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FLIGHT TO SAFETY:
HOW ECONOMIC DOWNTURNS AFFECT TALENT FLOWS TO STARTUPS

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ABSTRACT

Using proprietary data from AngelList Talent, we study how individuals' job search and application behavior changed during the COVID downturn. We find that job seekers shifted their searches toward more established firms and away from early-stage startups, even within the same individual over time. Simultaneously, they broadened their other search parameters. Relative to more established firms, early-stage startups experienced a decline in applications, primarily driven by higher quality candidates. These declines hold within a firm or job posting over time. Our findings uncover a flight to safety channel in the labor market, which may amplify the pro-cyclical nature of entrepreneurial activities.

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1 Introduction

Economists have long debated the role of entrepreneurship during economic downturns. Under the cleansing hypothesis, recessions are times of accelerated reallocation, where inefficient incumbents are replaced by new firms who seize market opportunities (Davis and Haltiwanger, 1992; Foster et al., 2001; Collard-Wexler and De Loecker, 2015). However, an increasing body of evidence highlights that early-stage startups may be particularly vulnerable to economic downturns, and therefore less able to drive such cleansing effects (Parker, 2009; Decker et al., 2016; Fabrizio and Tsolmon, 2014). Existing explanations of startup vulnerability during recessions primarily focus on the financing constraints that early-stage firms face when attempting to raise capital during downturns (Barlevy, 2003; Aghion et al., 2012; Townsend, 2015; Nanda and Rhodes-Kropf, 2016; Howell et al., 2020). In this paper, we explore a new channel—the ability of early-stage companies to attract human capital during economic downturns.

It is theoretically unclear how downturns should affect the ability of early-stage startups to attract human capital. On the one hand, downturns may lead to increased risk aversion among workers, making safer and more established firms more appealing than startups. This could be viewed as analogous to the phenomenon of "flight to safety" among investors (Caballero and Krishnamurthy, 2008; Baele et al., 2020). On the other hand, many workers lose their jobs during downturns or face worse career trajectories at established firms, lowering their opportunity costs of joining early-stage startups (Gottlieb et al., 2019). Thus, the overall increase in the supply of potential workers for early-stage startups may offset any changes in worker preferences away from them.

Empirically exploring whether and how the supply of talent available to startups changes during economic downturns is challenging due to the difficulty of distinguishing between supply and demand factors that drive labor market outcomes. For example, a decline in hiring by early-stage startups could reflect a change in the hiring policies of such firms (labor demand), a decline in worker interest in such firms (labor supply), or both. A handful of recent studies have used online job posting data to investigate various questions about labor demand (Campello et al., 2019, 2020b; Kahn et al., 2020); however, such data tell us little about labor supply.

In order to analyze labor supply, we make use of a novel data set that we obtained from AngelList Talent, the largest online recruitment platform for private and entrepreneurial companies. In the most recent completed year, AngelList Talent had 3.6 million active job seekers and over 185,000 new jobs listed. The data we use come from their back-end system, and therefore include not only publicly visible job postings, but also the history of each user's job searches on the platform, their application submissions, as well as whether employers responded to these submitted applications. Because we can observe the activities of job seekers in these data, we can learn about changes in labor supply. In particular, we are able to track changes in the search behavior of *the same job seeker* over time. This allows us to explore whether worker preferences shift during downturns, independently of changes in labor demand—and if so, what type of workers experience changes in preferences. In addition, we are also able to track changes in job applications for *the same job posting* over time. This allows us to examine whether, for firms, changes in worker preferences following a downturn are offset by changes in the number of workers seeking employment. Both analyses isolate supply side factors much more cleanly than has been possible with standard data sets.

We focus on the economic downturn that followed the emergence of the COVID pandemic. The pandemic caused massive economic disruptions, and its origins were external in nature, providing an ideal, exogenous setting to study the response of job seekers to adverse economic shocks. While the COVID downturn was distinct from others in many ways, it shares some important similarities for our purposes. As during other recessions, the economic expectations of workers declined at the start of the COVID downturn before eventually rebounding. This decline in expectations is what could drive a change in job seekers' preferences and behavior. Survey evidence suggests that the magnitude of the decline in expectations during the COVID downturn was in line with past recessions and, if anything, was smaller. However, economic expectations declined much more quickly during the COVID downturn than in the past and also rebounded more quickly. The sharpness of this decline in expectations is advantageous for our identification, as it allows us to focus on a short window in the months surrounding the start of the pandemic. Within this short window, it is unlikely that talent flows to startups coincidentally changed sharply at the same time as workers' economic expectations. Moreover, the unusually quick rebound in expectations that occured subsequently does not affect our interpretation of results. Rather, our results suggest that talent flows to startups are likely affected for a longer period of time during a more typical recession.

Exploring changes in the search parameters of AngelList Talent users, we find that job candidates searched for significantly larger companies after March 13, 2020, the date that a state of national emergency was first announced in the U.S. Specifically, the average size of firms searched by candidates increased by 29%, and candidates became 20% more likely to search for firms with more than 500 employees. This result holds both across candidates and, importantly, within the same candidate over time. In other words, the COVID downturn led job candidates to shift their search preferences toward more established firms. At the same time, job candidates became less choosy as they broadened their search criteria on other dimensions in order to be employed by more established firms. Candidates became more likely to search for part-time jobs or internships, to lower their minimum required salary, and to search for a wider range of roles, locations, and markets. Next, we examine whether changes in the search preferences of job seekers also translated into job applications. Consistent with the changes in job searches, we find a significant increase in the average size and financing stage of firms receiving job applications after the start of the downturn. Again, these effects not only hold in the cross section across all candidates on the platform, but also within candidates, suggesting that the crisis changed the type of firms candidates chose to apply to.

Next, we explore whether the flight to safety effects that we document differ for high- and low-quality job seekers. In particular, we partition candidates according to two characteristics that we can observe in the data: their number of years of work experience and an estimated score of their overall quality. The latter measure is created by AngelList Talent based on an algorithm that accounts for applicants' experience, skills, and education. Interestingly, we find that higher quality job seekers drive most of the flight to safety in job applications, shifting away from early-stage startups. This could reflect the potentially better outside options such job candidates have, which may make them more averse to startup jobs when startups are perceived to be riskier during downturns.

The results described above suggest a shift in worker preferences away from early-stage firms during the COVID downturn. However, it is possible that despite this shift, early-stage firms had no difficulties attracting human capital during the downturn, or even had an easier time. In particular, it could be that there was a large enough influx of new, high-quality job seekers that it offset the change in worker preferences. Thus, in the second part of the paper, we turn to estimating effects at the firm level. We find that, on average, the number of applications received per job posting did decline significantly after the onset of the pandemic. We also find again that the decline was concentrated within early-stage firms and was driven by a decline in high-quality applicants. In principle, these results could reflect changes in the type of jobs posted by these firms. However, we find similar results within job postings as well. That is, holding the job posting fixed, high-quality applications declined after the crisis, and more so for jobs posted by early-stage firms. We also find that the deterioration in the applicant pool for early-stage startups likely affected their actual hiring, as these startups responded to far fewer of the applications they received. These results highlight the difficulty early-stage startups face when attempting to attract human capital during downturns.

We conduct a variety of robustness tests. First, we show that our main results are absent over the same time period in 2019, suggesting that our results are not driven by seasonality or unobserved trends. Second, we show through non-parametric graphs that our main results do not reflect a general trend in the labor market. Instead, reactions are steep and immediate, and coincide with the emergence of the pandemic in the U.S. These graphical results also show that more established and early-stage startups shared similar trends in the months before the crisis. Third, we show that our results on changes in worker preferences hold within subsamples of searches that were not preceded by another recent search, suggesting that the results are not driven by individuals adjusting their search parameters in response to the job postings they see from previous searches. Fourth, we show that our results hold within searches and job applications that are in the same location as the candidate, suggesting that relaxed geographical constraints due to remote work do not drive our findings. Fifth, our results hold within job postings that firms took action on, suggesting that stale job postings do not explain our results. Lastly, we show that our results are similar when we use the state-level number of COVID cases as a continuous treatment variable, and also when we exclude from the analysis candidates/startups from California and Massachusetts, suggesting that the documented patterns are national, rather than concentrated in innovation hubs.

Ultimately, flight to safety in the labor market likely stems from a belief among workers that more established employers offer better job security or promotion prospects during downturns, due to, for example, their better ability to secure financing or to maintain product demand. These beliefs need not be rational, and could reflect overreaction by job candidates. Although pinning down the source of flight to safety and its rationality is beyond the scope of this paper, our results present a new channel that helps to explain startups' vulnerability to economic downturns. Our results also suggest that labor market frictions may amplify the pro-cyclical nature of entrepreneurship activities.

Our paper contributes to the literature on business cycles and entrepreneurship. Caballero and Hammour (1994), Davis et al. (1996), Foster et al. (2001), and Collard-Wexler and De Loecker (2015) document accelerated reallocation and cleansing of inefficient incumbents during economic downturns; Koellinger and Roy Thurik (2012) find that upswings in unemployment rates are followed by increases in entrepreneurship. In contrast, Parker (2009), Decker et al. (2014), Decker et al. (2016), and Fabrizio and Tsolmon (2014) show that entrepreneurship and R&D are pro-cyclical rather than counter-cyclical. This pro-cyclicality has been attributed to financing frictions (Aghion et al., 2012; Townsend, 2015; Nanda and Rhodes-Kropf, 2016), R&D externality (Barlevy, 2007), and entrepreneurs' human capital choice (Rampini, 2004). Our paper introduces a new labor channel to explain startup vulnerability during economic downturns. Related to our paper, Howell et al. (2020) and Gompers et al. (2020) examine the impact of the COVID crisis on VC investment, while Bartik et al. (2020a), Fairlie (2020), and Bartlett and Morse (2020) study its impact on small businesses.

We also add to an emerging literature on the startup labor market. Babina and Howell (2018) and Babina et al. (2020) study human capital flows between incumbents and startups. Moscarini and Postel-Vinay (2012) and Babina et al. (2019) examine employment and wage dynamics by young firms and their cyclicality. These papers study equilibrium employment outcomes, while we focus on individuals' labor supply in the job search process. In that sense, our paper is related to a handful of papers that study job searches and applications

(Brown and Matsa, 2016; Kuhnen, 2017; Gortmaker et al., 2019; Brown and Matsa, 2020; Cortes et al., 2020). Different from these papers, we focus on the startup labor market, which has received little attention relative to the broader labor market. In that regard, this paper relates to Bernstein et al. (2021) who study how venture capital backing affects the nature of human capital startups are able to attract.

Lastly, we add to a recent string of papers that study the labor market consequence of COVID. Using job posting and unemployment insurance data, Kahn et al. (2020) document a broad-based decline in job postings of 30% by the end of March 2020. Using household survey data, Coibion et al. (2020) estimate a 20 million job loss and a 7-percentage-point drop in labor participation rate by April 2020, both of which are greater than what happened over the entire Great Recession. Bartik et al. (2020b) show that low-wage workers and business closures drive most of the decline in small business employment at the onset of COVID. Using job posting data, Campello et al. (2020b) show that, among public firms, small and credit constrained firms cut back on job postings more during COVID; there is also a larger decline in high-skill jobs relative to low-skill ones. Our paper focuses on labor supply and the ability of startups to attract talent during the COVID crisis. We also highlight the stark contrast between established and early-stage firms, as well as the disparate responses by high-quality and low-quality job candidates.

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 entrepreneurial ecosystem. Firms recruiting on the platform range from nascent startups, with less than 10 employees, to mature technology companies such as Google, Facebook, and Dropbox. Over its lifetime, more than 10 million job seekers have joined the platform, more than 100,000 companies have posted a job there, and more than 5 million connections have been made between job seekers and companies. In the most recent completed year, AngelList Talent had 3.6 million active users, 185,000 new jobs listed, and 1 million connections made.

The way that AngelList Talent works is illustrated in Panel A of Figure 1. Companies 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 (Figure A.1 shows an example). Job postings are also linked to AngelList company 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 company characteristics above (Panel B of Figure 1 shows an example). Importantly for our purposes, a user must register on the site and provide basic resume information before she can perform a search. Thus, all searches can be linked to a user by AngelList—although user searches are not publicly visible to companies or other users.

Users can engage with search results in multiple ways. First, they can click on the name/logo of the company 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 company 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 company, the company 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 Talent does not directly observe if a given candidate ends up being hired.

3 Data

3.1 Measurement

The data we use in this paper were provided directly by AngelList and were collected by their back-end system. Our sample period runs from February 5 to May 14, 2020, and for comparison we also obtain data from the same period in 2019.[1,2] In the data we can observe all user activities, including searches, clicks, applications by job candidates, and responses to those applications by firms. We also observe all jobs ever posted on AngelList

[1]Our search data goes until June 18, 2020. These dates were determined by AngelList as the data were originally extracted by them for another purpose.

[2]We do not examine data in the later half of 2020 because of other confounding events that were happening in that period (e.g., racial unrest in the US). Ultimately, our goal is not to evaluate the full impact of COVID on the startup labor market, but rather to test the flight-to-safety mechanism using a clean window where there is a drastic shift in job seekers' expectations. Section 4.1 discusses this in more detail.

Talent, with associated job- and firm-level characteristics, and the dates the jobs were live for search. Finally, we also observe candidate characteristics, including location, current role, experience, and a measure of overall candidate quality developed by AngelList.

In our analysis of job searches, our main focus is the size of the firms workers search for, as measured by the number of employees.[3] Users can filter on employment size by selecting any of the seven size bins: 1-10, 11-50, 51-200, 201-500, 501-1000, 1001-5000, and 5000+. We take the mid point of each bin, average it across all bins a user selects, and then log transform it.[4] Additionally, we define a large firm indicator variable equal to one if the average selected size is above 500 employees. We also examine additional search parameters that capture other job dimensions, such as job type (full-time, internship, contractor), minimum required salary, roles, markets (i.e., sectors), locations, as well as the number of keywords used for screening. These search dimensions capture how flexible or selective job seekers are in their screening for jobs.

To measure talent flows to firms, we look at job application volume. Although not all job applicants are eventually hired, job applications allow us to measure the size of the talent pool available to firms. Specifically, we measure the number of job applications at the job posting level. This allows us to condition the supply of applications within each "unit" of labor demand, thus addressing concerns that changing talent flows to startups are driven by shifts in their labor demand or job requirements. We also study firms' responses to job applications. As discussed earlier, we are able to observe whether a firm requests an introduction from the applicant, which indicates the initiation of further interactions. Although we do not observe the final hiring decision, these introduction requests are precursors to eventual hiring.

Finally, we exploit two measures of job candidate quality. The first measure is the

[3] Job candidates can also filter on companies' financing stage, but these data are only available after late March in our search sample.

[4] For the "5000+" bin, we set the upper bound to be 20,000 employees. Our results are similar if we use a lower or higher upper bound.

number of years of job experience an individual has. The second is a quality score created by AngelList Talent based on a proprietary algorithm that scores candidates based on their experience, education, and skills.

3.2 Sample Restrictions

We limit our sample to include only the activities of users and firms located in the U.S. in order to ensure that our findings do not reflect a mix of countries with very different startup ecosystems or labor markets. We also exclude the top 1% of users in terms of their number of searches during the sample period so as to limit the influence of "bots" (i.e., fake users) that might be scraping the AngelList website. Consistent with the idea that these users are bots, their search activity does not fluctuate between weekdays and weekends in the same way as that of other users. Our final sample includes 178,793 users and 83,921 job applicants that were active during our sample period, and 113,382 jobs that were live for search during that period.

4 Empirical Strategy

Our goal is to explore whether worker preferences toward early-stage startups changed following the start of the COVID downturn and whether any such change in preferences affected the ability of early-stage startups to hire high-quality employees. We use the online search and application activities of job candidates on AngelList to identify changes in their preferences and labor supply. Our data have several advantages relative to existing data used in the literature. First, our search parameter data allow us to capture job seekers' preferences independent of the job vacancies posted by firms, thus separating the labor supply from labor demand. This is not feasible with job posting data that has been used thus far

(Campello et al., 2019, 2020b; Kahn et al., 2020). Second, compared with surveys of job seekers (Coibion et al., 2020; Mui and Schoefer, 2020), our data also allows us to measure job seekers' preferences at a higher frequency and without potential self-reporting biases. Lastly, our granular job application data contain complete information on candidates, jobs, and firms. This allows us to conduct within-candidate and within-job analyses, which are critical in controlling for compositional changes among job seekers and changes in labor demand by firms.

4.1 External Validity

Before discussing our empirical specifications, we first begin by considering how generalizable any results that we find are likely to be with respect to other downturns. While the COVID downturn was distinct from others in many ways, it does share some important similarities for our purposes. As during other recessions, the economic expectations of workers declined at the start of the COVID downturn. This decline in expectations is what could drive a flight-to-safety effect. One may worry that the decline in economic expectations may have been more severe during the COVID recession, making it a poor setting for understanding the effects of typical recessions on talent flows to startups. However, if anything, survey evidence suggests that economic expectations actually declined less from peak to trough during the COVID recession than in previous ones. Figure 2 shows the consumer confidence time series over the past two decades, with Panel A using the Conference Board's Consumer Confidence Index and Panel B using the University of Michigan's Consumer Sentiment Index.[5] The shaded regions correspond to recessions, as dated by the NBER. The figure shows that during the COVID recession consumer confidence declined by 29%-35%. By comparison, consumer confidence declined by 40%-77% during the financial crisis and by 29%-41% during

[5]Economic expectations about business condition and employment are key components of both indices.

the dotcom crash.

In terms of changes in economic expectations, a more distinctive feature of the COVID downturn was that expectations declined much more quickly than in past recessions. During the COVID downturn consumer confidence went from its pre-recession high to its recession low over the course of 2-3 months. In contrast, it took 19 months to go from peak to trough during the financial crisis and 18 months during the dotcom crash. The sharpness of the decline in economic expectations is advantageous for us in terms of identification, as it allows us to focus on a short window in the months (February 2020 to May 2020) surrounding the start of the pandemic. Within this short window, it is unlikely that talent flows to startups coincidentally changed sharply at the same time as workers' economic expectations.

Another distinctive feature of the COVID downturn was that economic expectations rebounded more quickly than usual. Again, because we focus on a short window around the start of the pandemic, this subsequent rebound does not affect our findings.[6] It is also worth emphasizing that our goal is not to evaluate the full impact of the COVID downturn on the startup labor market. Rather, our goal is to test whether there is a potentially generalizable flight-to-safety effect among workers during recessions. We do this using a clean window where there was a sharp shift in workers' economic expectations. To the extent that expectations usually take longer to recover in other recessions, that would suggest that talent flows to startups may be impacted for a longer period of time in other recessions.

Finally, the COVID recession was also somewhat unique in that the government responded with more extreme economic interventions than in past recessions. It could be argued that almost all of these interventions served to economically protect workers to some extent, either directly or indirectly. Therefore, if anything, the government's policy response would have muted a flight-to-safety effect among workers. Overall, since the decline in eco-

[6]The rebound happened mainly after June 2020.

nomic expectations during the COVID downturn was smaller in magnitude and shorter-lived than in past recessions—and the government policy response was also more robust—our results could be argued to represent a lower bound on the effect of a more typical recession on talent flows to startups.

4.2 Effect on Worker Preferences

4.2.1 Search Parameters

We first explore changes in the search parameters of job seekers on AngelList Talent around the start of the COVID downturn. Specifically, we estimate the following specification at the search level:

$$y_{it} = \alpha_i + \beta \mathbb{1}(PostCOVID_t) + \epsilon_{it} \tag{1}$$

where y_{it} is a search parameter specified by candidate i searching at time t, such as firm size, job type, role, market, location, etc, and $PostCOVID_t$ is an indicator equal to one on dates after March 13, 2020, the date that a state of national emergency was first announced in the U.S.[7] Our main specification includes job seeker fixed effects α_i, which means that we estimate how the preferences of the same individual change in response to the downturn. In some specifications we eliminate these individual fixed effects to allow for compositional changes in the types of individuals seeking jobs around the crisis. We cluster standard errors by the state in which the user is located.

4.2.2 Applications

We also use a similar specification to explore changes in the types of firms job seekers apply to. Specifically, we explore whether individuals tended to submit applications to larger or

[7] In robustness tests, we show our results are similar if we use the national or state-level number of COVID cases as continuous treatment variables.

older startups after the downturn. To do so, we estimate the following specification at the job application level:

$$y_{it} = \alpha_i + \beta \mathbb{1}(PostCOVID_t) + \boldsymbol{\delta}' \boldsymbol{X_t} + \epsilon_{i,f,t} \tag{2}$$

where y_{it} represents either the number of employees or the financing stage of the firm candidate i applied to at time t, and $\boldsymbol{X_t}$ is a vector of day-level controls that include the average number of employees of firms hiring on AngelList and the total number of job postings on AngelList. Similar to equation (1), we include candidate fixed effects α_i in the full specification to examine within-candidate changes in application preferences. Standard errors are clustered by a candidate's state.

4.3 Effect on Firms

The estimation strategies described above allow us to learn about how worker preferences shifted after the start of the downturn. However, it is possible that the effect of such a shift in preferences on firms could be offset or even reversed by a large enough influx of new job seekers after the crisis. In other words, even though existing workers on the platform may be less interested in working for early-stage startups, there may be enough additional workers seeking jobs due to the crisis that these firms actually find it easier to attract human capital. To explore this possibility, we also estimate effects on job applications at the job posting $\times$ day level.

Our baseline specification here examines whether the number of applications received by jobs declined following the onset of the crisis. In addition, we examine whether applications declined more for early-stage startups than for more established firms. We estimate the following equation at the job posting $\times$ day level:

$$
\begin{aligned}
Applications_{fjt} = \alpha_j + \theta_{jt} + \beta \mathbb{1}(PostCOVID_t) + \\
\gamma \mathbb{1}(PostCOVID_t) \times \mathbb{1}(EarlyStageStartup_{ft}) + \boldsymbol{\delta}' \boldsymbol{X_{ft}} + \epsilon_{fjt} \quad (3)
\end{aligned}
$$

where $Applications_{fjt}$ is the number of new applications to job j at startup f on day t; $EarlyStageStartup_{ft}$ is either an indicator for whether a startup has fewer than 50 employees or an indicator for whether its last financing round was a series B round or earlier at the time of application;[8] θ_{jt} are fixed effects for the number of days since the job was posted, which account for temporal patterns in application volumes over the lifecycle of a job posting; $\boldsymbol{X}_{ft}$ is a vector of controls that includes the total number of live job postings associated with a startup on a given day and the average size (i.e., number of employees) of all startups hiring on AngelList on a given day. In some specifications, we include firm fixed effects, α_f, thus exploring changes in application volumes within firms. However, changes in application volumes under this specification may reflect changes in the number or type of job vacancies posted by a firm, thus picking up both supply and demand side factors. Therefore, in our main specification we include job posting fixed effect, α_j. By examining *within-job* changes in applications, we are able to hold labor demand factors constant. This allows us to isolate changes in labor supply. We cluster standard errors by a firm's state.

Lastly, we also examine how the downturn impacted the average quality of talent flowing to startups. To do this, we estimate the following specification at the application level:

$$
\begin{aligned}
ApplicantQuality_{ifjt} = \alpha_j + \beta \mathbb{1}(PostCOVID_t) + \\
\gamma \mathbb{1}(PostCOVID_t) \times \mathbb{1}(EarlyStageStartup_{ft}) + \boldsymbol{\delta}' \boldsymbol{X_{ft}} + \epsilon_{ifjt} \quad (4)
\end{aligned}
$$

[8] Not all firms have financing round information, thus our samples are smaller when using financing round as the interaction variable.

where $ApplicantQuality_{ifjt}$ is the number of years of experience or the estimated quality score for candidate i applying to job j at startup f at time t; $EarlyStageStartup_{ft}$ and $\boldsymbol{X}_{ft}$ are defined the same way as those in equation (3). Standard errors are clustered by a firm's state. Similar to equation (3), we control for job fixed effects α_j in the main specification, which ensures that any identified changes in applicant quality are not driven by firms adjusting the types of jobs posted with different job requirements.

5 Results

5.1 Summary Statistics

Table 1 provides basic summary statistics. Panel A presents statistics on search parameters entered by job seekers when the unit of observation is at the search level. The average startup size searched by job seekers is 162 employees, with 30% of searches looking for companies with at least 500 employees. During our sample period, 89% of the searches are for full-time positions, and 10% and 13% are for internship and contractor positions, respectively.[9] The average minimum required salary is around \$66,000, and among searches with at least one filter, searches on average specify 1.6 roles, 3.0 markets, 1.5 locations, and 2.1 keywords. Finally, 61% of job searches include remote jobs.

Panels B and C present statistics on job applications at the job posting × day level and the application level, respectively. On an average day, a job posting receives 0.19 applications.[10] The average startup has about 7 live job postings on a given day. The average applicant has 4.2 years of work experience and a candidate quality score of 13.2. About 76% of the applications go to startups with fewer than 50 employees and 73% go to startups that are

[9] Users can search for multiple job types simultaneously.

[10] The average is low because our job posting × day level sample includes days on which a live job posting received no applications.

before their B-round funding. The average startup receiving applications has 26 employees.

5.2 Effect on Worker Preferences

5.2.1 Job Search Parameters

We start by analyzing whether job seekers changed their job search and screening criteria following the start of the downturn. Table 2 presents the results estimated from equation (1) with dependent variables related to the size of firms users search for, as measured by the number of employees. The dependent variable in columns 1–2 is the log of the firm size searched for and in columns 3–4 it is an indicator for whether the firm size searched for is greater than 500 employees. The sample is at the individual search level. In column 1, we find that following the start of the COVID downturn, users increased the firm size they were searching for. The coefficient of 0.223 is highly statistically significant and indicates a 25%(=exp(0.223)) increase in the size of firms searched for after the crisis began. In column 2, we add job candidate fixed effects, which ensures that the results are not driven by compositional changes in the type of users seeking jobs on AngelList Talent. We find a similar result, with a coefficient of 0.254, reflecting a 29% increase in the size of firms searched for by the same user. Columns 3 and 4 reveal similar findings when examining the likelihood of searching for companies with least 500 employees. Based on the coefficient in column 4 with candidate fixed effects, users are 20% more likely to search for large firms with above 500 employees after the crisis compared with the pre-crisis mean. Overall, the results from Table 2 are consistent with a flight-to-safety channel, in which the preferences of job seekers shift towards more established firms.

In Table 3, we explore whether other search criteria changed simultaneously with the shift towards more established firms. We find that, post COVID, candidates were more likely to search for part-time jobs, such as internships (column 1) or contractor positions (column 2). Additionally, job seekers were willing to accept a lower minimum salary, and became more flexible along other dimensions as they increased the number of roles, markets, locations, and keywords included in their searches. Moreover, consistent with the prevalence of working from home during the pandemic, we also find a 21% increase in candidates' willingness to work remotely. These results suggest that job seekers became less selective and more flexible in their job searches during the downturn. Together with the results from Table 2, it appears that users' flight to safety—the desire to find employment with more established firms—is accompanied by a willingness to compromise on other job dimensions.

We check the validity of the above results in several ways. First, we plot the non-parametric relationship between searched firm size and the date of search in Figure 3, removing user fixed effects. We see a sharp jump in searched firm size around late March and early April, which coincides with the outbreak of COVID in the U.S. This sharp increase, together with the lack of pre-trend, helps alleviate concerns that other non-COVID-related events may drive such changes. To further alleviate such concerns, we examine whether such changes are present in 2019 data over the same time period. Panel A of Table 8 presents the result of this placebo test. We find no statistically significant changes in searched employment size around March 13 in 2019. Not only are the coefficients insignificant, they are economically small. Consistent with this, Figure A.3 shows a largely flat non-parametric relationship between searched firm size and search date around March of 2019. These results suggest that the flight-to-safety finding documented around the start of the COVID downturn is unlikely to be driven by seasonality or unobserved trends in the data.

5.2.2 Job Applications

Do changes in search preferences translate into job applications? In Table 4, we investigate this question using the specification in equation (2). The analysis is at the job application level and the dependent variables are the log size (number of employees) of the firm applied to and an indicator for whether the firm applied to has raised a series B round or later. Consistent with our findings on changes in search parameters, in Panel A we find that job candidates applied to larger and older firms after the onset of the crisis. Again, these changes hold even within the same candidate over time (Panel B). In particular, columns 1 and 4 of Panel B show that job seekers applied to firms that are 8% larger and that are 16% more likely to be late stage after the start of the downturn. Similar results are not found in a placebo test using 2019 data (Panel B of Table 8). Further, in Table A.1, we show that our results are similar even when we include job role fixed effects and startup industry fixed effects, suggesting that changing preferences for certain positions or industries do not drive our results: even within the same role and industry, candidates shift applications towards more established firms. Thus, flight-to-safety appears to persist from search activities to job applications.

Next, we explore whether the flight-to-safety effects that we document differ for high- and low-quality job seekers. High-quality workers may tend to already be employed at more established firms and therefore have greater access to an economically resilient outside option. As a result, when the perceived riskiness of early-stage startups increases during a downturn, the interest of high-quality candidates may shift away from early-stage startups more so than that of low-quality candidates. To examine whether this is the case, we partition candidates according to two characteristics that we can observe in the data: their number of years of experience and an estimated score of their overall quality. Consistent with the resilient outside option hypothesis, in Panel B of Table 4, we find stronger effects among high-quality applicants, who shift their applications to firms that are 14% larger and 19% more likely to be late-stage.

5.3 Effect on Firms

So far, we have documented a significant shift in worker preferences away from early-stage startups during the downturn, an effect driven mostly by high-quality workers. How do these changes impact startups? In this section, we examine the effect of the downturn on the quantity and quality of talent flows to startups.

5.3.1 Job Applications

We first examine how the downturn impacted the volume of job applications to startups. If flight-to-safety is prevalent, we should see a drop in job applications to all startups, as job seekers who would otherwise work for startups turn instead to non-startup employers. Further, such flight-to-safety should also drive a wedge between early-stage startups and startups that are more established.

Panel A of Table 5 presents the results. The specification is based on equation (3) and the dependent variable is the number of new applications to a job posting in a given day. We find that, within a firm, the average number of applications to a job posting declined by 14.1% overall during the COVID downturn, when compared with pre-COVID means (column 1).[11] Given that AngelList Talent focuses primarily on entrepreneurial firms, this result in itself is consistent with a flight-to-safety across platforms, where job candidates

[11]Note that the decline in applications that we find on AngelList is not inconsistent with the massive layoffs that occurred during this period. First, most of the layoffs were in the service and hospitality sectors such as restaurants, travel, and hotels rather than the high-tech sectors that startups typically operate in. Second, given that AngelList Talent focuses mainly on startups, laid-off workers could generally shift away from AngelList Talent to other job platforms with larger firms.

leave AngelList to search for jobs in more established firms. We then examine whether this decline is homogeneous across firms in columns 2–3. We find that the decline is stronger for early-stage startups. For example, startups with fewer than 50 employees saw a 21.4% decline in applications compared with no decline for startups with above 50 employees (column 2). Similarly, job applications to pre-series-B startups declined by 23.8%, while those going to post-series-B startups declined by only 4.7% (column 3). In columns 4–6, we further include job-posting fixed effects, therefore exploring the shift in the number of applications within the same job posting. We find similar results with slightly smaller magnitudes. This within-job analysis rules out the possibility that our results are driven by changes in the types of jobs posted by firms during the downturn.[12]

We then explore what type of candidates drive the declines in applications to early-stage startups. Specifically, we split the number of applications by candidate experience or quality score at the median. Panels B and C of Table 5 show the results, controlling for firm fixed effects and job fixed effects, respectively. In both panels, we find that the stronger declines in applications to early-stage startups are driven entirely by high-quality candidates (columns 1–2 and 5–6), while low-quality candidates did not apply differentially to early-stage startups (columns 3–4 and 7–8), as indicated by the insignificant interaction terms. These results hold whether we measure candidate quality by experience or AngelList's proprietary quality score. Moreover, the results are absent in a placebo test using 2019 data (Panel C of Table 8), suggesting they are not driven by general time trends over these particular months of the year.

How do these application patterns impact the average quality of talent available to startups? Table 6 investigates this, focusing on applicant quality at the application level.

[12]The decline in applications does not contradict our prior results that job candidates became less choosy in searches. In unreported results, we find that fewer people are submitting applications on AngelList after COVID, but the number of applications submitted per person did not decline.

Columns 1 and 4 of Panel A show that, within a firm, the average applicant experience declined by 3.1% and applicant quality by 6.5% during the COVID downturn. However, such an average decline is driven entirely by early-stage startups, as shown in columns 2–3 and 5–6. In particular, startups with fewer than 50 employees experienced a 4.2% decline in applicant experience and a 8.1% decline in applicant quality. Similarly, average applicant experience dropped by 3.8% for pre-series-B startups and applicant quality dropped by 6.4%. In contrast, more established startups saw no significant declines in applicant quality and, if anything, experienced slight increases. Panel B shows that these results hold not only within firms, but also within jobs, suggesting declining applicant quality is not driven by firms lowering job requirements or canceling higher-skilled jobs (i.e., downskilling in labor demand).

Figures 4 and 5 show changes in applications and applicant quality graphically. In Figure 4, we see that large and small firms, as well as late-stage and early-stage firms had very similar trends in the number of applications received per job before mid-March. Yet they started to diverge significantly after mid-March, when the COVID crisis started. In particular, smaller and earlier-stage startups saw a larger drop in the number of applications per job than larger and later-stage startups. Further, all firms saw a precipitous drop in applications around mid-March, suggesting the result is not simply a continuation of a previous downward trend. In contrast, Panels A and B of Figure A.4 show that applications per job in 2019 were largely flat around mid-March 2019 and did not differ between small and large (or early-stage and late-stage) firms.

Figure 5 shows that the average quality of job applicants to small or early-stage startups dropped sharply around mid-March. This holds whether we measure quality by job experience (Panels A and C) or AngelList's quality score (Panels B and D). In contrast, applicant experience and quality score did not decline significantly for large or late-stage startups and, if anything, somewhat increased. Further, small and large startups trended similarly in applicant quality measures before COVID, and so did early- and late-stage startups. Panels C and D in Figure A.4 show the placebo graphs for average applicant quality over the same months in 2019. We see no differential trends between the experience or quality of the candidates applying to less and more established firms. These patterns suggest that our results are not driven by a general downward trend in applicant quality for less established startups, or these startups being on a differential trend than more established ones.

Taken together, our results show that workers' desire to join safer firms during economic downturns has real adverse consequences for early-stage startups in terms of their ability to attract talent. During downturns, job candidates, especially high-quality ones, shift toward more established firms.

5.3.2 Response to Job Applications

Does the decline in talent flows to startups affect their actual hiring during downturns? If there was an oversupply of candidates prior to COVID and the post-COVID decline was concentrated among candidates that startups would not hire anyway, then actual startup hiring may not have been impacted. Although we do not observe eventual hirings, we can proxy for them using positive responses by startups to submitted applications—requests for introductions. As discussed earlier, intro requests are required to facilitate further interactions with candidates such as interviews or job offers, which are precursors to eventual hiring.[13] We can therefore examine whether the number of candidates receiving intro requests declined after COVID, as well as changes in their average quality. Importantly, this approach allows us to focus on the candidates that startups are most likely to hire, without taking a stance on the characteristics of these candidates (i.e., a revealed preference approach).

[13] About 7% of the submitted applications receive intro requests from firms.

We estimate the following equations that are analogous to equations 3 and 4:

$$IntroRequests_{fjt} = \alpha_j + \theta_{jt} + \beta \mathbb{1}(PostCOVID_t) + \gamma \mathbb{1}(PostCOVID_t) \times \mathbb{1}(EarlyStageStartup_{ft}) + \boldsymbol{\delta}' \boldsymbol{X_{ft}} + \epsilon_{fjt} \quad (5)$$

$$QualityOfApplicantReceivingIntro_{ifjt} = \alpha_j + \beta \mathbb{1}(PostCOVID_t) + \gamma \mathbb{1}(PostCOVID_t) \times \mathbb{1}(EarlyStageStartup_{ft}) + \boldsymbol{\delta}' \boldsymbol{X_{ft}} + \epsilon_{ifjt} \quad (6)$$

where $IntroRequests_{fjt}$ is the number of intro requests on job j by startup f on day t, $QualityofApplicantReceivingIntro_{ifjt}$ is the years of experience or quality score of candidate i who received an intro request from startup f on job j on day t, and all other variables are the same as those in equations 3 and 4. We estimate equation 5 at the job posting $\times$ day level and equation 6 at the intro level.

Because intro requests are firm actions, we take extra care to control for firm demand and to make sure we only capture supply-driven changes. In both equations, we examine within-job posting changes. We further mitigate concerns about changing demand *within* an open job posting (i.e., stale job postings) by focusing on jobs that were actively monitored by startups. Specifically, in both equations, we restrict to jobs that firms took some action on, either in the form of a rejection or an intro request. In equation 5, we additionally restrict to days from a job's posting date to the last day the firm took action on the job. These restrictions make sure that changes in intro requests are driven by changing talent flows within jobs, rather than firms' weaker labor demand.

Table 7 presents the results. Panel A shows that within a job, the daily number of intro requests declined substantially after COVID by 29%; such a decline was concentrated among smaller and earlier-stage firms (45% and 38% respectively), and was largely absent among larger and later-stage firms. In contrast, Panel B shows that there was no differential change in the experience/quality of the applicants that less established firms made intro requests to.

Overall, the large decline in intro requests by less established startups suggests that the decline in applications to these firms is likely consequential for their hiring. Further, facing a deteriorated talent pool, less established startups adjusted potential hirings mainly through the quantity margin, without significantly sacrificing the quality of the candidates they consider. This result suggests that labor demand by early-stage firms is quite sensitive to talent quality. The type of human capital available to startups is therefore crucial to understanding the unique challenges facing startups in economic downturns.[14]

6 Robustness

In this section, we present the results from a number of additional robustness tests.

Continuous treatment measure. First, we show in Table A.2 that our main results are similar if we use state-level cumulative number of COVID cases as an alternative treatment variable. The local number of cases captures not only the onset of COVID but also the differential escalations of the pandemic in different regions, which may shape job candidates' or firms' expectations.[15]

Excluding tech hubs. Second, to make sure that our results are not just driven by job candidates or firms in traditional tech hubs, we show in Table A.3 that our results are robust to excluding workers or firms from California and Massachusetts from our samples.

[14] One may wonder why early-stage startups do not simply adjust compensation to attract talent during downturns. There are two potential reasons. First, early-stage firms are known to be particularly cash-constrained during a downturn. Howell et al. (2020) show that early-stage financing tends to dry up during downturns, including the COVID downturn, while later-stage financing does not. Second, new ventures may be limited in their ability to use equity to attract talent during a downturn due to perceived higher risk of failure, which reduces the value of equity to job seekers.

[15] It is also possible that job candidates or firms react to the pandemic situation at the national rather than at the local level. Our main results are similar if we use the national number of COIVD-19 cases as another alternative treatment variable.

The magnitudes also remain similar, suggesting that the labor market reactions we document are broad-based and not just concentrated in tech hubs.[16]

Measuring preferences with clicks. Third, we exploit candidates' clicking behavior as an alternative measure job search interests. After inputting search filters, candidates can click on the returned job postings to obtain more information, or click on the startup name to view detailed startup info. In both cases, startup employment size is visible before candidates make these clicks. These clicks are therefore good indicators of candidates' job preferences.[17] Table A.4 estimates a specification analogous to equation (2), examining how the size and stage of the startups clicked by candidates changed around the downturn. We find that candidates clicked on larger and later-stage firms after COVID: within candidates, they clicked on firms that are 13.8% larger after the downturn, and they were 13.5% more likely to click on post-B-round startups.

Quality-adjusted talent pool measure. Lastly, we explore an alternative measure of the supply of human capital pool to startups — total experience or total quality score across all job applicants. Table A.5 presents the results, where the dependent variable is the sum of all job applicants' numbers of years experience or quality scores at the job posting-day level. We find a similar decline in this quality-adjusted talent pool measure, especially for early-stage startups. For example, within a job posting, total applicant experience dropped by 18% for early-stage startups after COVID, while it barely changed for more established firms.

[16]This finding is consistent with Kahn et al. (2020), who document that the drop in job vacancies happened similarly across all U.S. states, regardless of the intensity of the initial virus spread or timing of stay-at-home policies.

[17]These clicks do not include applications.

7 Alternative Explanations

In this section, we address several potential alternative explanations for our main findings.

Adjustment of search parameters in response to job postings. One potential concern with our results on changes in search parameters is that users may adjust their filters in response to the jobs postings they see from previous searches. In this case, within-user changes in search parameters may reflect learning about demand rather than changes in preferences. In particular, some job seekers may prefer early-stage startup jobs throughout, but begin searching for later-stage startup jobs during the downturn if there is a decline in early-stage job postings. However, it is not clear that a user would actively filter out their preferred type of jobs from their search results, simply because that type of job is less common. In addition, in Table A.6, we show that our findings remain similar when we restrict our sample to "fresh" searches that are the first search by a user in a day, a week, or a month. Thus, it does not seem that our results are driven by users modifying their search parameters in response to the jobs they see from recent searches. Further, our firm-level results are also inconsistent with a lack of change in worker preferences. Absent such a change, it is not clear why early-stage startups would experience a decline in applications during the downturn—even within a given job posting.

Sample selection associated with within-candidate analysis. Another potential concern is that our within-candidate estimates are based on individuals who searched/applied for jobs both before and after the start of the downturn. This could introduce potential sample selection issues, as such workers may be the ones who had a harder time getting hired. For example, it is possible that workers with a preference for a job at an early-stage startup eventually shift to searching/applying for jobs at more established startups due to lack of success in getting hired, rather than due to the economic downturn. However, we do not find similar results in 2019, when similar sample selection issues exist but without a downturn. In addition, such sample selection concerns would not explain the similar results we find without individual fixed effects, the heterogeneity we find between high-quality and low-quality candidates, or the effects that we find within job postings, which allow for compositional changes in job candidates.

Sample selection associated with AngelList Talent. Because we use data from a single job platform, one may be concerned that our results may not be representative of what was happening in the overall labor market, or that our results are driven by candidates shifting across platforms. However, our goal is not to capture the universe of job seekers. Rather, we are interested in the set of candidates who might consider startup jobs—that is, those who face a choice between working for a startup versus a more established firm. Within the startup sector, AngelList Talent is the leading recruiting platform. In fact, the overall decline in applications we found on AngelList during COVID is exactly consistent with a cross-platform flight-to-safety, as job seekers switch to other platforms that tend to host more established companies.

Relaxation of geographical constraints. One unique aspect of the COVID downturn is that it led to a rise in remote work, which potentially could have relaxed geographical constraints in workers' job searches. Relaxed geographical constraints could provide an alternative explanation for the shift in interest that we document towards more established firms. In particular, those who wanted to work for more established firms before, but could not due to a lack of proximity to such firms, might have had greater access to their desired type of jobs following start of the pandemic. In this case, our results would not be driven by the economic downturn but by the rise of remote work. However, it is unclear why such relaxation of geographical constraint is stronger for high-quality candidates than for low-quality candidates, especially given the co-location of skilled labor and large successful firms

(Kerr et al., 2015; Håkanson et al., 2020). To further address this concern, we also restrict our analyses to searches or applications that are local to the candidate's location. Specifically, we restrict to searches that exclude remote options or searches in the same location as the candidate's location. We also restrict to applications to jobs in the same location as the candidate's location. The results remain similar in these subsamples (Table A.7).[18]

Shift in job searches from offline to online. Because we use online job search data, one may be concerned that our results are driven by a shift in job searches from offline to online during COVID, when in-person recruiting became less feasible. However, this shift would not explain our within-candidate search results, which are identified off of individuals who were already searching jobs online before COVID. In other words, although COVID may affect the likelihood that a worker searches for jobs online, *conditional on* her conducting an online search, it is unclear why she would exclude larger firms from her searches pre-COVID simply because there were more offline recruitment opportunities. Moreover, an offline-online shift would go against us finding an overall decline in applications on AngelList, as it would predict an increase in online job applications. Lastly, it is unclear why such a shift would be concentrated among larger firms or among lower-quality candidates, which would be necessary to explain our results.

Stale job postings. Another potential explanation for our flight-to-safety results is that candidates may believe job postings by early-stage startups are more likely to be stale during downturns. That is, they may believe that early-stage startups are less likely to actively monitor their job postings and to remove them when they no longer have a hiring

[18]Relatedly, one might also worry that our results are driven by worker preferences shifting toward remote jobs, which may tend to be associated with more established startups. However, it would not be necessary for job seekers on AngelList to use firm size or age as a proxy for a firm's ability to offer remote work, since jobs on AngelList explicitly specify whether they can be remote and searches can be filtered directly on this characteristic. Moreover, we actually find that early-stage startups are in fact more likely to offer remote jobs than more established startups: following COVID, 39% of jobs posted by firms with fewer than 50 employees offered remote options, while only 15% of jobs posted by firms with more than 50 employees did so.

need. To address this possibility, we restrict our analysis to job postings that the firm took some action on, either in the form of a rejection or an intro request. These job postings were not ignored by firms are thus unlikely to be stale. Although these job postings can still be *perceived* to be stale, we can evaluate whether such beliefs, if exist, are warranted. Table A.8 shows that we find similar results on these subsamples. This suggests that our results are not driven by rational expectation about firms' inability to maintain labor demand during downturns.

8 Further Discussion

The main contribution of our paper is to document a flight to safety in labor market that negatively affects the ability of startups to attract talent during economic downturns. But what explains this flight-to-safety preference? Just as investors shift to safer assets during financial crises (Vayanos, 2004; Caballero and Krishnamurthy, 2008; Baele et al., 2020), job candidates may shift to larger employers due to beliefs that these employers offer better job security or job prospects during a recession. For example, larger firms may be better able to secure financing or maintain product demand in downturns; they may also have steadier labor policies. Importantly, these beliefs need not be rational, and could instead reflect overreaction or irrational responses by workers. Pinning down the source of flight to safety and the rationality of these beliefs is beyond the scope of this paper. However, regardless, such behavior by job seekers represents a novel mechanism through which economic downturns negatively impact startups. If downturns do not make startups riskier through non-talent flow channels, the talent flow channel that we document would represent the main way that downturns negatively impact startups. If downturns do make startups riskier through non-talent flow channels, the talent flow channel would amplify the other channels.

9 Conclusion

Young firms are central to innovation and productivity growth. Yet their ability to grow and innovate depends crucially on their ability to attract high-quality talent, potentially from established firms. Before achieving standardization, human capital is fundamentally intertwined with the success of early-stage startups. In this paper, we show that young firms' ability to attract talent suffered during the most recent economic downturn—the COVID crisis. Using unique job search data as well as within-candidate and within-job analysis, we show that job seekers pivot to larger and more mature firms when a downturn hits. This leads to a decline in talent flows to startups, especially to less established ones. Importantly, such flight-to-safety is stronger among higher-quality candidates, leading to a deterioration in the quality of human capital available to small, young startups. Our results provides a novel mechanism through which economic downturns negatively impact entrepreneurship. More broadly, our study highlights the importance of labor market frictions in understanding the pro-cyclicality of entrepreneurship.

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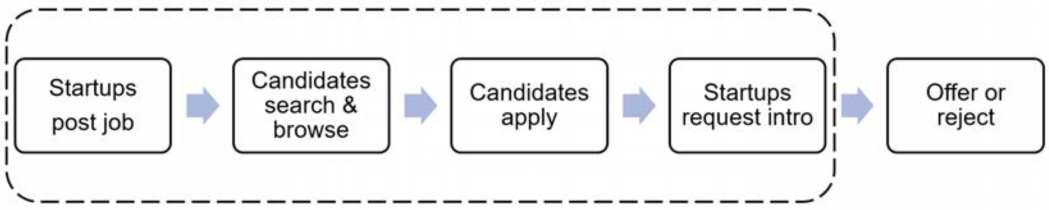
Figure 1
AngelList Talent Platform

Panel A shows the job search and match process on the AngelList Talent platform. The dashed box indicates activities that happen within the platform. Panel B shows a screen shot of the job search interface with various search filters.

Panel A: Job search and match process on AngelList



Panel B: Job search filters

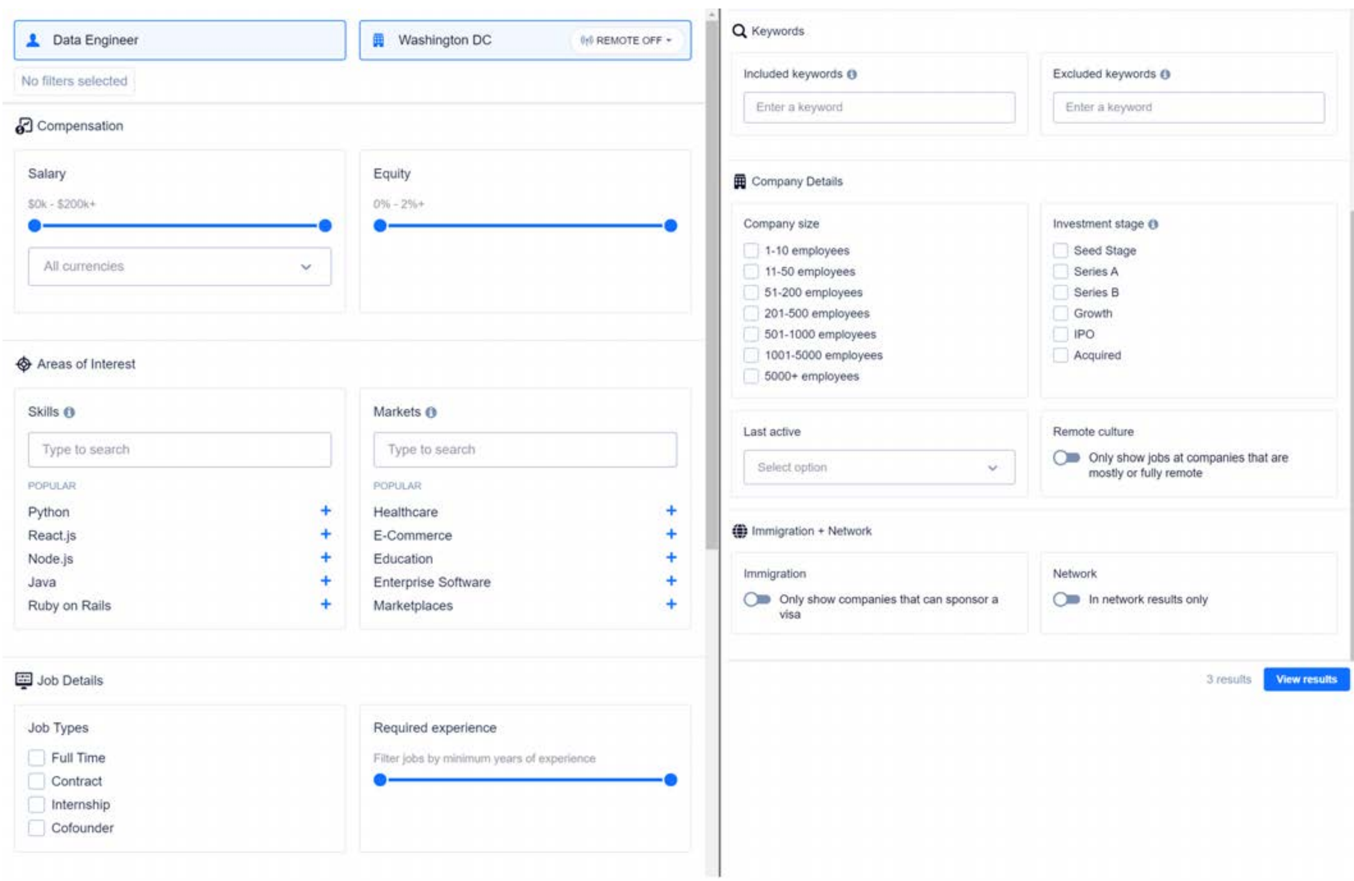
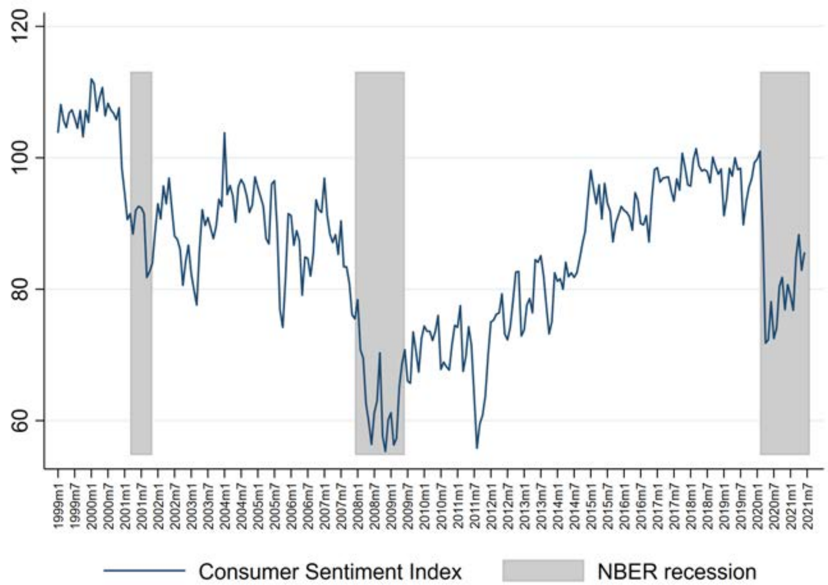


Figure 2
Time Series in Economic Exepectations

These figures show the time series in monthly consumer expectations over the last two decades. Panel A plots the Consumer Sentiment Index from the University of Michigan. The index reflects respondents' expectations about current and future conditions regarding personal finance, business condition, employment, and spending. Panel B plots the Consumer Confidence Index from the Conference Board. The index reflects expectations about current conditions and likely developments for the months ahead regarding business condition, employment, and household income. The shaded regions correspond to the last three recessions dated by the NBER: the dotcom crash, the Great Recession, and the COVID crisis.

Panel A: Consumer Sentiment Index from the University of Michigan



Panel B: Consumer Confidence Index from the Conference Board

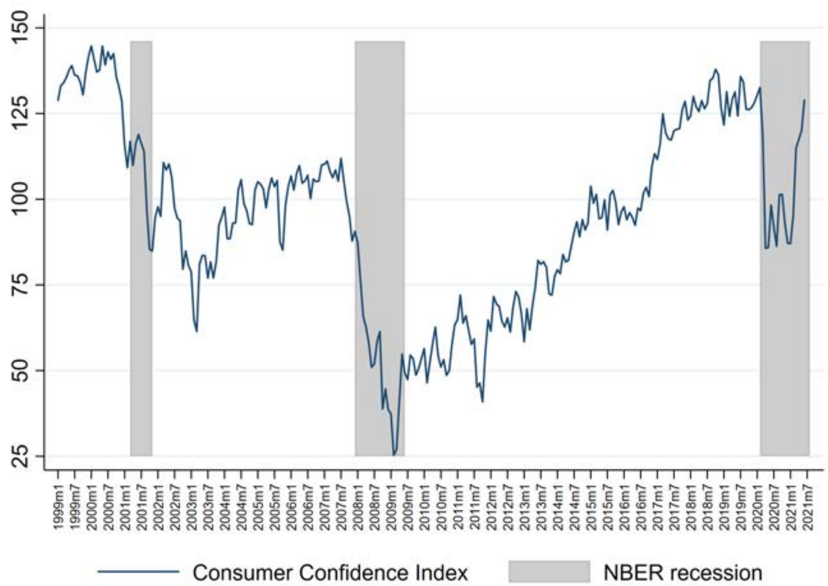
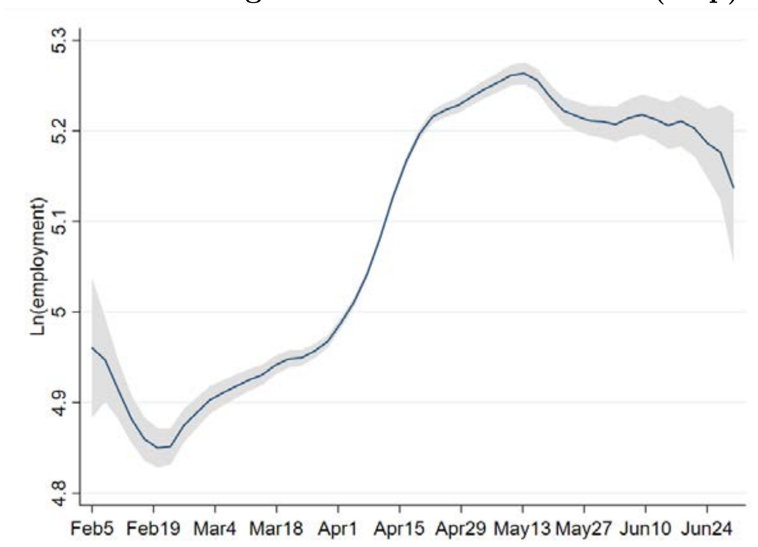


Figure 3
Changes in Searched Firm Size

Panel A (Panel B) shows within-user changes in the logarithm of average employment size searched by users (the likelihood of average searched employment size being larger than 500) from February to June 2020. Each figure plots the fitted lines and 95% confidence bands estimated from local linear regressions, removing user fixed effects.

Panel A: Changes in searched firm size: ln(emp)



Panel B: Changes in searched firm size: emp>=500

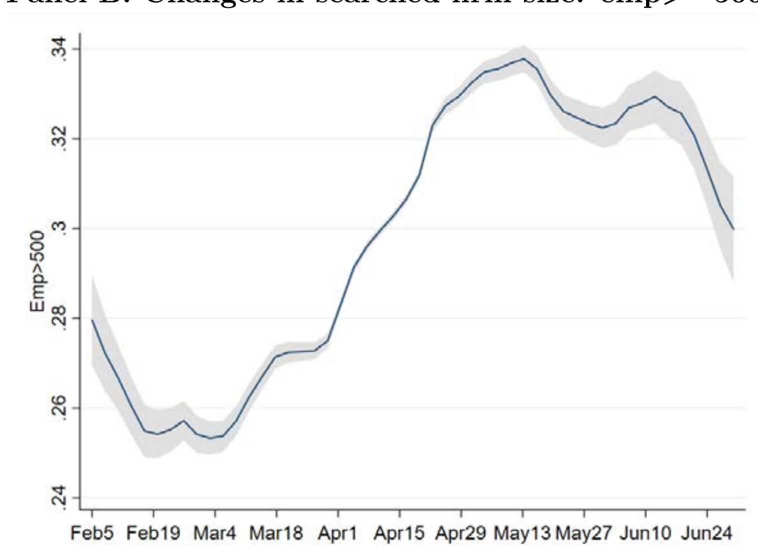
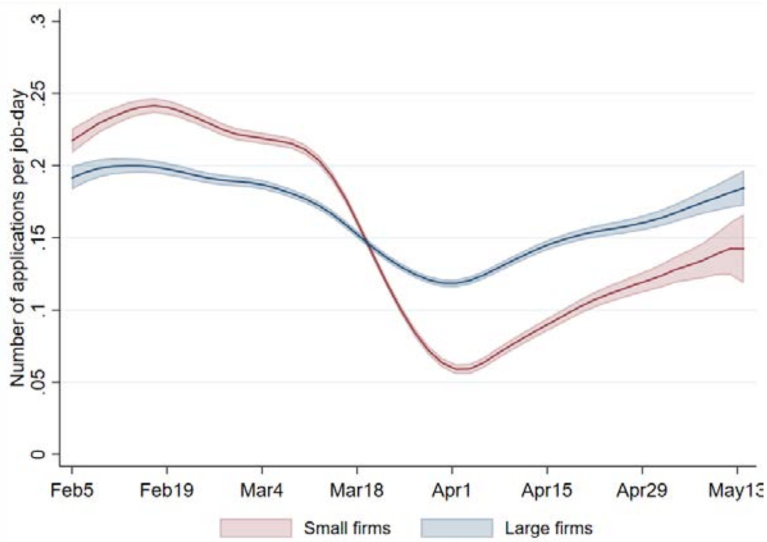


Figure 4
Changes in the Number of Applications Per Job

Panel A (Panel B) shows within-job changes in the number of applications received per job posting from February to May 2020. Each figure plots the fitted lines and 95% confidence bands estimated from local linear regressions, removing job posting fixed effects and controls such as the log number of active job postings by a firm on a given day and the average size of firms hiring on AngelList on a given day. Red lines and areas indicate small firms or early-stage firms. Blue lines and areas indicate large firms or late-stage firms. Small (large) firms are startups with no more than (more than) 50 employees at the time of application. Early-stage (late-stage) firms are startups with financing stage before (at or post) series B round at the time of application.

Panel A: Number of applications per job by firm size



Panel B: Number of applications per job by firm stage

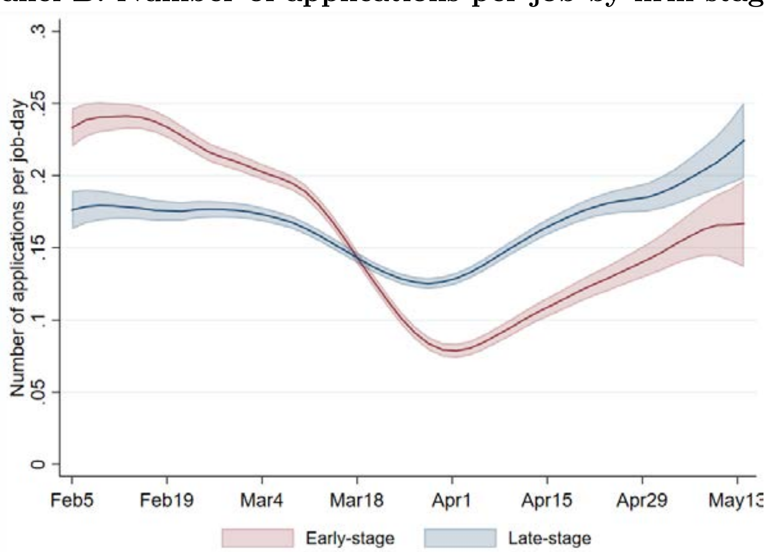
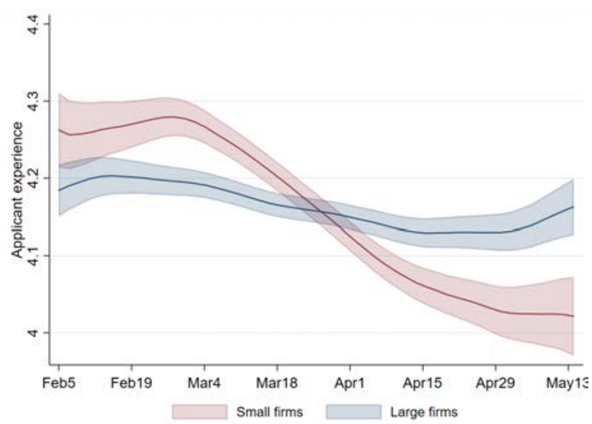


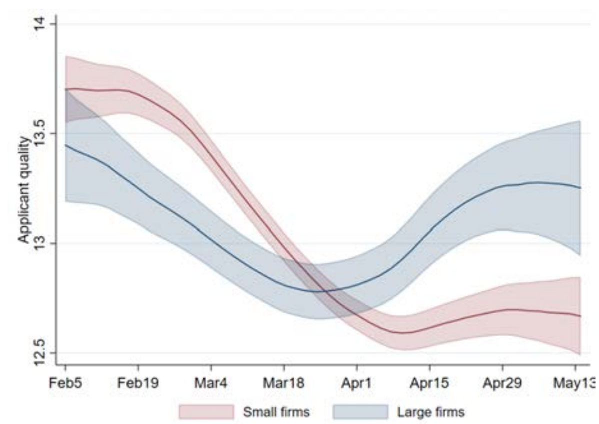
Figure 5
Changes in Applicant Quality

Panel A (Panel B) shows within-job changes in the average number of years of experience (quality score) of job applicants from February to May 2020 by firms size. Panel C (Panel D) shows within-job changes in the average number of years of experience (quality score) of job applicants from February to May 2020 by firm stage. Each figure plots the fitted lines and 95% confidence bands estimated from local linear regressions, removing job posting fixed effects and controls such as the log number of active job postings by a firm on a given day and the average size of firms hiring on AngelList on a given day. Red lines and areas indicate small firms or early-stage firms. Blue lines and areas indicate large firms or late-stage firms. Small (large) firms are startups with no more than (more than) 50 employees at the time of application. Early-stage (late-stage) firms are startups with financing stage before (at or post) series B round at the time of application.

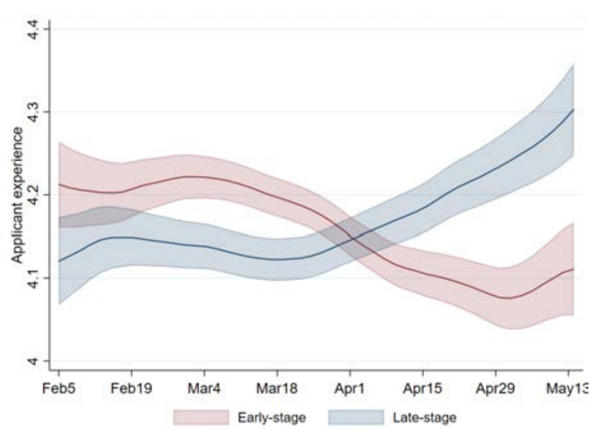
Panel A: Applicant experience by size



Panel B: Applicant quality by size



Panel C: Applicant experience by stage



Panel D: Applicant quality by stage

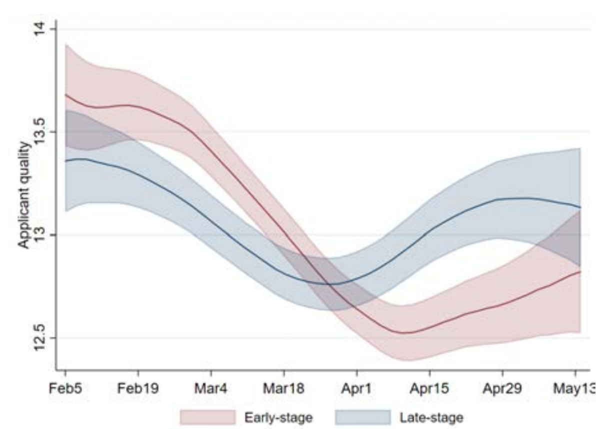


Table 1
Summary Statistics

This table presents summary statistics for the main variables used in our analysis. Panel A presents the statistics for search parameters at the search level. Panel B presents statistics on job application volume and control variables at the job posting-day level. Panel C presents statistics on the characteristics of job applications at the application level.

Panel A: Search level

Variable	N	Mean	Std. dev.	P5	Median	P95
Ln(emp)	390,005	5.09	2.11	1.87	4.86	7.93
Emp>500	390,005	0.30	0.46	0.00	0.00	1.00
Internship	3,903,401	0.10	0.30	0.00	0.00	1.00
Contractor	3,903,401	0.13	0.33	0.00	0.00	1.00
Full-time	3,903,401	0.89	0.32	0.00	1.00	1.00
Ln(min. salary)	1,120,913	4.19	0.96	1.61	4.39	5.07
No. of roles	3,572,005	1.55	1.38	1.00	1.00	4.00
No. of markets	337,116	2.96	2.39	1.00	2.00	8.00
No. of locations	4,645,381	1.50	1.23	1.00	1.00	4.00
Open to remote	5,397,027	0.61	0.49	0.00	1.00	1.00
No. of keywords	186,916	2.11	1.85	1.00	2.00	5.00

Panel B: Applications: job posting-day level

Variable	N	Mean	Std. dev.	P5	Median	P95
No. of applications	1,421,197	0.19	0.81	0.00	0.00	1.00
No. of applications - experienced	1,421,197	0.09	0.50	0.00	0.00	1.00
No. of applications - inexperienced	1,421,197	0.09	0.46	0.00	0.00	1.00
No. of applications - high quality	1,421,197	0.09	0.47	0.00	0.00	1.00
No. of applications - low quality	1,421,197	0.09	0.45	0.00	0.00	1.00
Emp≤50	1,421,197	0.68	0.47	0.00	1.00	1.00
Pre-B	722,649	0.61	0.49	0.00	1.00	1.00
Avg ln(emp) of recruiting firms	1,421,197	3.50	0.13	3.29	3.51	3.70
Ln(no. of active jobs by the firm)	1,421,197	2.10	1.15	0.69	1.95	4.37

Panel C: Applications: application level

Variable	N	Mean	Std. dev.	P5	Median	P95
Applicant experience	418,450	4.19	3.47	0.00	3.00	10.00
Applicant quality	418,450	13.24	15.62	0.00	7.38	44.27
Ln(emp)	418,450	3.25	1.42	1.70	3.42	5.86
Emp≤50	418,450	0.76	0.43	0.00	1.00	1.00
Pre-B	221,888	0.73	0.44	0.00	1.00	1.00
Post-B	221,888	0.27	0.44	0.00	0.00	1.00

Table 2
Change in Search Parameters: Startup Employment Size

This table examines changes in employment size searched by job candidates around the onset of COVID from February to June 2020. The sample is at the search level. The dependent variable *Ln(emp)* is the log number of employees averaged across all size bins selected in a search; *Emp>500* is an indicator equal to one if the average searched employment size is larger than 500. *PostCOVID* is a dummy indicating dates after March 13, 2020, the date that a state of national emergency was first announced in the U.S. Columns 1 and 3 include fixed effects for candidate's state and columns 2 and 4 include candidate fixed effects. Standard errors are clustered by candidate's state. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Ln(emp)	Ln(emp)	Emp>500	Emp>500
	(1)	(2)	(3)	(4)
PostCOVID	0.223***	0.254***	0.053***	0.052***
	(0.052)	(0.018)	(0.013)	(0.005)
Candidate FE	No	Yes	No	Yes
Candidate state FE	Yes	No	Yes	No
N	390,005	390,005	390,005	390,005
Adj. R-sq	0.013	0.811	0.014	0.733
% change	25%	29%	20%	20%

Table 3
Change in Search Parameters: Other Search Dimensions

This table examines changes in other search parameters by job candidates around the onset of COVID from February to June 2020. The sample is at the search level. *PostCOVID* is a dummy indicating dates after March 13, 2020, the date that a state of national emergency was first announced in the U.S. All columns include candidate fixed effects. Standard errors are clustered by candidate's state. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Internship	Contractor	Full-time	Ln(min. salary)	No. of roles	No. of markets	No. of locations	Open to remote	No. of keywords
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
PostCOVID	0.006***	0.032***	-0.001	-0.018***	0.069***	0.083**	0.043***	0.111***	0.233***
	(0.001)	(0.003)	(0.001)	(0.006)	(0.010)	(0.040)	(0.007)	(0.007)	(0.064)
Candidate FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3,903,401	3,903,401	3,903,401	1,120,913	3,572,005	337,116	4,645,381	5,397,027	186,916
Adj. R-sq	0.853	0.74	0.857	0.935	0.749	0.752	0.698	0.640	0.794
% change	6.5%	27.6%	-0.1%	-1.8%	4.4%	2.7%	2.9%	21.2%	11.1%

Table 4
Change in Size and Stage of Firms Applied To

This table examines changes in the size and financing stage of the firms candidates applied to around the onset of COVID from February to May 2020. The sample is at the application level. The dependent variable *Ln(emp)* the log number of employees of the firm being applied to. *Post-B* indicates that the firm being applied to has a financing stage at or later than series B at the time of application. *PostCOVID* is a dummy indicating dates after March 13, 2020, the date that a state of national emergency was first announced in the U.S. *Experienced* indicates candidates with above median number of years of experience. *High-quality* indicates candidates with above median quality score as estimated by AngelList. Panel A include fixed effects for candidate's state. Panel B includes candidate fixed effects. All columns control for day-level average employment size of firms hiring on AngelList and total number of job postings on AngelList. Standard errors are clustered by candidate's state. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Without candidate FE

	Ln(emp)			Post-B		
	(1)	(2)	(3)	(4)	(5)	(6)
PostCOVID	0.041**	-0.015	0.010	0.022**	0.007	0.014
	(0.020)	(0.025)	(0.023)	(0.009)	(0.011)	(0.011)
PostCOVID × Experienced		0.116***			0.031***	
		(0.022)			(0.008)	
PostCOVID × High-quality			0.083***			0.021**
			(0.014)			(0.008)
Candidate state FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	418,450	418,450	418,450	221,888	221,888	221,888
Adj. R-sq	0.013	0.013	0.013	0.012	0.013	0.012
% change - worse	4.2%	-1.5%	1.0%	7.4%	2.4%	4.7%
% change - better		10.6%	9.7%		12.8%	11.8%

Panel B: With candidate FE

	Ln(emp)			Post-B		
	(1)	(2)	(3)	(4)	(5)	(6)
PostCOVID	0.077***	0.023	0.034**	0.046***	0.036***	0.038***
	(0.017)	(0.015)	(0.017)	(0.008)	(0.008)	(0.009)
PostCOVID × Experienced		0.109***			0.020***	
		(0.021)			(0.006)	
PostCOVID × High-quality			0.096***			0.019**
			(0.023)			(0.008)
Candidate FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	418,450	418,450	418,450	221,888	221,888	221,888
Adj. R-sq	0.144	0.144	0.144	0.099	0.099	0.099
% change - worse	8.0%	2.3%	3.5%	15.5%	12.2%	12.8%
% change - better		14.1%	13.9%		18.9%	19.3%

Table 5
Job Applications

This table examines changes in job applications received by startups around the onset of COVID from February to May 2020. The sample is at the job posting-day level and includes days on which a live job posting received no applications. The dependent variable in Panel A, *No. of applications,* is the number of new applications to a job posting on a given day. In Panels B and C, the dependent variables are the number of applications to a job posting on a given day from candidates with above/below median experience or above/below median quality score. *PostCOVID* is a dummy indicating dates after March 13, 2020, the date that a state of national emergency was first announced in the U.S. *Emp≤50* indicates startups with no more than 50 employees at the time of job application. *Pre-B* indicates startups whose last round of financing was series A round or earlier at the time of job application. All panels include fixed effects for the number of days since a job was posted and control for the log number of active job postings by a startup on a given day and the average employment size of all startups hiring on AngelList on a given day. Panel B controls for firm fixed effects and Panel C controls for job posting fixed effects. Standard errors are clustered by firm's state. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: All applications

	No. of applications					
	(1)	(2)	(3)	(4)	(5)	(6)
PostCOVID	-0.029*	0.000	-0.010	-0.021	0.003	-0.009
	(0.014)	(0.017)	(0.015)	(0.015)	(0.016)	(0.015)
PostCOVID × Emp≤50		-0.044***			-0.037***	
		(0.007)			(0.006)	
PostCOVID × Pre-B			-0.041***			-0.030***
			(0.009)			(0.007)
Firm FE	Yes	Yes	Yes	No	No	No
Job FE	No	No	No	Yes	Yes	Yes
Days since posting FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	1,421,197	1,421,197	722,649	1,421,197	1,421,197	722,649
Adj. R-sq	0.230	0.230	0.211	0.365	0.365	0.383
% change - large/late-stage	-14.1%	0.0%	-4.7%	-10.2%	1.5%	-4.2%
% change - small/early-stage		-21.4%	-23.8%		-16.5%	-18.2%

Table 5
(Continued)

Panel B: Applications by applicant experience and quality, within-firm

	No. of applications							
	Experienced		Inexperienced		High-quality		Low-quality	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PostCOVID	0.005	0.004	-0.007	-0.010	-0.005	-0.004	0.002	-0.001
	(0.010)	(0.009)	(0.007)	(0.006)	(0.010)	(0.010)	(0.008)	(0.006)
PostCOVID × Emp≤50	-0.018***		0.004		-0.014***		0.000	
	(0.004)		(0.004)		(0.003)		(0.004)	
PostCOVID × Pre-B		-0.021***		0.001		-0.019***		-0.002
		(0.004)		(0.004)		(0.005)		(0.005)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Days since posting FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1,421,197	722,649	1,421,197	722,649	1,421,197	722,649	1,421,197	722,649
Adj. R-sq	0.196	0.181	0.163	0.138	0.178	0.161	0.156	0.141
% change - large/late-stage	5.0%	4.0%	-7.3%	-9.6%	-4.8%	-3.6%	2.0%	-1.0%
% change - small/early-stage	-13.0%	-17.0%	-3.1%	-8.7%	-18.1%	-20.7%	2.0%	-2.9%

Panel C: Applications by applicant experience and quality, within-job

	No. of applications							
	Experienced		Inexperienced		High-quality		Low-quality	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PostCOVID	0.006	0.003	-0.002	-0.004	-0.003	-0.002	0.006	0.002
	(0.010)	(0.007)	(0.007)	(0.006)	(0.011)	(0.009)	(0.008)	(0.006)
PostCOVID × Emp≤50	-0.024***		0.002		-0.014***		-0.002	
	(0.006)		(0.003)		(0.005)		(0.003)	
PostCOVID × Pre-B		-0.014**		-0.001		-0.015**		-0.001
		(0.006)		(0.004)		(0.006)		(0.005)
Job FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Days since posting FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1,421,197	722,649	1,421,197	722,649	1,421,197	722,649	1,421,197	722,649
Adj. R-sq	0.304	0.320	0.267	0.260	0.267	0.273	0.245	0.245
% change - large/late-stage	6.0%	3.0%	-2.1%	-3.8%	-2.9%	-1.8%	5.9%	1.9%
% change - small/early-stage	-18.0%	-11.0%	0.0%	-4.8%	-16.2%	-15.3%	4.0%	1.0%

Table 6
Applicant Quality

This table examines changes in applicant quality around the onset of COVID from February to May 2020. The sample is at the application level. The dependent variables are the number of years of experience or the quality score of the applying candidate. *PostCOVID* is a dummy indicating dates after March 13, 2020, the date that a state of national emergency was first announced in the U.S. *Emp≤50* indicates startups with no more than 50 employees at the time of job application. *Pre-B* indicates startups whose last round of financing was series A round or earlier at the time of job application. Panel A includes firm fixed effects and Panel B includes job posting fixed effects. Controls include the log number of active job postings by a startup on a given day and the average employment size of all startups hiring on AngelList on a given day. Standard errors are clustered by firm's state. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Within-firm

	Applicant experience			Applicant quality		
	(1)	(2)	(3)	(4)	(5)	(6)
PostCOVID	-0.132***	0.004	0.077	-0.833***	-0.276	-0.020
	(0.046)	(0.074)	(0.083)	(0.287)	(0.280)	(0.309)
PostCOVID × Emp≤50		-0.182***			-0.767***	
		(0.050)			(0.220)	
PostCOVID × Pre-B			-0.232***			-0.819***
			(0.055)			(0.306)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	418,450	418,450	221,888	418,450	418,450	221,888
Adj. R-sq	0.233	0.233	0.196	0.064	0.064	0.053
% change - large/late-stage	-3.1%	0.1%	1.9%	-6.5%	-2.2%	-0.2%
% change - small/early-stage		-4.2%	-3.8%		-8.1%	-6.4%

Panel B: Within-job

	Applicant experience			Applicant quality		
	(1)	(2)	(3)	(4)	(5)	(6)
PostCOVID	-0.133***	-0.09	-0.017	-0.832***	-0.465	-0.009
	(0.048)	(0.062)	(0.071)	(0.281)	(0.296)	(0.337)
PostCOVID × Emp≤50		-0.057**			-0.482***	
		(0.028)			(0.175)	
PostCOVID × Pre-B			-0.116***			-0.673**
			(0.035)			(0.297)
Job FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	418,450	418,450	221,888	418,450	418,450	221,888
Adj. R-sq	0.351	0.351	0.351	0.097	0.097	0.093
% change - large/late-stage	-3.1%	-2.1%	-0.4%	-6.5%	-3.6%	-0.1%
% change - small/early-stage		-3.5%	-3.3%		-7.4%	-5.2%

Table 7
Intro Requests by Firms

This table examines changes in intro requests sent out by startups around the onset of COVID from February to May 2020. Panel A examines the number of intro requests sent out by firms. The sample is at the job-day level, restricting to job-days that were actively monitored by the firm (i.e., from posting to the last rejection or intro request on the job by the firm). Panel B examines the quality of applicant receiving intro requests at the intro request level. The dependent variables are the number of years of experience or the quality score of the candidate receiving intro request. Both panels include job posting fixed effects. *PostCOVID* is a dummy indicating dates after March 13, 2020, the date that a state of national emergency was first announced in the U.S. *Emp≤50* indicates startups with no more than 50 employees at the time of job application. *Pre-B* indicates startups whose last round of financing was series A round or earlier at the time of job application. Controls include the log number of active job postings by a startup on a given day and the average employment size of all startups hiring on AngelList on a given day. Standard errors are clustered by firm's state. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Within-job changes in the number of intro requests

	No. of intro requests		
	(1)	(2)	(3)
PostCOVID	-0.017**	0.000	0.003
	(0.007)	(0.004)	(0.003)
PostCOVID × Emp≤50		-0.026***	
		(0.008)	
PostCOVID × Pre-B			-0.023***
			(0.006)
Job FE	Yes	Yes	Yes
Days since posting FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
N	334,457	334,457	192,004
Adj. R-sq	0.354	0.354	0.234
% change - large/late-stage	-28.3%	0.0%	5.0%
% change - small/early-stage		-43.3%	-33.3%

Panel B: Within-job changes in the quality of applicants receiving intro requests

	Applicant experience			Applicant quality		
	(1)	(2)	(3)	(4)	(5)	(6)
PostCOVID	-0.209***	-0.175**	-0.415*	0.374	0.563	2.214
	(0.060)	(0.069)	(0.237)	(0.710)	(1.083)	(1.613)
PostCOVID × Emp≤50		-0.064			-0.356	
		(0.058)			(0.956)	
PostCOVID × Pre-B			0.265			-2.051
			(0.232)			(1.406)
Job FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	30,614	30,614	9,910	30,614	30,614	9,910
Adj. R-sq	0.410	0.410	0.405	0.17	0.17	0.146
% change - large/late-stage	-4.7%	-3.9%	-9.3%	2.4%	3.7%	12.7%
% change - small/early-stage		-5.4%	-3.3%		1.3%	0.9%

Table 8
Placebo Tests Based on 2019

This table presents placebo tests for our main analysis using 2019 data over the same months. Panel A examines changes in average firm size searched by candidates at the search level. Panel B examines changes in the size and stage of firms candidates applied toat the application level. Panel C examines within-job posting changes in the number of applications by firm size and candidate quality at the job posting-day level. *PostMar13* is a dummy indicating dates after March 13, 2019. Other variables and controls are defined in the same way as those in Tables 2, 4, and 5. Standard errors are clustered by candidate's state in Panels A and B and by firm's state in Panel C. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Average employment size searched

	Ln(emp)	Ln(emp)	Emp>500	Emp>500
	(1)	(2)	(3)	(4)
PostMar13	-0.062	0.035	-0.001	0.001
	(0.037)	(0.036)	(0.001)	(0.003)
Candidate FE	No	Yes	No	Yes
Candidate state FE	Yes	No	Yes	No
N	170,057	170,057	170,057	170,057
Adj. R-sq	0.011	0.718	0.004	0.324
% change	-6%	3.5%	-3.8%	3.8%

Panel B: Size and stage of firms applied to

	Ln(emp)	Ln(emp)	Post-B	Post-B
	(1)	(2)	(3)	(4)
PostMar13	0.012	0.004	0.001	-0.007
	(0.015)	(0.020)	(0.005)	(0.004)
Candidate FE	No	Yes	No	Yes
Candidate state FE	Yes	No	Yes	No
N	592,982	592,982	327,115	327,115
Adj. R-sq	0.002	0.129	0.003	0.065
% change	1.2%	0.4%	0.4%	-3.0%

Panel C: Number of applications per job

	No. of applications			
	All	All	High quality	Low quality
	(1)	(1)	(3)	(4)
PostMar13	0.003	0.001	-0.001	0.003
	(0.019)	(0.019)	(0.010)	(0.010)
PostMar13 × Emp≤50		0.002		
		(0.003)		
Job FE	Yes	Yes	Yes	Yes
Days since posting FE	Yes	Yes	Yes	Yes
Controlsf	Yes	Yes	Yes	Yes
N	759,727	759,727	759,727	759,727
Adj. R-sq	0.308	0.308	0.184	0.232
% change - large	1.7%	1.1%	-1.1%	3.7%
% change - small	1.7%	3.4%		

Appendix For Online Publication

A Appendix Exhibits

Figure A.1
Example of Job Posting on AngelList Talent

This figure shows an example of a job posting on AngelList Talent.

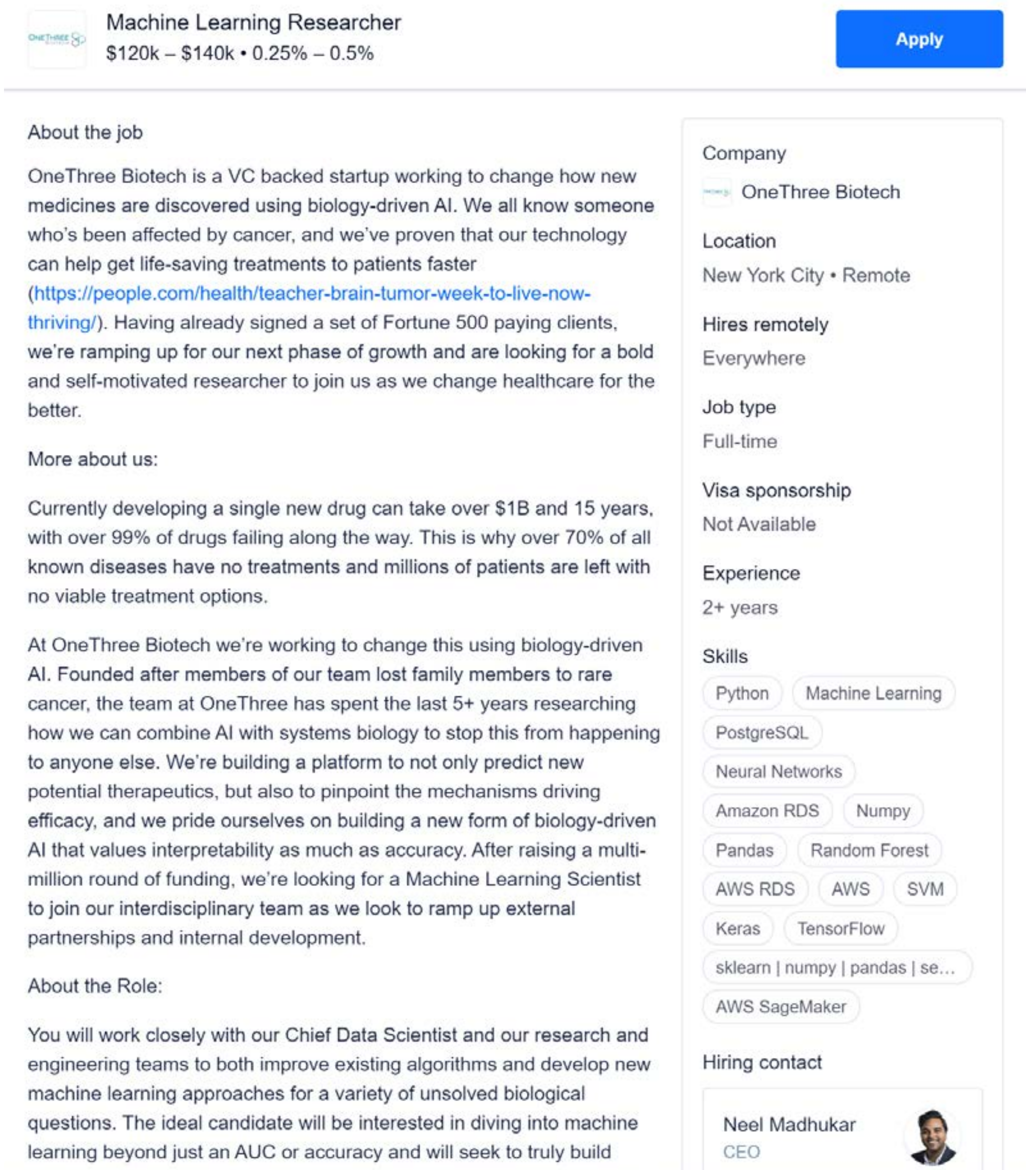
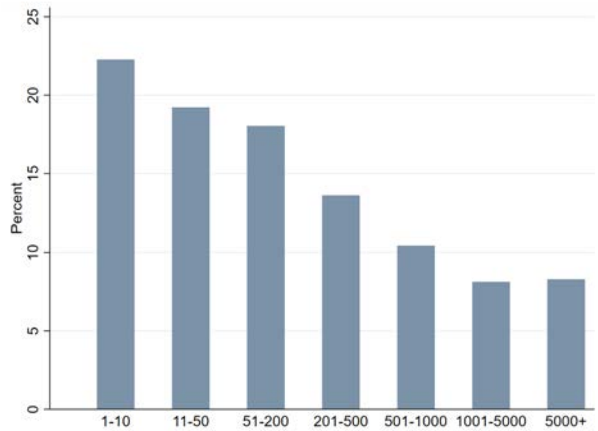


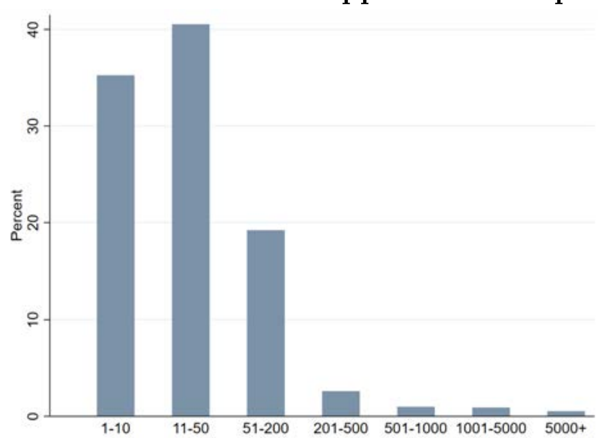
Figure A.2
Distribution of Firm Size and Financing Stage

Panel A shows the distribution of searched employment bins in the search sample. Each search may be associated with multiple employment bins. Panels B and C show the distribution of firms' employment size and financing stage in the application sample, respectively.

Panel A: Firm size in search sample



Panel B: Firm size in application sample



Panel C: Firm stage in application sample

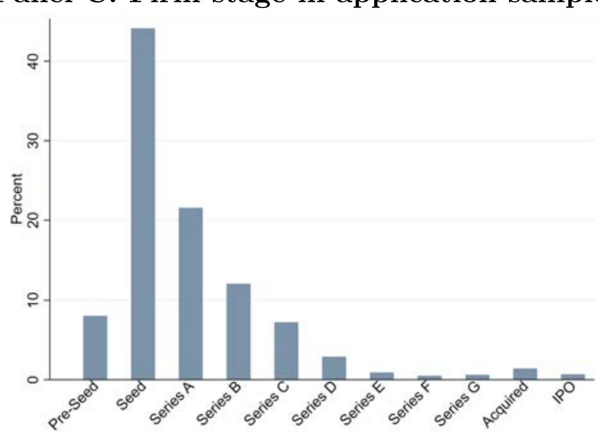
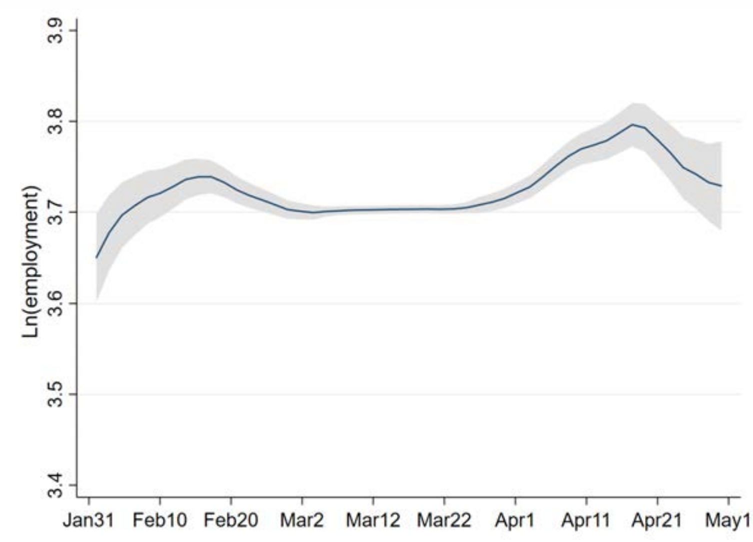


Figure A.3
Placebo Graph in 2019: Searched Firm Size

This figure reproduces graphs in Figure 3 using 2019 data. Panel A (Panel B) shows within-user changes in the logarithm of average employment size searched by users (the likelihood of average searched employment size being larger than 500) from February to May 2019. Each graph plots the fitted line and 95% confidence band estimated from local linear regression, removing user fixed effects.

Panel A: Changes in searched firm size: ln(emp)



Panel B: Changes in searched firm size: emp>=500

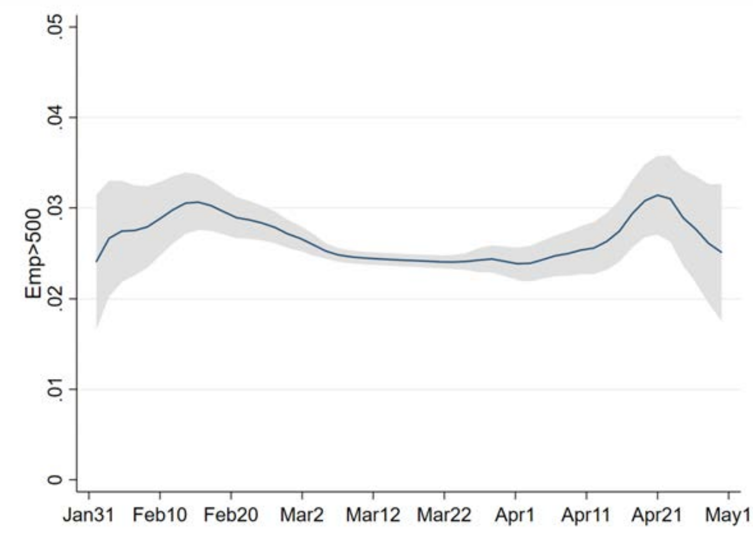
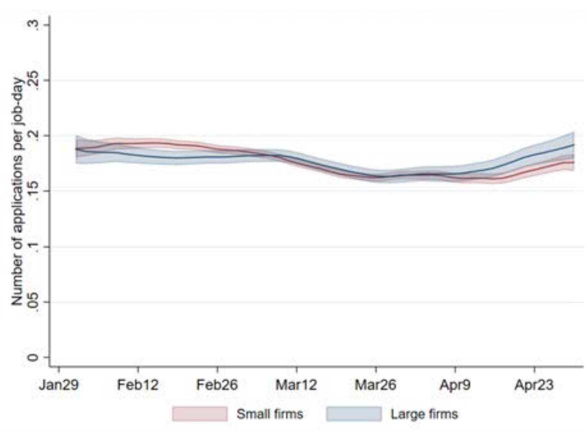


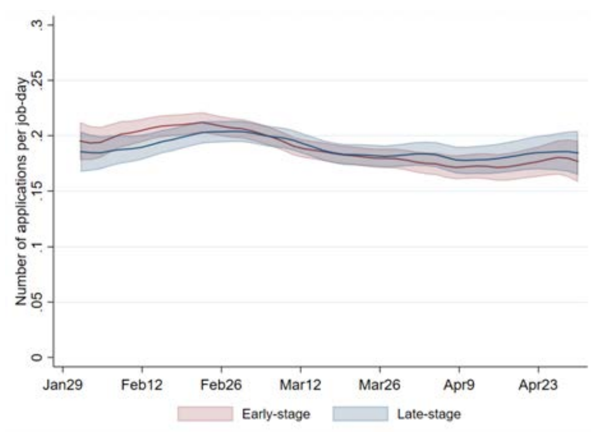
Figure A.4
Placebo Graphs in 2019: Application Quantity and Quality

These graphs reproduce Figures 4 and 5 using 2019 data. Panels A and B show within-job changes in the number of applications received by a job posting from February to end of April 2019 by firm size and firm stage, respectively. Panels C and D show within-job changes in the quality score of job applicants from February to end of April 2019 by firm size and firm stage, respectively. Each figure plots the fitted lines and 95% confidence bands estimated from local linear regressions, removing corresponding fixed effects and controls as described in Figures 4 and 5. Red lines and areas indicate small firms or early-stage firms. Blue lines and areas indicate large firms or late-stage firms. Small (large) firms are startups with no more than (more than) 50 employees at the time of application. Early-stage (late-stage) firms are startups with financing stage before (at or post) series B round at the time of application.

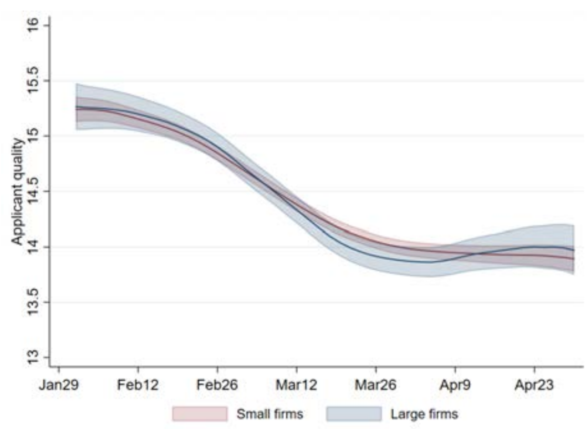
Panel A: No. of applications per job by firm size



Panel B: No. of applications per job by firm stage



Panel C: Applicant quality by firm size



Panel D: Applicant quality by firm stage

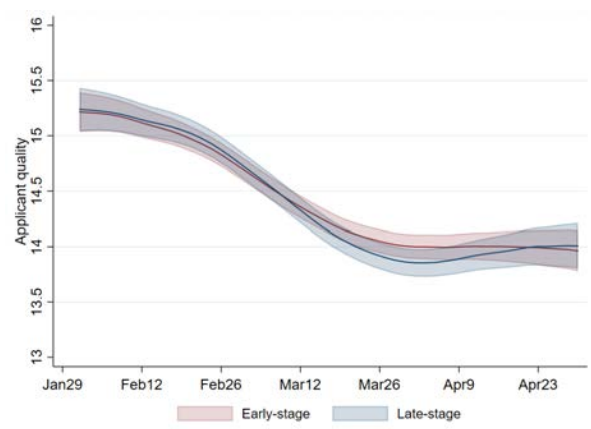


Table A.1
Size and Stage of Firms Applied To: Additional Fixed Effects

This table shows robustness of Table 4, Panel B to including job role fixed effects and startup industry fixed effects. The table examines changes in the size and financing stage of the firms candidates applied to around the onset of COVID from February to May 2020. The sample is at the application level. The dependent variable *Ln(emp)* is the log number of employees of the firm being applied to. *Post-B* indicates that the firm being applied to has a financing stage at or later than series B round at the time of application. *PostCOVID* is a dummy indicating dates after March 13, 2020, the date that a state of national emergency was first announced in the U.S. *Experienced* indicates candidates with above median number of years of experience. *High quality* indicates candidates with above median quality score as estimated by AngelList. All columns control for day-level average employment size of firms hiring on AngelList and total number of job postings on AngelList. Standard errors are clustered by candidate's state. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel B: With candidate FE

	Ln(emp)			Post-B		
	(1)	(2)	(3)	(4)	(5)	(6)
PostCOVID	0.058***	0.003	0.017	0.041***	0.031***	0.032***
	(0.017)	(0.014)	(0.016)	(0.008)	(0.008)	(0.009)
PostCOVID × Experienced		0.109***			0.021***	
		(0.020)			(0.006)	
PostCOVID × High quality			0.092***			0.019**
			(0.021)			(0.007)
Candidate FE	Yes	Yes	Yes	Yes	Yes	Yes
Job role FE	Yes	Yes	Yes	Yes	Yes	Yes
Startup industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	418,450	418,450	418,450	221,888	221,888	221,888
Adj. R-sq	0.158	0.158	0.158	0.108	0.108	0.108
% change - worse	6.0%	0.3%	1.7%	13.9%	10.5%	10.8%
% change - better		11.9%	11.5%		17.6%	17.2%

Table A.2
Local Number of COVID Cases as Treatment

This table shows robustness of our main results to using the state-level number of COVID cases as an alternative treatment variable. Panel A examines within-candidate changes in the average employment size searched by candidates (column 1) as well as the employment size and financing stage of the firms candidates applied to (columns 2 and 3). Panel B examines within-job posting changes in the number of applications by firm size and stage at the job posting-day level. Panel C examines within-job posting changes in applicant experience or quality. *Ln(no. of cases)* is the logarithm of the cumulative number of COVID cases reported at the state-day level obtained from the New York Times COVID database. All variables and controls are defined in the same way as those in Tables 2, 4, 5, and 6. Standard errors are clustered by candidate's state in Panel A and by firm's state in Panels B and C. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Size and stage of firms searched or applied to

	Ln(emp)	Ln(emp)	Post-B
	Searches	*Applications*	
	(1)	(2)	(3)
Ln(no. of cases)	0.037***	0.007*	0.008***
	(0.006)	(0.004)	(0.002)
Candidate FE	Yes	Yes	Yes
N	390,005	418,450	221,888
Adj. R-sq	0.811	0.144	0.099

Panel B: Number of applications per job

	No. of applications	
	(1)	(2)
Ln(no. of cases)	0.001	0.002
	(0.003)	(0.004)
Ln(no. of cases) × Emp≤50	-0.004***	
	(0.001)	
Ln(no. of cases) × Pre-B		-0.009***
		(0.001)
Job FE	Yes	Yes
Days since posting FE	Yes	Yes
Controls	Yes	Yes
N	1,421,197	722,649
Adj. R-sq	0.365	0.383

Panel C: Applicant quality

	Applicant experience		Applicant quality	
	(1)	(2)	(3)	(4)
Ln(no. of cases)	-0.023*	-0.013	-0.102**	-0.044
	(0.013)	(0.017)	(0.038)	(0.040)
Ln(no. of cases) × Emp≤50	-0.010***		-0.073***	
	(0.003)		(0.024)	
Ln(no. of cases) × Pre-B		-0.015***		-0.102**
		(0.004)		(0.039)
Job FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
N	418,450	221,888	418,450	221,888
Adj. R-sq	0.351	0.351	0.097	0.094

Table A.3
Dropping California and Massachusetts

This table shows robustness of our main results to removing candidates in California and Massachusetts (Panel A) or firms in California and Massachusetts (Panels B and C). Panel A examines within-candidate changes in the average employment size searched by candidates (column 1) as well as the employment size and financing stage of the firms candidates applied to (columns 2 and 3). Panel B examines within-job posting changes in the number of applications by firm size and stage at the job-day level. Panel C examines within-job posting changes in applicant experience or quality. All variables and controls are defined in the same way as those in Tables 2, 4, 5, and 6. Standard errors are clustered by candidate's state in Panel A and by firm's state in Panels B and C. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Size and stage of firms searched or applied to

	Ln(emp)	Ln(emp)	Post-B
	Searches	*Applications*	
	(1)	(2)	(3)
PostCOVID	0.227***	0.094***	0.056***
	(0.028)	(0.029)	(0.012)
Candidate FE	Yes	Yes	Yes
N	170,057	263,293	133,729
Adj. R-sq	0.718	0.139	0.092

Panel B: Number of applications per job

	No. of applications	
	(1)	(2)
PostCOVID	0.007	0.012
	(0.026)	(0.024)
PostCOVID × Emp≤50	-0.038***	
	(0.009)	
PostCOVID × Pre-B		-0.065***
		(0.009)
Job FE	Yes	Yes
Days since posting FE	Yes	Yes
Controls	Yes	Yes
N	897,343	429,927
Adj. R-sq	0.386	0.409

Panel C: Applicant quality

	Applicant experience		Applicant quality	
	(1)	(2)	(3)	(4)
PostCOVID	-0.099	-0.045	-0.154	0.106
	(0.066)	(0.054)	(0.378)	(0.441)
PostCOVID × Emp≤50	-0.113***		-0.716**	
	(0.040)		(0.314)	
PostCOVID × Pre-B		-0.155***		-0.610
		(0.046)		(0.466)
Job FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
N	263,293	133,729	263,293	133,729
Adj. R-sq	0.238	0.205	0.066	0.056

Table A.4
Size and Stage of Firms Clicked by Candidates

This table examines changes in the size and financing stage of firms candidates clicked on around the onset of COVID from February to May 2020. The sample is at the click level and includes all clicks on job postings or firms excluding job applications. The dependent variable *Ln(emp)* is the log number of employees of the firm being clicked (or firm associated with the job being clicked). *Post-B* indicates that the firm being clicked (or whose job being clicked) has a financing stage at or later than series B round at the time of application. *PostCOVID* is a dummy indicating dates after March 13, 2020, the date that a state of national emergency was first announced in the U.S. Columns 1 and 3 include candidate state fixed effects and columns 2 and 4 include candidate fixed effects. All columns control for day-level average employment size of all firms with job openings on AngelList and total number of job postings on AngelList. Standard errors are clustered by candidate's state. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Ln(emp)		Post-B	
	(1)	(2)	(3)	(4)
PostCOVID	0.074***	0.129***	0.040***	0.054***
	(0.020)	(0.023)	(0.008)	(0.007)
Candidate FE	No	Yes	No	Yes
Candidate state FE	Yes	No	Yes	No
Controls	Yes	Yes	Yes	Yes
N	899,280	899,280	502,452	502,452
Adj. R-sq	0.016	0.191	0.014	0.156
% change	7.7%	13.8%	10.0%	13.5%

Table A.5
Total Applicant Experience and Quality

This table examines changes in the total applicant experience (Panel A) and total applicant quality (Panel B) received by startups around the onset of COVID from February to May 2020. The sample is at the job posting-day level. The dependent variable in Panel A is the total number of years of experience of all applicants applying to a job on a given day. The dependent variable in Panel B is the sum of the quality scores of all applicants applying to a job on a given day. *PostCOVID* is a dummy indicating dates after March 13, 2020, the date that a state of national emergency was first announced in the U.S. *Emp≤50* indicates startups with no more than 50 employees at the time of job application. *Pre-B* indicates startups whose last round of financing was series A round or earlier at the time of job application. All panels include fixed effects for the number of days since a job was posted and control for the log number of active job postings by a startup on a given day and the average employment size of all startups hiring on AngelList on a given day. Columns 1-3 control for firm fixed effects and columns 4-6 control for job posting fixed effects. Standard errors are clustered by firm's state. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Total applicant experience

	Total applicant experience					
	(1)	(2)	(3)	(4)	(5)	(6)
PostCOVID	-0.114***	0.055*	0.016	-0.084***	0.052	-0.006
	(0.023)	(0.031)	(0.022)	(0.022)	(0.032)	(0.026)
PostCOVID × Emp≤50		-0.258***			-0.205***	
		(0.034)			(0.032)	
PostCOVID × Pre-B			-0.254***			-0.160***
			(0.036)			(0.028)
Firm FE	Yes	Yes	Yes	No	No	No
Job FE	No	No	No	Yes	Yes	Yes
Days since posting FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	1,421,197	1,421,197	722,649	1,421,197	1,421,197	722,649
Adj. R-sq	0.206	0.207	0.192	0.316	0.316	0.333
% change - large/late-stage	-13.2%	6.4%	1.8%	-9.7%	6.0%	-0.7%
% change - small/early-stage		-23.5%	-27.5%		-17.7%	-19.1%

Panel B: Total applicant quality score

	Total applicant quality score					
	(1)	(2)	(3)	(4)	(5)	(6)
PostCOVID	-0.399***	-0.019	-0.024	-0.322***	-0.018	-0.057
	(0.067)	(0.078)	(0.107)	(0.063)	(0.078)	(0.082)
PostCOVID × Emp≤50		-0.579***			-0.462***	
		(0.094)			(0.083)	
PostCOVID × Pre-B			-0.650***			-0.449***
			(0.177)			(0.148)
Firm FE	Yes	Yes	Yes	No	No	No
Job FE	No	No	No	Yes	Yes	Yes
Days since posting FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	1,421,197	1,421,197	722,649	1,421,197	1,421,197	722,649
Adj. R-sq	0.167	0.167	0.15	0.25	0.25	0.253
% change - large/late-stage	-14.8%	-0.7%	-0.8%	-11.9%	-0.7%	-2.0%
% change - small/early-stage		-22.1%	-23.4%		-17.8%	-17.6%

Table A.6
Fresh Searches

This table examines changes in searched firm size around the onset of COVID, restricting to fresh searches that are the first search by a user in a day (columns 1-2), a week (columns 3-4), or a month (columns 5-6). The sample is at the search level. The dependent variable *Ln(emp)* is the log number of employees averaged across all size bins selected in a search. *PostCOVID* is a dummy indicating dates after March 13, 2020, the date that a state of national emergency was first announced in the U.S. Columns 1, 3, and 5 include fixed effects for candidate's state and columns 2, 4, and 6 include candidate fixed effects. Standard errors are clustered by candidate's state. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Ln(emp)					
	By day		By week		By month	
	(1)	(2)	(3)	(4)	(5)	(6)
PostCOVID	0.240***	0.199***	0.265***	0.205***	0.192*	0.142***
	(0.047)	(0.018)	(0.051)	(0.020)	(0.097)	(0.045)
Candidate FE	No	Yes	No	Yes	No	Yes
Candidate state FE	Yes	No	Yes	No	Yes	No
N	29,399	29,399	15,859	15,859	6,924	6,924
Adj. R-sq	0.016	0.910	0.011	0.906	0.007	0.882
% change	27%	22%	30%	23%	21%	15%

Table A.7
Local Searches and Applications

This table examines changes in job searches and applications around the onset of COVID, restricting to local searches or applications. Panel A restrict to searches that do not include remote options (column 1) or searches and applications in the same location as the candidate's location (columns 2-4). Panels B and C examine application volume and quality restricting to local applications (i.e., applications to jobs in the same location as the candidate). The sample is at the search level in columns 1-2 of Panel A, at the job posting-day level in Panel B, and at the application level in columns 3-4 of Panel A and Panel C. *PostCOVID* is a dummy indicating dates after March 13, 2020, the date that a state of national emergency was first announced in the U.S. Standard errors are clustered by candidate's state in Panel A and by firm's state in Panels B and C *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Size and stage of firms searched or applied to

	Ln(emp)	Ln(emp)	Ln(emp)	Post-B
	Non-remote searches	*Local searches*	*Local applications*	
	(1)	(2)	(3)	(4)
PostCOVID	0.150***	0.151***	0.048**	0.031***
	(0.033)	(0.055)	(0.021)	(0.009)
Candidate FE	Yes	Yes	Yes	Yes
N	166,751	88,174	146,573	93,138
Adj. R-sq	0.832	0.819	0.123	0.081

Panel B: Number of applications per job

	No. of applications	
	(1)	(2)
PostCOVID	-0.016	-0.009
	(0.013)	(0.013)
PostCOVID × Emp≤50	-0.021***	
	(0.005)	
PostCOVID × Pre-B		-0.029**
		(0.013)
Job FE	Yes	Yes
Days since posting FE	Yes	Yes
Controls	Yes	Yes
N	848,002	381,087
Adj. R-sq	0.221	0.209

Panel C: Applicant quality

	Applicant experience		Applicant quality	
	(1)	(2)	(3)	(4)
PostCOVID	0.012	0.051	-0.107	0.142
	(0.089)	(0.101)	(0.303)	(0.384)
PostCOVID × Emp≤50	-0.098**		-0.435***	
	(0.039)		(0.096)	
PostCOVID × Pre-B		-0.169***		-0.469***
		(0.035)		(0.146)
Job FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
N	146,573	93,138	146,573	93,138
Adj. R-sq	0.348	0.341	0.098	0.096

Table A.8
Applications that Received Any Response

This table examines changes in the size and stage of firms applied to (Panel A), changes in application volume (Panel B), and changes in applicant quality (Panel C) around the onset of COVID, restricting to applications that received any form of response from the startup (i.e., either a rejection or intro request). The sample is at the application level in Panels A and C and at the job posting-day level in Panel B. *PostCOVID* is a dummy indicating dates after March 13, 2020, the date that a state of national emergency was first announced in the U.S. Standard errors are clustered by firm's state. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Size and stage of firms applied to

	Ln(emp)	Post-B
	(1)	(2)
PostCOVID	0.097***	0.070***
	(0.028)	(0.010)
Candidate FE	Yes	Yes
N	253,049	138,995
Adj. R-sq	0.150	0.099

Panel B: Number of applications per job

	No. of applications	
	(1)	(2)
PostCOVID	0.001	0.003
	(0.033)	(0.029)
PostCOVID × Emp≤50	-0.068***	
	(0.011)	
PostCOVID × Pre-B		-0.091***
		(0.015)
Job FE	Yes	Yes
Days since posting FE	Yes	Yes
Controls	Yes	Yes
N	650,302	267,858
Adj. R-sq	0.369	0.386

Panel C: Applicant quality

	Applicant experience		Applicant quality	
	(1)	(2)	(3)	(4)
PostCOVID	-0.087	-0.011	-0.587**	-0.216
	(0.075)	(0.078)	(0.291)	(0.318)
PostCOVID × Emp≤50	-0.086**		-0.473*	
	(0.040)		(0.265)	
PostCOVID × Pre-B		-0.160***		-0.652*
		(0.039)		(0.340)
Job FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
N	253,049	138,995	253,049	138,995
Adj. R-sq	0.357	0.349	0.097	0.091

Table A.9
NEW: Change in Searched Employment Size: Robustness

This table examines changes in employment size searched by job candidates around the onset of COVID from February to June 2020. The sample is at the search level. The dependent variable *Ln(emp)* is the log number of employees averaged across all size bins selected in a search; *Emp>500* is an indicator equal to one if the average searched employment size is larger than 500. *PostCOVID* is a dummy indicating dates after March 13, 2020, the date that a state of national emergency was first announced in the U.S. Columns 1 and 3 include fixed effects for candidate's state and columns 2 and 4 include candidate fixed effects. Standard errors are clustered by candidate's state. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Emp>50		Emp>200	
	(1)	(2)	(3)	(4)
PostCOVID	0.027***	0.051***	0.054***	0.054***
	(0.010)	(0.006)	(0.012)	(0.006)
Candidate FE	No	Yes	No	Yes
Candidate state FE	Yes	No	Yes	No
N	390,005	390,005	390,005	390,005
Adj. R-sq	0.007	0.740	0.015	0.765
% change	4%	7%	14%	14%

Table A.10
NEW: Consumer Expectations as Alternative Treatment

This table shows robustness of our main results to using the Consumer Sentiment Index from the University of Michigan. Panel A examines within-candidate changes in the average employment size searched by candidates (column 1) as well as the employment size and financing stage of the firms candidates applied to (columns 2 and 3). Panel B examines within-job posting changes in the number of applications by firm size and stage at the job posting-day level. Panel C examines within-job posting changes in applicant experience or quality. *ConsumerSentimentIndex* is the monthly Consumer Sentiment Index from the University of Michigan. The index reflects respondents' expectations about current and future conditions regarding personal finance, business condition, employment, and spending. The index is divided by 100 for ease of interpretation. All variables and controls are defined in the same way as those in Tables 2, 4, 5, and 6. Standard errors are clustered by candidate's state in Panel A and by firm's state in Panels B and C. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Size and stage of firms searched or applied to

	Ln(emp)	Ln(emp)	Post-B
	Searches	*Applications*	
	(1)	(2)	(3)
ConsumerSentimentIndex	-1.009***	-0.218**	-0.166**
	(0.115)	(0.094)	(0.071)
Candidate FE	Yes	Yes	Yes
N	390,005	418,450	221,888
Adj. R-sq	0.811	0.144	0.098

Panel B: Number of applications per job

	No. of applications	
	(1)	(2)
ConsumerSentimentIndex	0.017	-0.072***
	(0.029)	(0.026)
ConsumerSentimentIndex × Emp≤50	-0.163***	
	(0.032)	
ConsumerSentimentIndex × Pre-B		-0.099**
		(0.044)
Job FE	Yes	Yes
Days since posting FE	Yes	Yes
Controls	Yes	Yes
N	1,421,197	722,649
Adj. R-sq	0.365	0.383

Panel C: Applicant quality

	Applicant experience		Applicant quality	
	(1)	(2)	(3)	(4)
Ln(no. of cases)	0.212	-0.088	-0.758	-1.884
	(0.150)	(0.136)	(1.252)	(1.473)
ConsumerSentimentIndex× Emp≤50	0.370***		2.778***	
	(0.134)		(0.665)	
ConsumerSentimentIndex × Pre-B		0.499***		3.443***
		(0.115)		(1.167)
Job FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
N	418,450	221,888	418,450	221,888
Adj. R-sq	0.351	0.351	0.097	0.093