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Abstract

Attracting talent is widely believed to be critical to the success of a startup. In this paper, we investigate whether potential employee interest in a startup is affected by venture capital funding. We do so by analyzing a field experiment conducted on 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. High-quality job candidates care the most about the identities startup investors. The results provide direct evidence of the certification role played by VCs and their impact on the labor market.

1 Introduction

Attracting talent is widely believed to be critical to the success of a startup. Indeed, it is often claimed that people are a startup's most valuable asset.[1] However, startups face obvious challenges in convincing talented individuals to work for them when they could instead work at more established and stable firms. Moreover, with the recent surge in U.S. startups, there is increased competition for those with the skills needed in high-growth environments. Practitioners often claim that there is currently a skill shortage hindering startups from building products on time, and being able to market and sell those products.[2]

Despite the apparent importance for startups of attracting talent, there has been very little research on what drives talent flows to these firms. In this paper, we investigate whether potential employee interest is affected by venture capital (VC) funding. In particular, we study whether startups funded by top-tier VCs and/or startups funded more recently, have an easier time attracting talent as a result. Potential employees may be drawn to such firms because they believe them more likely to succeed. They may also believe that their experience working at such firms will be more valued by the labor market, regardless of firm success. However, it is also possible that potential employees do not understand venture capital 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.

Anecdotally, some practitioners claim that venture funding matters a lot for startup recruiting. For example, in a case study of Nerdwallet's talent reboot, Firstround Capital

[1] https://www.entrepreneur.com/article/244826

[2] 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

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."[3] On the other hand, 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."[4]

The question of whether venture funding matters 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 if one could obtain data on non-founder employees, it would still only be possible to observe those who were actually hired, not all those who applied. This makes it difficult to estimate how the quality of the talent pool available to startups relates to venture funding.

In terms of identification, there are also many potential endogeneity issues involved in estimating the effect of VC funding on recruiting. Most obviously, 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. In addition, a more subtle concern is that 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

[3]https://firstround.com/review/the-total-talent-reboot-how-this-startup-overhauled-its-workforce/
[4]https://medium.com/costanoa-ventures/busting-myths-about-startup-success-in-attracting-talent-198deee1d399

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 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. In 2019 the site had 3.6M active job seekers and over 185,000 new jobs listed.[5] 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 it applied to, 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 highlighted. While the information encoded in the badges is public, and thus could be discovered anyway, the badges make this information more salient and accessible. This allows

[5] https://angel.co/2019/

us to assess the importance of each type of 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, then the badge should increase their interest by making this fact more salient and accessible.

Our main finding is 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 39% increase in the probability of a click, relative to base rates. This is driven by a 27% increase in clicks for further information about a job, a 46% increase in the probability of click to begin the application process, and a 50% increase in the probability of actually submitting an application. 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-tier investor badge. These findings 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.

Exploring heterogeneity in the effect of the top-tier investor badge by candidate role, we find that those who care the most about top-tier investors are in engineering and sales roles. Exploring heterogeneity by candidate location, we find that the candidates located in major innovation hubs (San Francisco, New York, Boston, Los Angeles) care about top-tier investors similarly to those located outside of these hubs.

The results are robust to a variety of different sample restrictions and specifications. Notably, since the experiment spanned the COVID crisis, one concern may be that the results we find are 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 care during a crisis. However, we show that the results are similar prior to March 17, when the first shelter-in-place order was issued in the U.S.

Finally, we examine how the effect of the top-tier investor badge varies with candidate quality. We proxy for the quality of a candidate using a measure developed by AngelList based on the candidate's resume. 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 they can make their own assessment of a startup's prospect 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 is smaller than it seems. 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 things. 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.

Our analysis shows that the effect of the top-tier investor badge is in fact significantly stronger among high-quality candidates. These results confirm that being funded by a top-tier investor does not simply increase interest among low-quality candidates who would not have been hired anyway. The results also help to rule out the possibility that candidates do not understand what the top-tier investor badge means, or else incorrectly react to it, as we would expect stronger effects among low-quality candidates in that case.

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)). Many of these papers emphasize active ways in which VCs might add value, such as by providing advice, connecting startups with individuals in their network, and making changes to management if necessary. However, it is also possible that VCs add value passively as well, simply by attaching their name to a startup. While the potential for such certification effects has long been discussed, this is the first paper, as far as we are aware, to provide empirical evidence of certification effects. Specifically, we show that top-tier VCs aid in recruiting, not only by actively convincing talented individuals in their network to join, but also passively attracting talented individuals from outside of their network. It seems plausible that similar certification effects extend to other outcomes as well such as attracting valuable costumers, suppliers, etc.

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. 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 job seekers to be attracted to startups funded by VCs with good past performance. Indeed, consistent with this idea, we find that it is the high-quality candidates who respond to the top-tier investor badge.

The rest of the paper proceeds as follows. Section 2 provides background on the the AngelList Talent platform, Section 3 discusses the design of the field experiment that we study, Section 4 discusses the data, Section 5 presents the results, and Section 6 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. One of the key features of AngelList Talent was that it did not allow third party recruiters. It also encouraged transparency about salary and equity upfront, before candidates applied.

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. In the most recent completed year, AngelList Talent had 3.6M active users, 185,000 new jobs listed, and 1M connections made.

The way that AngelList Talent works is fairly straightforward. Startups can post job openings, specifying their job's 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), "newest" (i.e., most recently posted), or "last active" (i.e., jobs that engaged most recently). Sorting by recommended is the default. 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

From February 5, 2020 to April 15, 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.[6]

The first badge highlighted startups funded by top-tier investors. AngelList's preliminary

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

user research suggested that users may not recognize the names of top-tier VCs, therefore it identified top-tier VCs by one of their well-known past investments. For example, startups funded by Kleiner Perkins got a badge with the text "Same Investor as Amazon" and startups funded by Accel Partners got a badge with the text "Same Investor as Facebook." When the user hovered their mouse over the badge, additional text would appear saying, "Kleiner Perkins invested in both [this startup] and Amazon" or "Accel Partners invested in both [this startup] and Facebook." The second badge highlighted startups that had raised funding in the past six months. This badge had the text "Recently Funded" and when a user hovered their mouse over it, additional text appeared saying, "Raised funding in the past six months."

Feedback from users indicates 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. Some users who were knowledgeable about VC stated that they would have been familiar with investors names if provided directly on the top-tier investor badge, but they understood what the badge was trying to convey. Overall, 138/175(=79%) of respondents said they found the top-investor badge helpful and 82/93(=93%) or respondents said they found the recently-funded badge helpful. Of course, it should be noted that there is selection bias in terms of who chose to provide feedback.

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 40%. Thus, a user with the top-tier investor (recently-funded) badge feature enabled, would see the badge for all startups it applied to, 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 by performed by logged-in users as discussed previously.

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, we estimate equations of the form:

$$Interest_{ifs} = TopInvestorBadge_{ifs} + RecentlyFundedBadge_{ifs} + \eta_f + \epsilon_{isf}, \qquad (1)$$

where i indexes users, s indexes searches, f indexes startups, $Interest_{isf}$ is a measure of user i's interest in startup f following search s, $TopInvestorBadge_{ifs}$ is an indicator equal to one if user i saw startup f represented with a top-tier investor badge following search s, $RecentlyFundedBadge_{ifs}$ defined analogously for the recently-funded badge, and η_f is a startup fixed effect.

While it is impossible to experimentally manipulate the actually funding history of a startup, experimentally manipulating the salience/accessibility of this history still helps us to understand whether potential employees care about this information. 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, then the badge should increase their interest by making this fact more salient and accessible. Bernstein et al. (2017) use a similar experimental approach to study which startup characteristics potential investors care about.

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 corresponding their 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, because AngelList displays search results for the same startup grouped together and because the badges only vary at the startup level rather than job level characteristics, we consolidate all jobs from the same startup into a single observation.

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 for searches sorted by "Recommended," as recency is heavily weighted in the recommendation algorithm.[7]

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. 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. Thus, we would estimate lower coefficients on the badge variables and these coefficients would be interpreted relative to lower baseline click rates. We also show that the 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

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

might be scraping the AngelList website. Third, we only include basic searches in which a users specify a location and role.

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.

We observe clicks on search results in the data, but these clicks are not tied to a specific search by any kind of search identifier. We therefore tie a click to a search if the click occurred some time before the user's next distinct search. In other words, for a given user-search-startup, we consider the startup appearing in the search's results to have been clicked, if it was clicked before the user's next search. However, it is possible for a user to perform a search, save a result to their "saved" list, and then return to it latter and click on it, after some intervening searches. To allow for this we also consider alternative versions of our dependent variables that tie a click to a search if the click occurred some time in the next 1 hour or the next 24 hours after the search.

Overall, we are left with a sample of 8,823 users who performed 16,471 searches that yielding 17,732 startups (in the top 50 results).

5 Results

Having discussed our setting and experimental design, we next we turn to our empirical analysis.

5.1 Summary Statistics

We begin by presenting various summary statistics for our sample. Table 1 shows summary statistics at the user level. In the data, we observe two measures related to user quality. The first is the number of years of experience the user has in her current role. The second is an overall candidate quality score developed by AngelList based on the user's work experience, skills, and education. In unreported analysis, we find that candidate quality scores correlate more strongly with startup requests for introductions than candidate experience. Panel A shows that the average candidate in our sample has approximately 4 years of experience in her current role with a quality score of approximately 12.

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 2 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 these five markets account for approximately 32% of our 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. Most of the startups in our sample are fairly small. Approximately 47% of the startups in our sample have 1-10 employees, and 76% have 1-50 employees.

Next, Table 3 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. The variable in the second three rows is an indicator equal to one if the startup in the search result had the top-tier investor badge displayed. The variables in the next six rows are analogous but for recently-funded status and the recently-funded badge. From the second column we see that approximately 18% of the search results were associated with startups funded by a top-tier investor, and approximately 7.5% of the results actually displayed the top-tier investor badge. Approximately 5% 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.

Panel B of Table 3 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 3% probability of a result getting a click (of any type), but within the top 50 search results, there is a 2.3% probability of a result getting a click, and within the top 100 search results there is only a 1.7% probability of a result getting a click. These decreasing click rates likely reflect both a preference among users 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 3.1% for results that displayed the top-tier investor badge and 2.2% 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 3.2% for results that displayed the recently-funded badge and 2.3% for results that did not display the badge.

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 to be associated with a top-tier investor in order for it to display the top-tier investor badge, and top-tier investors likely invest in higher-quality startups. Therefore users may tend to click on search results with the top-tier 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 as well. Therefore, we next turn to within-startup comparisons.

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 4 show 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-tier investor badge increases the probability of a click by 0.9 ppt, with the estimated coefficient statistically significant at the 1% level. The estimated effect is also economically significant. The unconditional probability of a click in this sample of 2.3%, therefore the coefficient on the top-tier investor badge indicator implies a 39% increase in the probability of the click. Interestingly, we find no significant effect of the recently-funded badge on clicks. This findings 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 find 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 job) and clicks to begin the application process. We find that both measures of potential employee interest increase in response to the top-tier investor badge but no the recently-funded badge. In particular clicks for further information increase by 0.3ppt, or 27% relative to the unconditional probability, and clicks to begin the application process increase by 0.6ppt, or 46% relative to the unconditional probability. In columns 4 and 6 we again find to evidence of interaction effects for these outcomes.

Finally in columns 7–8 we examine application submissions. Again, we find that the top-tier 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 tier investor badge increases application submissions by .4ppt or 50%. This shows that are 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.

Determining exactly why employees care about the identity of a startups investors is beyond the scope of this paper. However, two potential explanations seem most likely. First, employees may be drawn to firms with top investors because they believe they are more likely to ultimately succeed. Second, employees may also believe that their experience working at such firms will be more valued by the labor market, regardless of firm success. These two explanations are not mutually exclusive. However, 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 bit little more context of maybe how this startup in particular will perform in the future."

5.3 Robustness

Because our results are based on an experiment, they are likely to be internally valid. One may still worry, however, about their external validity. In particular, one concern that one might have is that. since the experiment spanned the COVID crisis, 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 care during a crisis. To help address this concern, Panel A of Table 5, we repeat our baseline analysis limiting the sample to dates prior to March 17—when the first shelter-in-place order was issued 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, even during non-crisis times.

Another potential concern is that 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. 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 B of Table 5, 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, we 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 Candidate Quality

Next, we examine how the effect of the top-tier investor badge varies with candidate quality. We proxy for the quality of a candidate using a measure developed by AngelList based on the candidate's resume. 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 they can make their own assessment of a startup's prospect 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 is smaller than it seems. 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 things. 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 7, we partition our sample into high (above-median) and low (below-median) quality candidates based and repeat our baseline analysis in each sample. Interestingly, we that for most of our measures of potential employee interest, high-quality candidates responds to the top-tier investor badge for but low quality candidates do not. The difference in the effect across the two samples is also statistically significant. The only measure of potentially employee interest for which this pattern does not hold is clicks for further information. However, this outcome is the least consequential and it also yields only a small difference in magnitudes across the two samples. In contrast, application clicks are much more consequential and the application clicks of high-quality candidates respond to the top-tier investor badge nearly an order of magnitude more strongly than the application clicks of low-quality candidates.

These results confirm that being funded by a top-tier investor does not simply increase interest among low-quality candidates who would not have been hired anyway. The results also help to rule out the possibility that candidates do not understand what the top-tier investor badge means, or else incorrectly react to it, as we would expect stronger effects among low-quality candidates in that case.

5.4.2 Candidate Role and Geography

In Table 8, we also examine whether the effect of the top-tier investor badge varies across candidates with different types of roles. We focus on the the six most common roles in our sample for this analysis: developer, marketing, operations, product, designer, and sales. Interesting, we find that developers and individuals who work in sales respond the most strongly to the top-tier investor badge.

Finally, in Table 9, we also examine whether the effect of the top-tier investor badge varies across candidates in different types of geographies. For this analysis we partition users in to those who are located in innovation hubs (San Francisco, New York, Boston, and Los Angeles) and those who are not. Interestingly, in this case we estimate similar effects across both groups.

6 Conclusion

Attracting talent is widely believed to be critical to the success of a startup. In this paper, we investigate whether potential employee interest in a startup is affected by venture capital funding. 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. High-quality job candidates care the most about the identities startup investors. The results provide direct evidence of the certification role played by VCs.

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Table 1: User Summary Statistics

This table shows summary statistics at the user level. Panel A shows summary statistics for the number of years of experience a user has in her current role and an overall candidate quality score developed by AngelList based on the user's work experience, skills, and education. Panel B shows the geographic distribution of the users in our sample across the 20 most common cities. Panel C shows the distribution of users across different roles.

Panel A: User Experience and Quality

	Obs	Mean	Std. Dev.
Experience in Current Role	7,828	4.319	3.502
Quality Score	8,531	12.539	16.575

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

	Freq	Percent
New York	1,692	20.19
San Francisco	1,621	19.34
Los Angeles	746	8.90
Boston	440	5.25
Seattle	267	3.19
Chicago	245	2.92
Austin	197	2.35
Atlanta	164	1.96
San Diego	138	1.65
Washington DC	129	1.54
Denver	125	1.49
Dallas	106	1.26
Philadelphia	101	1.21
Portland	89	1.06
Houston	87	1.04
Miami	60	0.72
Minneapolis	54	0.64
Boulder	51	0.61
Pittsburgh	45	0.54
Total	6,401	76.38

Table 1: (Continued)

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

	Freq	Percent
Developer	1,203	13.92
Marketing	762	8.82
Operations	551	6.38
Product Manager	499	5.77
Designer	423	4.89
Sales	404	4.67
UI/UX Designer	379	4.39
Data Scientist	356	4.12
Customer Service	316	3.66
Finance	316	3.66
Business Development	296	3.43
Business Analyst	283	3.27
Full Stack Developer	253	2.93
Project Manager	236	2.73
Frontend Developer	175	2.02
Content Creator	173	2.00
CEO	153	1.77
Operations Manager	150	1.74
Human Resources	128	1.48
Recruiter	127	1.47
Total	7,183	83.12

Table 2: Startup Summary Statistics

This table 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. Panel B shows the distribution of startups across different size categories, where size is measured in terms of number of employees.

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

	Freq	Percent
Mobile	1,039	9.20
E-Commerce	790	6.99
Enterprise Software	782	6.92
SaaS	543	4.81
Health Care	477	4.22
Financial Services	336	2.97
Software	293	2.59
Education	289	2.56
Technology	240	2.12
Marketplaces	224	1.98
Social Media	211	1.87
Big Data	189	1.67
Web Development	188	1.66
Digital Media	187	1.66
Real Estate	174	1.54
Health and Wellness	172	1.52
Advertising	152	1.35
Sales and Marketing	141	1.25
Food and Beverages	111	0.98
Finance Technology	108	0.96
Total	6,646	58.83

Panel B: Distribution of Startups Across Number of Employees

	Freq	Percent
1-10	5,327	46.70
11-50	3,343	29.31
51-200	1,685	14.77
201-500	537	4.71
501-1000	251	2.20
1001-5000	185	1.62
5000+	79	0.69
Total	11,407	100.00

Table 3: 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-tier 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
Top Investor						
Top 25 Results	316,329	0.178	56,243	1.000	15,764	0.420
Top 50 Results	523,963	0.176	92,388	1.000	25,733	0.411
Top 100 Results	825,240	0.174	143,853	1.000	40,431	0.440
Top Investor Badge						
Top 25 Results	316,329	0.076	56,243	0.427	15,764	0.167
Top 50 Results	523,963	0.075	92,388	0.424	25,733	0.169
Top 100 Results	825,240	0.074	143,853	0.422	40,431	0.186
Recently Funded						
Top 25 Results	316,329	0.050	56,243	0.118	15,764	1.000
Top 50 Results	523,963	0.049	92,388	0.115	25,733	1.000
Top 100 Results	825,240	0.049	143,853	0.124	40,431	1.000
Recently Funded Badge						
Top 25 Results	316,329	0.021	56,243	0.048	15,764	0.429
Top 50 Results	523,963	0.021	92,388	0.049	25,733	0.433
Top 100 Results	825,240	0.022	143,853	0.053	40,431	0.440

Table 3: (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. *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, *Top Inv. Badge* is an indicator for whether the search result displayed the top-tier 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
Any Click										
Top 25 Results	316,329	0.030	23,999	0.039	292,330	0.029	6,766	0.044	309,563	0.030
Top 50 Results	523,963	0.023	39,150	0.031	484,813	0.022	11,155	0.032	512,808	0.023
Top 100 Results	825,240	0.017	60,678	0.024	764,562	0.017	17,783	0.026	807,457	0.017
Info Click										
Top 25 Results	316,329	0.014	23,999	0.018	292,330	0.014	6,766	0.020	309,563	0.014
Top 50 Results	523,963	0.011	39,150	0.013	484,813	0.011	11,155	0.014	512,808	0.011
Top 100 Results	825,240	0.008	60,678	0.010	764,562	0.008	17,783	0.010	807,457	0.008
App. Click										
Top 25 Results	316,329	0.016	23,999	0.021	292,330	0.015	6,766	0.025	309,563	0.015
Top 50 Results	523,963	0.012	39,150	0.018	484,813	0.012	11,155	0.019	512,808	0.012
Top 100 Results	825,240	0.009	60,678	0.014	764,562	0.009	17,783	0.016	807,457	0.009
Applied										
Top 25 Results	316,329	0.010	23,999	0.013	292,330	0.010	6,766	0.019	309,563	0.010
Top 50 Results	523,963	0.008	39,150	0.010	484,813	0.008	11,155	0.014	512,808	0.008
Top 100 Results	825,240	0.006	60,678	0.008	764,562	0.006	17,783	0.013	807,457	0.006

Table 4: Baseline Results

This table show our baseline findings from estimating equation 1 within the sample of top 50 search results. Variables are as defined in Table 3. ***, **, 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	0.009***	0.009***	0.003***	0.003***	0.006**	0.006**	0.004**	0.004**
	(0.003)	(0.003)	(0.001)	(0.001)	(0.003)	(0.003)	(0.002)	(0.002)
Recently Funded Badge	0.001	0.002	-0.001	-0.000	0.002	0.002	0.000	0.002
	(0.004)	(0.004)	(0.002)	(0.002)	(0.003)	(0.004)	(0.003)	(0.003)
Top Investor Badge × Recently Funded Badge		-0.007		-0.004		-0.003		-0.007
		(0.006)		(0.003)		(0.006)		(0.004)
Startup FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.094	0.094	0.064	0.064	0.100	0.100	0.086	0.086
Observations	523,963	523,963	523,963	523,963	523,963	523,963	523,963	523,963

Table 5: Robustness

Panel A of this table repeats the analysis of Table 4 limiting the sample to dates prior to March 16, 2020. Panel B repeats the analysi of Table 4 limiting the sample to top 100 and top 25 search results. ***, **, and * indicate significance at the 1%, 5% and 10% level, respectively.

Panel A: Pre-COVID (March 16, 2020)

	(1) Any Click	(2) Info Click	(3) App. Click	(4) Applied
Top Investor Badge	0.009***	0.003**	0.006***	0.004***
	(0.002)	(0.001)	(0.002)	(0.001)
Recently Funded Badge	-0.001	-0.002	0.001	0.001
	(0.004)	(0.002)	(0.003)	(0.003)
Startup FE	Yes	Yes	Yes	Yes
R-Squared	0.099	0.075	0.104	0.085
Observations	368,750	368,750	368,750	368,750

Table 6: (Continued)

Panel B: Alternative Result Rank Cutoffs

	Any Click		Info Click		App. Click		Applied	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Top 100	Top 25	Top 100	Top 25	Top 100	Top 25	Top 100	Top 25
Top Investor Badge	0.007***	0.011***	0.002***	0.004**	0.004**	0.007*	0.003***	0.006*
	(0.002)	(0.003)	(0.001)	(0.002)	(0.002)	(0.003)	(0.001)	(0.003)
Recently Funded Badge	0.002	0.001	-0.000	0.001	0.002	0.001	0.002	0.001
	(0.003)	(0.006)	(0.001)	(0.002)	(0.003)	(0.005)	(0.003)	(0.004)
Startup FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.077	0.123	0.052	0.083	0.081	0.134	0.068	0.113
Observations	825,240	316,329	825,240	316,329	825,240	316,329	825,240	316,329

Table 7: Heterogeneity by User Quality

This table repeats the analysis of Table 4 spliting the sample by a measure of candidate quality developed by AngelList. ***, **, 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)
User Quality	High	Low	High	Low	High	Low	High	Low
Top Investor Badge	0.011***	0.004	0.002	0.003**	0.009***	0.001	0.005**	0.001
	(0.003)	(0.003)	(0.001)	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)
Recently Funded Badge	0.003	-0.000	0.001	-0.001	0.002	0.001	0.001	0.000
	(0.006)	(0.004)	(0.003)	(0.002)	(0.005)	(0.003)	(0.005)	(0.002)
Startup FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.123	0.140	0.088	0.098	0.130	0.164	0.108	0.137
Observations	248,417	264,987	248,417	264,987	248,417	264,987	248,417	264,987

Table 8: Heterogeneity by User Role

This table repeats the analysis of Table 4 spliting the sample by candidate role. ***, **, and * indicate significance at the 1%, 5% and 10% level, respectively.

	Any Click					
	(1) Developer	(2) Marketing	(3) Operations	(4) Product	(5) Designer	(6) Sales
Top Investor Badge	0.016***	0.006	0.008*	0.010	-0.000	0.030***
	(0.005)	(0.005)	(0.004)	(0.007)	(0.005)	(0.009)
Recently Funded Badge	-0.007	0.010	-0.000	0.004	-0.015	-0.004
	(0.010)	(0.007)	(0.009)	(0.012)	(0.012)	(0.010)
Startup FE	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.177	0.248	0.297	0.223	0.282	0.253
Observations	88,723	48,870	33,425	33,221	25,495	27,658

Table 9: Heterogeneity by User Geography

This table repeats the analysis of Table 4 spliting the sample by candidate location. Candidates are defines as being in an innovation hub if theuy are location San Francisco, Bostom, New York, or Los Angeles. ***, **, 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 Hub	Yes	No	Yes	No	Yes	No	Yes	No
Top Investor Badge	0.008**	0.008***	0.003***	0.003	0.005	0.005**	0.003	0.003*
	(0.003)	(0.003)	(0.001)	(0.002)	(0.004)	(0.002)	(0.003)	(0.002)
Recently Funded Badge	-0.001	0.003	-0.002	0.001	0.001	0.002	0.001	-0.001
	(0.005)	(0.005)	(0.002)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
Startup FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.097	0.155	0.069	0.109	0.104	0.175	0.082	0.158
Observations	272,369	251,594	272,369	251,594	272,369	251,594	272,369	251,594