startup level) as well as search result rank and fixed effects for search date. Panel C limits the sample to dates prior to March 13, 2020, the date U.S. announced a state of national emergency due to COVID-19. Panel D limits the sample to top 100 and top 25 search results. Standard errors are clustered by startup in Panels B to D. ***, **, and * indicate significance at the 1%, 5% and 10% level, respectively.

Panel A. Double Cluster by Startup and User

	(1) Any Click	(2) Info Click	(3) App. Click	(4) Applied
Top Investor Badge	0.0054***	0.0028***	0.0026**	0.0029***
	(0.0016)	(0.0010)	(0.0012)	(0.0010)
Recently Funded Badge	0.0018	0.0006	0.0012	0.0007
	(0.0021)	(0.0015)	(0.0014)	(0.0014)
Startup FE	Yes	Yes	Yes	Yes
R-Squared	0.023	0.022	0.006	0.006
Observations	474,289	474,289	474,289	474,289

Panel B. Additional Controls

	(1) Any Click	(2) Info Click	(3) App. Click	(4) Applied
Top Investor Badge	0.0054***	0.0027***	0.0027***	0.0030***
	(0.0011)	(0.0008)	(0.0008)	(0.0008)
Recently Funded Badge	0.0022	0.0008	0.0013	0.0008
	(0.0020)	(0.0015)	(0.0013)	(0.0013)
Result Rank	-0.0005***	-0.0004***	-0.0002***	-0.0002***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
User Experience	-0.0004***	-0.0003***	-0.0001***	-0.0001*
	(0.0001)	(0.0000)	(0.0000)	(0.0000)
User from Top 50 School	0.0001	-0.0002	0.0003	0.0003
	(0.0004)	(0.0003)	(0.0003)	(0.0003)
User Has Grad Degree	0.0003	-0.0005	0.0008**	0.0002
	(0.0005)	(0.0004)	(0.0003)	(0.0003)
No Salary Info	-0.0054***	-0.0029**	-0.0025**	-0.0025**
	(0.0019)	(0.0014)	(0.0011)	(0.0011)
Ln(Salary)	0.0013***	0.0011***	0.0002	0.0002
	(0.0005)	(0.0004)	(0.0003)	(0.0003)
Equity Stake	-0.0000	0.0000	-0.0000	-0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Part-Time Job	-0.0028*	-0.0009	-0.0019**	-0.0009
	(0.0015)	(0.0011)	(0.0008)	(0.0008)
Remote Job	-0.0142***	-0.0104***	-0.0038***	-0.0038***
	(0.0014)	(0.0010)	(0.0007)	(0.0008)
Startup FE	Yes	Yes	Yes	Yes
Search date FE	Yes	Yes	Yes	Yes
R-Squared	0.028	0.025	0.008	0.007
Observations	477,639	477,639	477,639	477,639

Table 7
(Continued)

Panel C: Pre-COVID (before March 13, 2020)

	(1) Any Click	(2) Info Click	(3) App. Click	(4) Applied
Top Investor Badge	0.0052***	0.0027***	0.0026***	0.0033***
	(0.0013)	(0.0010)	(0.0009)	(0.0009)
Recently Funded Badge	0.0006	-0.0009	0.0016	0.0018
	(0.0023)	(0.0017)	(0.0015)	(0.0017)
Startup FE	Yes	Yes	Yes	Yes
R-Squared	0.069	0.070	0.047	0.050
Observations	345,438	345,438	345,438	345,438

Panel D: Alternative Result Rank Cutoffs

	Any Click		Info Click		App. Click		Applied	
	(1) Top 100	(2) Top 25	(3) Top 100	(4) Top 25	(5) Top 100	(6) Top 25	(7) Top 100	(8) Top 25
Top Investor Badge	0.0045***	0.0061***	0.0021***	0.0038***	0.0024***	0.0023**	0.0027***	0.0031***
	(0.0008)	(0.0016)	(0.0006)	(0.0013)	(0.0006)	(0.0011)	(0.0005)	(0.0011)
Recently Funded Badge	0.0015	0.0014	0.0005	0.0016	0.0010	-0.0002	0.0008	0.0002
	(0.0013)	(0.0029)	(0.0009)	(0.0023)	(0.0009)	(0.0018)	(0.0009)	(0.0020)
Startup FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.048	0.077	0.048	0.077	0.032	0.053	0.031	0.055
Observations	755,799	287,059	755,799	287,059	755,799	287,059	755,799	287,059

Table 8
Heterogeneity by Startup Financing Stage

This table repeats the analysis of Table 6 splitting the sample by startup's financing stage. *Early* indicates that a startup's financing stage at the time of search is before Series B. *Late* indicates that a startup's financing stage at the time of search is at or post Series B. P-value of difference in coefficients on *Top Investor Badge* across subsamples is reported at the bottom of the table. The sample only includes startups for which we have financing information. Standard errors are clustered by startup. ***, **, and * indicate significance at the 1%, 5% and 10% level, respectively.

	Any Click		Info Click		App. Click		Applied	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Financing Stage	Early	Late	Early	Late	Early	Late	Early	Late
Top Investor Badge	0.0094***	0.0033**	0.0051***	0.0016	0.0043***	0.0016	0.0056***	0.0014
	(0.0019)	(0.0014)	(0.0014)	(0.0010)	(0.0014)	(0.0010)	(0.0012)	(0.0010)
Recently Funded Badge	-0.0011	0.0074**	-0.0008	0.0034	-0.0003	0.0041*	-0.0005	0.0030
	(0.0023)	(0.0035)	(0.0018)	(0.0024)	(0.0015)	(0.0022)	(0.0017)	(0.0021)
Startup FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
P-Value of Difference	0.008	0.008	0.049	0.049	0.118	0.118	0.006	0.006
R-Squared	0.051	0.020	0.051	0.019	0.036	0.015	0.034	0.015
Observations	173,450	94,783	173,450	94,783	173,450	94,783	173,450	94,783

Table 9
Heterogeneity by User Geography

This table repeats the analysis of Table 6 splitting the sample by candidate location. Candidates are defines as being in an innovation hub if they are located in San Francisco Bay Area, New York, or Boston. ***, **, and * indicate significance at the 1%, 5% and 10% level, respectively.

	Any Click		Info Click		App. Click		Applied	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Innovation Hubs	Yes	No	Yes	No	Yes	No	Yes	No
Top Investor Badge	0.0082***	0.0007	0.0035***	0.0019	0.0047***	-0.0012	0.0044***	0.0001
	(0.0014)	(0.0017)	(0.0010)	(0.0015)	(0.0011)	(0.0010)	(0.0011)	(0.0009)
Recently Funded Badge	0.0006	0.0038	-0.0005	0.0026	0.0011	0.0013	0.0007	0.0008
	(0.0027)	(0.0033)	(0.0020)	(0.0026)	(0.0017)	(0.0018)	(0.0017)	(0.0020)
Startup FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
P-Value of Difference	0.000	0.000	0.345	0.345	0.000	0.000	0.001	0.001
R-Squared	0.017	0.038	0.021	0.039	-0.004	0.013	-0.001	0.012
Observations	249,996	227,643	249,996	227,643	249,996	227,643	249,996	227,643

Table 10
Heterogeneity by User Quality

This table repeats the analysis of Table 6 splitting the sample by various measures of candidate quality: above median number of years of experience in the candidate's current field (columns 1-2), graduated from a top 50 school (columns 3-4), or having a graduate degree (columns 5-6). Standard errors are clustered by startup. ***, **, and * indicate significance at the 1%, 5% and 10% level, respectively.

	Any Click					
	(1) Experienced	(2) Inexperienced	(3) Top Schools	(4) Non-Top Schools	(5) Grad Degree	(6) No Grad Degree
Top Investor Badge	0.0046**	0.0063***	0.0051**	0.0057***	0.0062***	0.0053***
	(0.0018)	(0.0015)	(0.0021)	(0.0013)	(0.0024)	(0.0013)
Recently Funded Badge	0.0020	0.0017	0.0027	0.0009	0.0120***	-0.0008
	(0.0032)	(0.0029)	(0.0038)	(0.0022)	(0.0045)	(0.0023)
Startup FE	Yes	Yes	Yes	Yes	Yes	Yes
P-Value of Difference	0.445	0.445	0.828	0.828	0.728	0.728
R-Squared	0.032	0.027	0.029	0.029	0.041	0.025
Observations	216,960	260,679	153,528	324,111	105,378	372,261

Table 11
Intro Request by Startups

This table examines the effect of badges on startups' likelihood of requesting introduction on the candidates who applied. The sample contains started applications in columns 1-2 and submitted applications in columns 3-4. The dependent variable is a dummy equal to one if the candidate received an intro request from the startup she applied to. Standard errors are clustered by startup. ***, **, and * indicate significance at the 1%, 5% and 10% level, respectively.

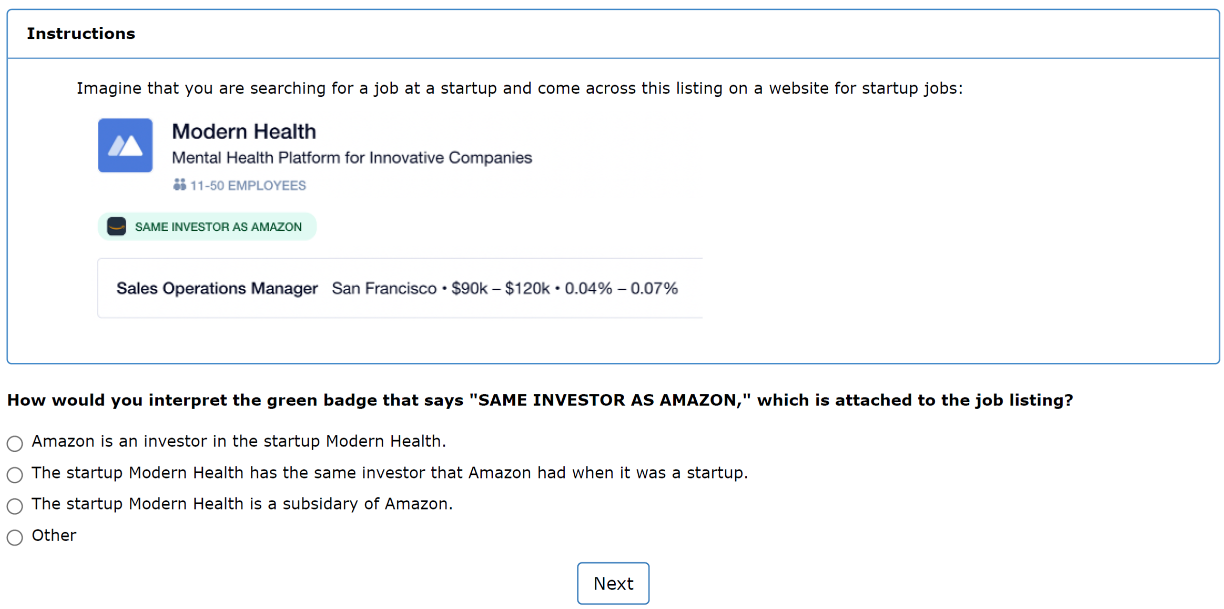
	(1)	(2)	(3)	(4)
	Request Intro			
Top Investor Badge	-0.0022	-0.0012	-0.0037	-0.0087
	(0.0090)	(0.0102)	(0.0146)	(0.0165)
Recently Funded Badge	0.0154	0.0158	-0.0197	-0.0283
	(0.0149)	(0.0170)	(0.0458)	(0.0467)
Startup FE	Yes	Yes	Yes	Yes
Search date FE	No	Yes	No	Yes
Sample	Started Applications		Submitted Applications	
R-Squared	0.253	0.262	0.323	0.320
Observations	3,043	3,043	2,829	2,829

Appendix For Online Publication

A Appendix Exhibits

Figure A.1
Survey Question on Interpretation of the Top Investor Badge

This figure shows the a screenshot of the survey we conducted on Amazon MTurk. The first three options were presented in a randomized order and respondents can choose only one of the four options.



Instructions

Imagine that you are searching for a job at a startup and come across this listing on a website for startup jobs:

Modern Health
Mental Health Platform for Innovative Companies
11-50 EMPLOYEES
SAME INVESTOR AS AMAZON

Sales Operations Manager San Francisco • $90k – $120k • 0.04% – 0.07%

How would you interpret the green badge that says "SAME INVESTOR AS AMAZON," which is attached to the job listing?

- ◯ Amazon is an investor in the startup Modern Health.
- ◯ The startup Modern Health has the same investor that Amazon had when it was a startup.
- ◯ The startup Modern Health is a subsidary of Amazon.
- ◯ Other

Next

Table A.1
Survey on Interpretation of the Top Investor Badge

This table presents the results of survey on MTurk respondents on their interpretation of the top investor badge. Appendix Figure A.1 shows a screenshot of the survey question. Panel A compares MTurk respondents to AngelList users in our sample along different demographics (we do not have information on the age of AngelList users). Columns 1 and 2 show the means and column 3 shows the p-values of cross-sample mean difference tests. Panel B shows the survey results. Column 1 presents the results for the full sample, columns 2-9 present the results for various subsamples by education, gender, age, and location. All numbers indicate the percentage of respondents choosing each answer in the sample. The last row indicates the number of respondents in that sample.

Panel A: MTurk Respondents vs. AngelList Users

	(1) MTurk respondents	(2) AngelList Users	(3) P-val of t-test
Graduate degree	0.073	0.229	0.000
Female	0.430	0.356	0.004
CA, NY, MA	0.180	0.527	0.000
Age>=45	0.323	N\A	
Observations	300	8,187	

Panel B: Survey Results

interpretation	(1) All	(2) BA & above	(3) Below BA	(4) Female	(5) Male	(6) Age<45	(7) Age>=45	(8) CA, NY, MA	(9) Other states
Modern Health has the same investor as Amazon	92.0%	92.4%	91.6%	93.0%	91.2%	92.1%	91.8%	98.2%	90.7%
Amazon is an investor in Modern Health	3.3%	3.2%	3.5%	2.3%	4.1%	3.0%	4.1%	0.0%	4.1%
Modern Health is a subsidary of Amazon	3.3%	3.8%	2.8%	4.7%	2.3%	3.5%	3.1%	1.9%	3.7%
Other	1.3%	0.6%	2.1%	0.0%	2.3%	1.5%	1.0%	0.0%	1.6%
No. of respondents	300	157	143	129	171	203	97	54	246

Table A.2
Click Rates by Whether Startups Had a Top Investor or Were Recently Funded

This table shows summary statistics for the various type of clicks that we study. The variable in the first three rows is an indicator for any click, in the next three rows it is an indicator for a click for further information, in the next three rows it is an indicator for a click to start the application process, and in the final three rows it is an indicator for a click to submit an application. In columns 3–4 and 5–6 we limit the sample to results associated with startups that had a top investor (hence meriting the top investor badge) or those that did not have a top investor, respectively. Columns 7-10 are defined analogously for whether startups were recently funded (hence meriting the recently-funded badge). *Any Click* is an indicator for whether the search results was clicked, *Info Click* is an indicator for whether the search result was clicked for further information, *App. Click* is an indicator for whether the search result was clicked to begin the application process, *Applied* is an indicator for whether the user submitted an application.

	All		Top Investor		No Top Investor		Recently Funded		Not Recently Funded	
	Obs	Mean	Obs	Mean	Obs	Mean	Obs	Mean	Obs	Mean
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Any Click										
Top 25 Results	287,059	0.0205	39,995	0.0221	247,064	0.0203	11,364	0.0265	275,695	0.0203
Top 50 Results	477,639	0.0162	66,086	0.0182	411,553	0.0159	18,979	0.0201	458,660	0.0160
Top 100 Results	755,799	0.0124	103,607	0.0144	652,192	0.0121	30,359	0.0152	725,440	0.0123
Info Click										
Top 25 Results	287,059	0.0128	39,995	0.0138	247,064	0.0126	11,364	0.0160	275,695	0.0126
Top 50 Results	477,639	0.0098	66,086	0.0107	411,553	0.0097	18,979	0.0117	458,660	0.0097
Top 100 Results	755,799	0.0074	103,607	0.0083	652,192	0.0073	30,359	0.0086	725,440	0.0074
App. Click										
Top 25 Results	287,059	0.0078	39,995	0.0083	247,064	0.0077	11,364	0.0105	275,695	0.0077
Top 50 Results	477,639	0.0064	66,086	0.0074	411,553	0.0062	18,979	0.0083	458,660	0.0063
Top 100 Results	755,799	0.0050	103,607	0.0060	652,192	0.0049	30,359	0.0066	725,440	0.0050
Applied										
Top 25 Results	287,059	0.0050	39,995	0.0044	247,064	0.0051	11,364	0.0076	275,695	0.0049
Top 50 Results	477,639	0.0042	66,086	0.0043	411,553	0.0042	18,979	0.0062	458,660	0.0041
Top 100 Results	755,799	0.0034	103,607	0.0036	652,192	0.0033	30,359	0.0048	725,440	0.0033

Table A.3
Test of Joint Equality of Investor-Specific Badge Effects

This table tests whether users react differentially to different investors featured in the top investor badge upon hovering over the badge. Specifically, it reports the p-values of joint equality tests of investor-specific badge effects across investors. Column 1 tests the joint equality of investor-specific effects (i.e., coefficients on $TopInvestorBadge_{ijs} \times \mathbb{1}_{badge\,investor_k}$) estimated from the following equation:

$$Interest_{ijs} = \sum_k \alpha_k \times TopInvestorBadge_{ijs} \times \mathbb{1}_{badge\,investor_k} + \beta \times RecentlyFundedBadge_{ijs} + \eta_j + \epsilon_{ijs}$$

Column 2 tests the joint equality of investor-specific effects removing badge-firm-specific effects based on the following equation:

$$\begin{aligned} Interest_{ijs} = & \sum_k \alpha_k \times TopInvestorBadge_{ijs} \times \mathbb{1}_{badge\,investor_k} \\ & + \sum_f \gamma_f \times TopInvestorBadge_{ijs} \times \mathbb{1}_{badge\,firm_f} + \beta \times RecentlyFundedBadge_{ijs} + \eta_j + \epsilon_{ijs} \end{aligned}$$

Column 3 is analogous to column 2 but includes additional controls used in Panel B of Table 7. The 23 investors and 15 badge firms are listed in Table 1. Twelve investors are associated with badge firms with multiple top investors. All specifications include startup fixed effects. Standard errors are clustered by startup.

	(1)	(2)	(3)
	P-val. of joint equality test of investor-specific badge effects		
Any Click	0.004	0.025	0.024
Info Click	0.002	0.126	0.072
App. Click	0.067	0.008	0.018
Applied	0.079	0.026	0.041
Startup FE	Yes	Yes	Yes
Investor-specific badge effects	Yes	Yes	Yes
Badge firm-specific badge effects	No	Yes	Yes
Additional controls	No	No	Yes
No. of identified investors	23	12	12
Observations	477,639	477,639	477,639