Flight to Safety: How Economic Downturns Affect Talent Flows to Startups*

Shai Bernstein
Havard Business School
and NBER

Richard R. Townsend
University of California San Diego
and NBER

Ting Xu
University of Virginia

November 21, 2020

Abstract

This paper investigates how economic downturns affect the flow of human capital to startups. Using proprietary data from AngelList Talent, we study how individuals' online job searches and applications changed during the emergence of the COVID-19 crisis. We find that job seekers shifted their searches toward larger firms and away from early stage ventures, even within the same individual over time. Simultaneously, job seekers broadened their other search parameters, considering lower salaries and a wider variety of job types, roles, markets, and locations. Relative to larger firms, early stage ventures experienced a decline in the number of applications per job posting, a decline driven by higher quality and more experienced job seekers. This led to a deterioration in the quality of the human capital pool available to early stage ventures during the downturn. These declines hold within a firm as well as within a 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.

JEL Classification: L26, J22, J24, M13, E32
Keywords: Startup Labor Market, Flight to Safety, COVID-19, Recession, Human Capital

---

*Bernstein: sbernstein@hbs.edu. Townsend: rrtownsend@ucsd.edu. Xu: xut@darden.virginia.edu. We thank Kunal Mehta for data assistance. We are grateful for helpful comments from Paul Gompers, Song Ma, Antoinette Schoar, and seminar participants at UVA Darden, Virginia Tech, Junior Entrepreneurial Finance/Innovation Lunch Group, and Junior Corporate Finance Workshop.

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 (Foster et al. (2001); Davis et al. (1996); Collard-Wexler and De Loecker (2015)). However, an increasing body of evidence highlights that early stage ventures may be particularly vulnerable to economic downturns, and therefore less able to drive such cleansing effects (Decker et al. (2014, 2016); Fabrizio and Tsolmon (2014)). Existing explanations of startup vulnerability during recessions primarily focus on the role of financing constraints early stage ventures 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 ventures 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, and thus face lower opportunity costs in joining riskier and less established firms (Gottlieb et al. (2019)). Thus, the overall increase in the supply of potential workers for early stage ventures 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 ventures 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. (2020b)); 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 3.6M active job seekers and over 185,000 new jobs listed. The data we use come from their backend 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, independently of changes in labor demand—and if so, what type of workers experience changes in preferences. Moreover, these data also allow us to explore how the quantity or quality of workers who apply to *the same job posting* changes after the onset of an economic downturn, which again is unconfounded by changes in labor demand. Thus, while it is difficult to fully disentangle demand side factors, we are able to do so much more cleanly than has been possible with standard data sets.

The economic downturn that we focus on is the emergence of the COVID-19 crisis. The crisis caused massive economic disruption with widespread and immediate impact. Importantly, the origins of the COVID-19 crisis did not arise from changes in underlying economic conditions, thus providing an ideal, exogenous setting to study the response of job seekers to adverse economic shocks.

Exploring changes in the search parameters of AngelList 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 25%, and candidates became 20% more likely to search for firms with more than 500 employees. This result holds both across candidates and, importantly, within candidates over time. In other words, the COVID crisis led job candidates to shift their search preferences toward established and mature 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 companies receiving job applications after the onset of the crisis. Again, these effects not only hold in the cross section across all candidates on the platform, but also take place 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 vary across different types of 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 in their current role and an estimated score of their overall quality. The latter measure is created by AngelList based on an algorithm that accounts for applicants' experience, skills, and education. During a downturn, high-quality candidates may have a greater shift in interest toward established firms than low-quality candidates due to career risk considerations (Gottlieb et al., 2019).

In particular, high-quality candidates may tend to already have good jobs. Thus, during normal times, they might consider joining a less-established startup under the belief that they could return to their old job (or a similar one) if the startup failed. However, during a downturn, they may fear that returning to their original career trajectory may be more difficult. In contrast, low-quality candidates may perceive the career risk they face in joining a less-established startup to be relatively stable over the business cycle. Consistent with career risk hypothesis, we find that more experienced as well as higher quality job seekers drive most of the flight to safety in job applications, shifting away from smaller and earlier stage firms.

The results described above suggest a shift in worker preferences away from early stage firms after the emergence of COVID-19. However, it is possible that despite this shift, early stage firms had no difficulties attracting human capital, or even had an easier time. In particular, it could be that there was a large enough influx of new, high-quality job seekers after the crisis, 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 crisis. We also find again that the decline was concentrated within smaller and earlier-stage startups and was driven by a decline in high-quality/experienced applicants. In principle, these results could reflect changes in the type of jobs posted by these firms. However, we find similar results within jobs. That is, holding the job posting fixed, high-quality/experienced applications declined after the crisis, and more so for jobs posted by smaller/younger firms. These results highlight the difficulty early stage ventures 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 our results are not driven by seasonality or unobserved trends. Second, through non-parametric graphs, we show that our main results do not reflect a general downward trend in the labor market. Instead, reactions are steep and immediate, and coincide with the onset of the COVID-19 outbreak in the U.S. Small startups and large startups also shared similar application trends in the months before the crisis. Third, we find a similar flight to safety when using candidates' clicks on job postings as an alternative indictor of job interest. Fourth, our results are similar when we use the state-level number of COVID cases as a continuous treatment variable; they are also similar when we drop candidates or startups from California and Massachusetts, suggesting that the documented patterns are national rather than concentrated in innovation hubs. Lastly, to address remaining concerns about demand side factors driving our results, we exploit job posting data to show that demand side changes are actually the opposite of what we find on labor supply: job postings by smaller firms declined less than those by larger firms during COVID. This may be because large firms hire for less essential positions, which can be cut during a downturn (Bartlett and Morse (2020)). Further, neither large nor small firms exhibited a downskilling in labor demand, as salaries and experience requirements remained unchanged. Our main results are thus unlikely to be driven by unobserved demand side factors.

Overall, our findings illustrate how the onset of COVID-19 impacted the quantity and quality of talent available to early stage ventures. Specifically, job seekers shift towards larger and more mature companies, consistent with a flight to safety channel in which workers seek firms that would be most likely to weather the economic downturn. Interestingly, the effect is mostly driven by higher quality job seekers, leading to a brain drain for early stage ventures relative to established firms. Importantly, our results are unlikely to be driven by changes in startups' demand for human capital, since we document changes in the search parameters of job candidates, as well as changes in applicants' response to the same job posting over time.

Ultimately, flight to safety in the labor market likely stems from a belief among workers that larger employers offer better job security 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 aggravate 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 rate 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-19 crisis on VC investment, while Bartik et al. (2020a) and Fairlie (2020) study its impact on small businesses.

We also add to an emerging literature on the startup labor market. Babina and Howell (2018), Babina et al. (2019), 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 and match process. In that sense, our paper is related to a handful of papers that study job searches and applications (Brown and Matsa (2016); 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.

Lastly, we add to a recent string of papers that study the labor market consequence of COVID-19. Using job posting and unemployment insurance data, Kahn et al. (2020a) 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-19. 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-19; 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 talents during the COVID-19 crisis. We also highlight the stark contrast between mature and early-stage companies, 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 startup ecosystem. Over its lifetime, more than 10M job seekers have joined the platform, more than 100,000 startups have posted a job there, and more than 5M connections have been made between job seekers and startups. In the most recent completed year, AngelList Talent had 3.6M active users, 185,000 new jobs listed, and 1M connections made.

The way that AngelList Talent works is illustrated in Panel A of Figure 1. Startups can post job openings, specifying their job's location, role, description, type (i.e., full-time/part-time), salary range, equity range, and other details (Figure A.1 shows an example). Job postings are also linked to AngelList startup profiles that provide further firm-level information, including funding status, size, industry, and team members. After job postings are reviewed for spam they become live for search. Users can search live job postings, potentially specifying a variety of filters based on the job and startup characteristics above (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 s/he can perform a search. Thus, all searches can be linked to a user by AngelList—although user searches are not publicly visible to startups or other users.

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

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

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

3 Data

3.1 Measurement

The data we use in this paper were provided directly by AngelList and were collected by their backend system. Our sample period runs from February 5 to June 18, 2020, and for comparison we also obtain data from the same period in 2019. In the data we can observe all user activities, including searches, clicks, applications by job candidates, and responses to those applications by startups. We also observe all jobs ever posted on AngelList Talent, with associated job and startup level characteristics, and the dates the jobs were live in search. Finally, we also observe candidate characteristics, including location, current role, experience in current role, and an measure of overall candidate quality developed by AngelList.

In our analysis of searches, our main focus is the size of the firms workers search for, as measured by the number of employees.[1] 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.[2] Additionally, we define a large startup 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 startups, 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 startups. 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 startup responses to job applications. As discussed earlier, we are able to observe whether a startup requests an introduction from the applicant, which indicates the initiation of further interactions. Al-

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

[2] 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.

though 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 number of years experience an individual has in her current role. The second is a quality score created by AngelList based on a proprietary algorithm that scores candidates based on their experience, education, skills, as well as platform activities.

3.2 Sample Restrictions

We limit our sample to include only the activities of users and startups located in the U.S. in order to ensure that our findings do not reflect a mix of countries with very different startup ecosystems. 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 startups changed following the emergence of the COVID-19 crisis in the U.S., which we use as an adverse economic shock. Unlike other economic crises, the COVID-19 crisis did not originate from changes in underlying economic conditions. Its timing is thus exogenous with respect to the outcomes we study. More importantly, the crisis caused immediate and massive economic disruptions, allowing us to observe labor market reactions within a relatively short period of time. Most of our analyses focus on the few months (February to May) surrounding the onset of the crisis, thus mitigating the effects of confounding events that could become relevant in the medium to long run.

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 seeker preferences independent of the job vacancies posted by firms, thus separating the supply of labor 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. (2020b)). Second, compared with surveys on 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 important 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 Effect on Worker Preferences

4.1.1 Search Parameters

We first explore changes in the search parameters of job seekers on AngelList Talent around the onset of the COVID-19 crisis. Specifically, we estimate the following specifications at the search level:

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

where $SearchParameter_{it}$ 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 a dummy indicating dates after March 13, 2020, the date that a state of national emergency was first announced in the U.S.[3] Our main specification includes job seeker fixed effects α_i to study how the preferences of the same individual change in response to the COVID crisis. 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.

4.1.2 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 later stage firms after COVID hit. In addition, we examine whether application preferences change differentially for higher quality job candidates. To do so, we estimate the following specification at the job application level:

$$StartupMaturity_{ift} = \alpha_i + \beta \mathbb{1}(PostCovid_t) + \gamma \mathbb{1}(PostCovid_t) \times \mathbb{1}(HighQuality_i) + \boldsymbol{\delta}' \boldsymbol{X_t} + \epsilon_{i,f,t} \quad (2)$$

where $StartupMaturity_{ift}$ represents either the number of employees or the financing stage of the firm f candidate i applied to at time t; $HighQuality_i$ is an indicator for whether candidate i had above median work experience in her current role or an above median quality score; $\boldsymbol{X_t}$ 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

[3] 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.

state.

4.2 Effect on Firms

The estimation strategies described above allow us to learn about how worker preferences shifted after the emergence of COVID-19. 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 workers may be less interested in working for small/early-stage startups, there may be enough additional workers seeking jobs due to the crisis that these startups actually find it easier to attract human capital. To explore this possibility, we also estimate effects on job applications at the job posting-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 less mature startups than for more mature startups. We estimate the following equation at the job posting-day level:

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

where $Applications_{fjt}$ is the number of new applications to job j at startup f on day t; $LowStartupMaturity_f$ is either an indicator for whether a startup has fewer than 50 employees or an indicator for whether it its last financing round was a series B round or earlier;[4] 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 active job postings by a startup on a given day

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

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 amount 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 COVID-19 impacted the average quality of talent flowing to startups. To do this, we estimate the following specification at the application level:

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

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; $LowStartupMaturity_f$ is either an indicator for whether a startup has fewer than 50 employees or an indicator for whether its last financing round was a seed or pre-seed round; $\boldsymbol{X}_{ft}$ includes the same controls 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.[5] 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 application level, respectively. On an average day, a job posting receives 0.2 applications. The average startup has about 2 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, 42% to startups in seed or pre-seed stage, and 18% to startups post-C round. The average startup receiving applications has 26 employees. Finally, 7% of the submitted applications receive intro requests from startups, which would lead to further interactions.

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

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 emergence of COVID-19. Table 2 presents the results estimated from equation (1) with dependent variables related to the size of firms users search for as measured by 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 COVID-19, users increased the firm size they were searching for. The coefficient of 0.223 is highly statistically significant and indicates a 22% 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. We find a similar result, with a coefficient of 0.254, reflecting a 25% 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. Overall, the results from Table 2 are consistent with a flight-to-safety channel, in which the preferences of job seekers shift towards larger and more established companies.

In Table 2, we explore whether other search characteristics changed simultaneously with the shift towards larger companies. 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 recession. 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 2, 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-19 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 minuscule. These results suggest that the flight-to-safety finding documented around COVID-19 is unlikely to be driven by seasonality or unobserved trends in the data.

One potential concern with interpreting the above results is that users may adjust filters in response to the search results they see, in which case our within-candidate results may reflect individuals' learning about demand—especially if such adjustments occur within a short period of time. To address this, in Table A.5, we restrict our sample to fresh searches that are the first search by a user in a day, a week, or a month. This ensures that we are not picking up any short-term modifications of search filters. The results on these subsamples are robust and similar in magnitude. Further, this alternative explanation would predict that job candidates actually prefer smaller firms, and only adjust their searches towards larger firms after discovering a lack of small firm jobs. However, as we show in Section 6, we find the opposite results on the demand side: smaller firms are much less likely to cut job postings than larger firms during COVID. This suggests that, if anything, the demand discovery story should go against our findings. Moreover, if candidates generally prefer small firms and only include larger firms as they broaden their searches, we should observe similar results in 2019 data; however, we find no such results in 2019. Lastly, this explanation is inconsistent with our subsequent findings at the firm level, which show that less-established startups experienced a larger decline in applications after the onset of the crisis—even within a given job posting. In other words, holding demand fixed by examining changes within job-postings that continued soliciting applications throughout, we still find a decline in job seeker interest in less-established startups.

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 (3). 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 is late stage (series C or later). We show results without candidate fixed effects in Panel A and with candidate fixed effects in Panel B. Consistent with our findings on changes in search parameters, we find that job candidates applied to larger and later-stage firms after the onset of the crisis. These changes hold even within the same candidate over time, as shown in Panel B. For example, column 1 of Panel B shows that job seekers applied to firms that are 8% larger and that are 22% more likely to be late-stage after the start of the COVID recession.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, and is stronger among higher-quality candidates.

Next, we examine whether the flight-to-safety effects that we document vary with candidate quality. During a downturn, high-quality candidates may have a greater shift in interest towards established firms than low-quality candidates due to career risk considerations (Gottlieb et al., 2019). In particular, high-quality candidates may tend to already have good jobs. Thus, during normal times, they might consider joining a less-established startup under the belief that they could return to their old job (or a similar one) if the startup failed. However, during a downturn, they may fear that returning to their original career trajectory may be more difficult. In contrast, low-quality candidates may perceive their career risk in joining a less-established startup to be relatively stable over the business cycle. The greater career risk faced by high-quality candidates can be explained by their higher wages (hence higher opportunity costs), or more specialized skills that are less redeployable. Indeed, prior studies find that high-skilled jobs are more pro-cyclical than low-skilled jobs (Hershbein and Kahn (2018); Campello et al. (2020b)). Consistent the career risk hypothesis, in columns 2–3 and 5–6 of Table 4, we find stronger effects among more experienced and higher quality applicants, who shift their applications to firms that are 13% larger and 25% more likely to be late-stage.

5.3 Effect on Firms

So far, we have documented a significant shift in worker preferences away from small and early-stage firms following the emergence of the COVID-19 crisis, an effect driven mostly by higher quality and more experienced workers. How do these changes impact startups?

In this section, we examine the effect of the crisis on the quantity and the quality of talent flows to startups.

We first examine how COVID-19 impacted the volume of job applications to startups. If flight-to-safety is prevalent, we should see a drop in job applications to startups, as job seekers who would otherwise work for startups turn to larger and more established employers. Further, such flight-to-safety should also drive a wedge between larger and smaller (or later- versus earlier-stage) startups.

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 10.2% overall during COVID, when compared with pre-COVID means (column 1). We then examine whether this decline is homogeneous across firms in columns 2–3. We find that the decline is stronger for smaller and earlier-stage firms. For example, startups with fewer than 50 employees saw a 13.7% decline in applications compared with just a 3% decline for startups with above 50 employees (column 2). Similarly, job applications to earlier-stage startups declined by 13.5%, while those going to later-stage startups declined by only 5.2% (column 3). In columns 4–6, we further include job-posting fixed effects, therefore exploring the shift in the number of applications holding fixed 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 quantity or type of jobs posted by firms.

In Panels B and C we explore what type of candidates drive the declines in applications to smaller and earlier-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 smaller and earlier-stage startups are driven entirely by high-quality candidates (columns 1–2 and 5–6), while low-quality candidates did not apply deferentially to startups of different sizes or stages (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. Columns 1 and 4 of Panel A show that, within a firm, the average applicant quality declined by 6.5% and applicant experience by 1.5% after COVID hits. However, such an average decline is driven entirely by smaller and earlier stage firms, as shown in columns 2–3 and 5–6. In particular, startups with fewer than 50 employees experienced a 8.4% decline in applicant quality and a 3% decline in applicant experience. Similarly, average applicant quality dropped by 6.7% for seed or pre-seed startups and applicant experience dropped by 5.1%. In contrast, larger and later-stage startups saw no significant declines in applicant quality and, if anything, experienced 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 3 and 4 show changes in applications and applicant quality graphically. In Figure 3, we see that large and small firms, as well as late-stage and early-stage firms have very similar trends in number of applications received per job before late March. Yet they start to diverge significantly after the end of March, when the COVID crisis intensified. 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 late March, suggesting the result is not simply a continuation of a previous downward trend. Figure 4 shows that the average quality of job applicants to small startups dropped sharply around mid-March. This holds whether we measure quality by job experience (Panel A) or AngelList's quality score (Panel B). In contrast, applicant experience did not decline significantly for large startups, and applicant quality in fact increased. Further, small and large startups trended similarly in applicant quality measures before COVID. These patterns suggest that our results are not driven by a general downward trend in applicant quality for small startups, or these startups being on a differential trend than large ones.

Taken together, our results show that workers' desire to join safe firms during economic downturns has real adverse consequences for smaller and younger firms in terms of their ability to attract talent. Job candidates, especially high-quality ones, fly to larger and later-stage firms, resulting in a brain drain for less mature ventures.

5.4 Firm Response to Job Applications

Our results thus far document a significant decline in both the quantity and quality of talent flows to startups during the COVID-19 crisis, especially for nascent startups. How do startups react to these changes? Do they simply hire the next best candidate, or do they cut back on hiring? We shed light on these questions by examining whether startups respond positively to applications by requesting introductions and thereby initiating further interactions. Although these further interactions do not necessarily lead to eventual hiring, they are a necessary precursor. We estimate the following specification at the application level similar to equation (4):

$$\begin{aligned}\mathbb{1}(RequestIntro_{ifjt}) = \alpha_j + \beta\mathbb{1}(PostCOVID_t) + \\ \gamma\mathbb{1}(PostCOVID_t) \times \mathbb{1}(LowStartupMaturity_f) + \delta X_{jt} + \epsilon_{ifjt}\end{aligned} \quad (5)$$

where $RequestIntro_{ifjt}$ is an indicator for whether the application submitted by candidate i at time t for job j received an intro request from startup f; α_j are job fixed effects; $LowStartupMaturity_f$ 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. We control for the log number of applications received by a job as of time t in X_{jt}.

Table 7 presents the results. We find that, within a firm, startups are 23% less likely to respond positively to an application with a request for an introduction after the onset of the COVID crisis (column 1). This decline is again driven by smaller and earlier-stage startups, which had a 31% and 38% decline in intro rate respectively (columns 2-3). Similar results obtain when we control for job fixed effects (columns 4 to 6). In contrast, larger and later-stage startups barely saw any changes in their intro rate within firms, and actually increased their intro rate within jobs during COVID. This dramatic divergence in the likelihood of responding to applications highlights the consequence of the diminished applicant quality available to small and young startups. Facing worse talent pools, rather than hiring a potentially unqualified candidate, smaller and earlier-stage ventures scaled back their hiring, potentially leading some of their positions to remain unfilled. These results also suggest that labor demand by nascent 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.

One alternative interpretation of the above results is that small firms have worse expectations about future growth prospects due to COVID, and thus are less likely to hire conditional on keeping a job posting outstanding. In this case, firms would choose to ignore all job applications irrespective of their quality. First, this unlikely explains our result because it contradicts our subsequent finding (see Section A.9) that smaller firms are actually less likely to cut back on job postings than larger firms. To further rule out this explanation, we restrict our analysis to a subsample of job postings that received at least some form of response from the firm, either in the form of a rejection or a request for intro. This subsample represents the set of jobs for which firms still intent to hire. Table A.3 presents the results, which are similar to our main results in Table 7.

6 Robustness

We provide additional robustness tests to our main analyses. First, we exploit candidates' clicking behavior as another indicator of their job 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. Because the size of a startup is visible before candidates click for more information, clicks are good indicators of candidates' preferences conditioning on the set of jobs they see.[6] We therefore estimate a specification similar to equation (2) to examine how the size and stage of the startups clicked by candidates changed around the onset the COVID recession. Table A.4 presents the results. We find that candidates clicked on larger and later-stage firms after COVID hit. Based on within-candidate results in columns 2 and 4, candidates clicked on firms that have 18% more employment after COVID starts, and were 12% more likely to click on late-stage firms that are post-C round.

Next, we show in Table A.6 that our main results are similar if we use the cumulative number of COVID-19 cases at the state-level as an alternative treatment variable in place of the post-March 13 indicator. The local number of cases captures not only the onset of COVID-19 but also the differential escalations of the pandemic in different regions, which may shape job candidates' or firms' expectations.[7]

[6] These clicks do not include applications.

[7] It is also possible that job candidates or firms react to the pandemic situation at the national rather

Third, to make sure that our results are not just driven by job candidates or firms in traditional tech hubs, in Table A.7 we show that our results are robust to dropping candidates or firms from California and Massachusetts from our samples. Further, the magnitudes are similar to our main results, suggesting that the labor market reactions we document are broad-based and not just concentrated in tech hubs.[8]

Fourth, we explore an alternative way to capture the supply of human capital pool to startups — the total number of years of experience or the total quality score of job applicants. Table A.8 presents the results, where the dependent variable is the sum of all job applicant's experience or quality score at the job posting-day level. We find a similar decline in this quality-adjusted talent pool measure, especially for smaller and earlier-stage firms. For example, total applicant experience dropped by 16% early-stage firms after COVID, while it barely changed for later-stage firms.

Fifth, because we do not observe actual hiring, one concern is that flight-to-safety by high-quality candidates may not affect small firms' eventual hiring if these candidates would have declined small firms' offers even if they received one. This would predict that high-quality candidates become more selective in their applications (due to, for example, time constraint), and stopped applying to small firms that they did not plan to join. To examine whether this is the case, we explore how the number of job applications changes within candidates, especially high-quality candidates. Table A.2 presents the results, where the outcome variable is the number of job applications at the candidate-day level. We find that high-quality candidates slightly increased, rather than decreased, their number of job applications after COVID, and so did low-quality candidates. This appears inconsistent with

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.

[8]This finding is consistent with Kahn et al. (2020b), 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.

the prediction above.

Lastly, to ameliorate any remaining concerns about demand side factors potentially driving our results, we explicitly examine changes in firms' labor demand in Appendix B by analyzing job posting data. Table A.9 shows that firm-level job postings on AngelList Talent declined by 13% over all, and by 27% within firms (Panel A). Interestingly, these declines are driven mainly by larger startups, while smaller startups did not see a significant decline. We find similar divergence when examining aggregate job posting volumes at the day level (Panel B): total job postings by large firms declined by 47% while those by small firms declined by 31%. This may be because smaller firms hire for more essential positions that are harder to cut during a downturn. Consistent with this, Bartlett and Morse (2020) show that larger firms have greater labor flexibility and are better able to adjust labor during COVID. In Panel C of Table A.9, we additionally show that neither large nor small firms exhibited a downskilling in labor demand, as salaries and experience requirements remained unchanged. These demand side results therefore go against what we find on the supply side, suggesting that our main findings are not driven by demand side factors.

7 Further Discussion

The main contribution of our paper is to document a flight to safety in labor market that negatively affects startups' ability to attract talent during economic downturns. But what explains this flight-to-safety preference? Just as investors fly to safer assets during financial crises (Vayanos (2004); Caballero and Krishnamurthy (2008); Baele et al. (2020)), job candidates may fly to larger employers due to beliefs that these employers offer better job security or job prospects during a recession. For example, larger companies 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 irrational responses by job candidates. Pinning down the source of flight to safety and the rationality of these beliefs is beyond the scope of this paper. However, regardless, such a preference by job seekers represents a mechanism that exacerbates difficulties already facing startups during downturns.

8 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 ventures. In this paper, we show that young firms' ability to attract talent suffered during the most recent economic downturn—the COVID-19 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 nascent 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.

REFERENCES

Aghion, Philippe, Philippe Askenazy, Nicolas Berman, Gilbert Cette, and Laurent Eymard, 2012, Credit Constraints and the Cyclicality of R&D Investment: Evidence from France, *Journal of the European Economic Association* 10, 1001–1024, Publisher: Oxford Academic.

Babina, Tania, and Sabrina T Howell, 2018, Entrepreneurial spillovers from corporate r&d, Technical report, National Bureau of Economic Research.

Babina, Tania, Wenting Ma, Christian Moser, Paige Ouimet, and Rebecca Zarutskie, 2019, Pay, employment, and dynamics of young firms, *Employment, and Dynamics of Young Firms (July 23, 2019)* .

Babina, Tania, Paige Ouimet, and Rebecca Zarutskie, 2020, Ipos, human capital, and labor reallocation, *Available at SSRN 2692845* .

Baele, Lieven, Geert Bekaert, Koen Inghelbrecht, and Min Wei, 2020, Flights to safety, *The Review of Financial Studies* 33, 689–746.

Barlevy, Gadi, 2003, Credit market frictions and the allocation of resources over the business cycle, *Journal of Monetary Economics* 50, 1795–1818.

Barlevy, Gadi, 2007, On the cyclicality of research and development, *American Economic Review* 97, 1131–1164.

Bartik, Alexander W, Marianne Bertrand, Zoe B Cullen, Edward L Glaeser, Michael Luca, and Christopher T Stanton, 2020a, How Are Small Businesses Adjusting to COVID-19? Early Evidence from a Survey, Working Paper 26989, National Bureau of Economic Research, Series: Working Paper Series.

Bartik, Alexander W, Marianne Bertrand, Feng Lin, Jesse Rothstein, and Matt Unrath, 2020b, Measuring the labor market at the onset of the COVID-19 crisis, Working Paper 27613, National Bureau of Economic Research, Series: Working Paper Series.

Bartlett, Robert P., and Adair Morse, 2020, Small business survival capabilities and policy effectiveness: Evidence from oakland, *Working Paper* .

Brown, Jennifer, and David A Matsa, 2016, Boarding a sinking ship? an investigation of job applications to distressed firms, *The Journal of Finance* 71, 507–550.

Brown, Jennifer, and David A Matsa, 2020, Locked in by leverage: Job search during the housing crisis, *Journal of Financial Economics* 136, 623–648.

Caballero, Ricardo, and Mohamad L. Hammour, 1994, The Cleansing Effect of Recessions, *American Economic Review* 84, 1350–68, Publisher: American Economic Association.

Caballero, Ricardo J, and Arvind Krishnamurthy, 2008, Collective risk management in a flight to quality episode, *The Journal of Finance* 63, 2195–2230.

Campello, Murillo, Janet Gao, and Qiping Xu, 2019, Personal income taxes and labor downskilling: Evidence from 27 million job postings, *Kelley School of Business Research Paper* .

Campello, Murillo, Gaurav Kankanhalli, and Pradeep Muthukrishnan, 2020b, Corporate Hiring under COVID-19: Labor Market Concentration, Downskilling, and Income Inequality, Working Paper 27208, National Bureau of Economic Research, Series: Working Paper Series.

Chiplunkar, Gaurav, Erin Kelley, and Gregory Lane, 2020, Which jobs are lost during a lockdown? evidence from vacancy postings in india, *SSRN* .

Coibion, Olivier, Yuriy Gorodnichenko, and Michael Weber, 2020, Labor Markets During the COVID-19 Crisis: A Preliminary View, Working Paper 27017, National Bureau of Economic Research, Series: Working Paper Series.

Collard-Wexler, Allan, and Jan De Loecker, 2015, Reallocation and technology: Evidence from the us steel industry, *American Economic Review* 105, 131–71.

Cortes, Patricia, Jessica Pan, Laura Pilossoph, and Basit Zafar, 2020, Gender differences in job search and the earnings gap: Evidence from business majors, *Available at SSRN* .

Davis, Steven J, John Haltiwanger, and Scott Schuh, 1996, Small business and job creation: Dissecting the myth and reassessing the facts, *Small business economics* 8, 297–315.

Decker, Ryan, John Haltiwanger, Ron Jarmin, and Javier Miranda, 2014, The Role of Entrepreneurship in US Job Creation and Economic Dynamism, *Journal of Economic Perspectives* 28, 3–24.

Decker, Ryan A., John Haltiwanger, Ron S. Jarmin, and Javier Miranda, 2016, Where has all the skewness gone? The decline in high-growth (young) firms in the U.S., *European Economic Review* 86, 4–23.

Fabrizio, Kira R, and Ulya Tsolmon, 2014, An empirical examination of the procyclicality of R&D investment and innovation, *Review of Economics and Statistics* 96, 662–675, Publisher: MIT Press.

Fairlie, Robert W, 2020, The impact of covid-19 on small business owners: Continued losses and the partial rebound in may 2020, Technical report, National Bureau of Economic Research.

Foster, Lucia, John C Haltiwanger, and Cornell John Krizan, 2001, Aggregate productivity growth: lessons from microeconomic evidence, in *New developments in productivity analysis*, 303–372 (University of Chicago Press).

Gompers, Paul A., Will Gornall, Steven N. Kaplan, and Ilya A. Strebulaev, 2020, Venture Capitalists and COVID-19, SSRN Scholarly Paper ID 3669345, Social Science Research Network, Rochester, NY.

Gortmaker, Jeff, Jessica Jeffers, and Michael Junho Lee, 2019, Labor reactions to financial distress: Evidence from linkedin activity, *Available at SSRN* .

Gottlieb, Joshua D, Richard R Townsend, and Ting Xu, 2019, Does career risk inhibit potential entrepreneurs? .

Hershbein, Brad, and Lisa B Kahn, 2018, Do recessions accelerate routine-biased technological change? evidence from vacancy postings, *American Economic Review* 108, 1737–72.

Howell, Sabrina T, Josh Lerner, Ramana Nanda, and Richard R Townsend, 2020, Financial distancing: How venture capital follows the economy down and curtails innovation, Technical report, National Bureau of Economic Research.

Kahn, Lisa B, Fabian Lange, and David G Wiczer, 2020a, Labor Demand in the Time of COVID-19: Evidence from Vacancy Postings and UI Claims, Working Paper 27061, National Bureau of Economic Research, Series: Working Paper Series.

Kahn, Lisa B, Fabian Lange, and David G Wiczer, 2020b, Labor Demand in the Time of COVID-19: Evidence from Vacancy Postings and UI Claims, Working Paper 27061, National Bureau of Economic Research, Series: Working Paper Series.

Koellinger, Philipp D, and A Roy Thurik, 2012, Entrepreneurship and the business cycle, *Review of Economics and Statistics* 94, 1143–1156.

Moscarini, Giuseppe, and Fabien Postel-Vinay, 2012, The contribution of large and small employers to job creation in times of high and low unemployment, *American Economic Review* 102, 2509–39.

Mui, Preston, and Benjamin Schoefer, 2020, Reservation raises: The aggregate labor supply curve at the extensive margin, Technical report, CEPR Discussion Paper No. DP14209.

Nanda, Ramana, and Matthew Rhodes-Kropf, 2016, Financing Risk and Innovation, *Management Science* 63, 901–918, Publisher: INFORMS.

Parker, Simon C, 2009, *The Economics of Entrepreneurship* (Cambridge University Press).

Rampini, Adriano A, 2004, Entrepreneurial activity, risk, and the business cycle, *Journal of Monetary Economics* 51, 555–573.

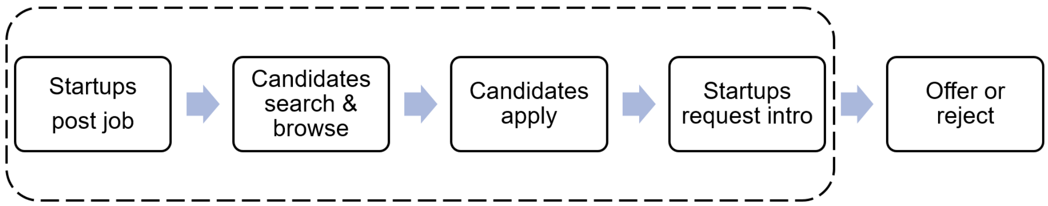
Townsend, Richard R., 2015, Propagation of Financial Shocks: The Case of Venture Capital, *Management Science* 61, 2782–2802, Publisher: INFORMS.

Vayanos, Dimitri, 2004, Flight to quality, flight to liquidity, and the pricing of risk, Technical report, National bureau of economic research.

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

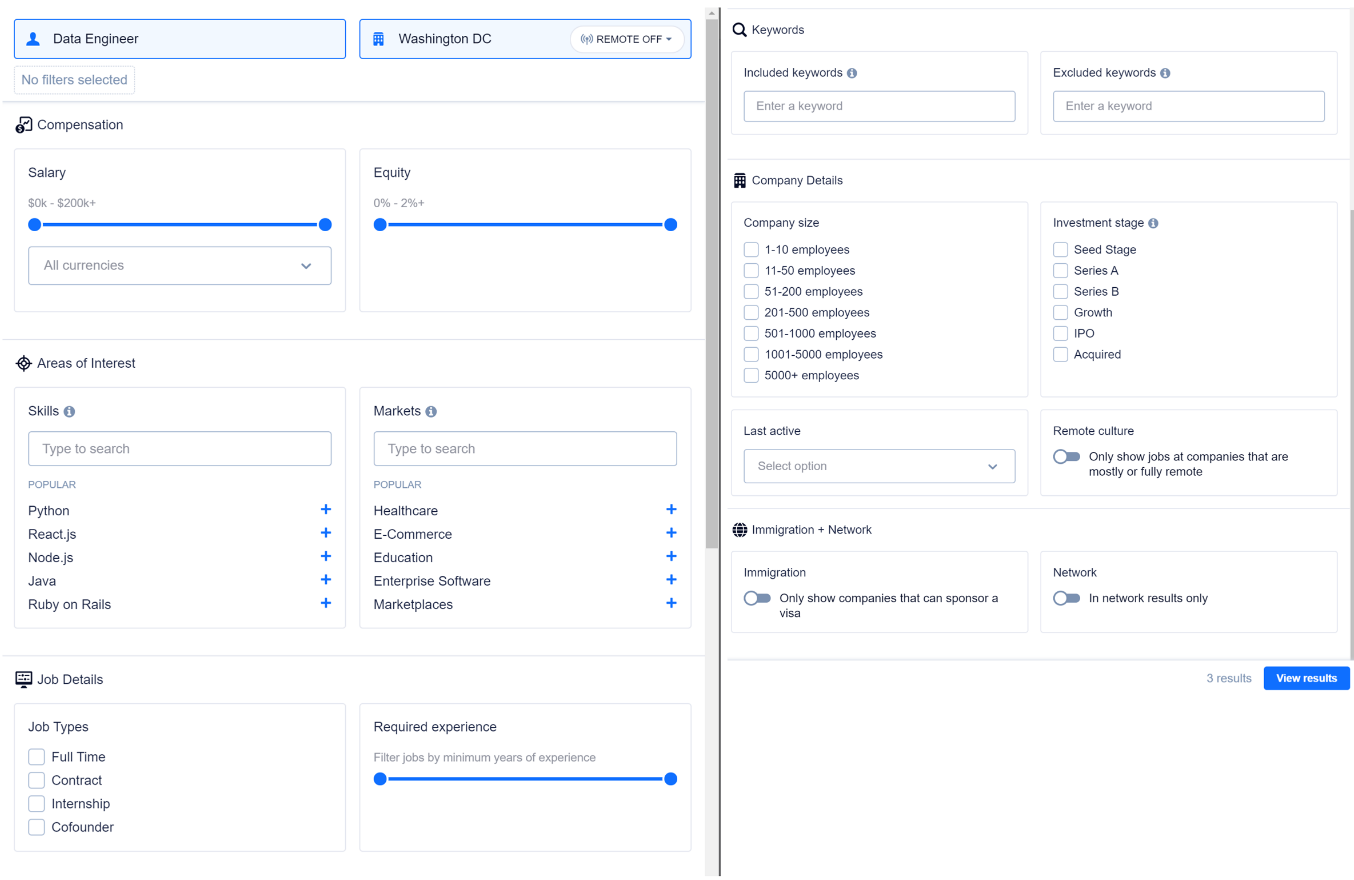
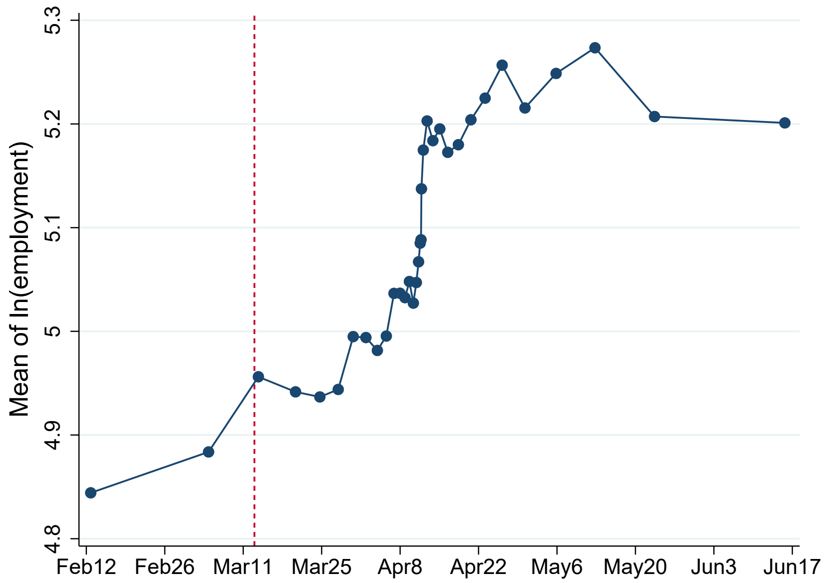


Figure 2
Changes in Searched Firm Size

Panel A (Panel B) shows within-user changes in the logarithm of average employment size searched by users (the likelihood of average employment size being larger than 500) from February to June 2020. The binscatter graphs remove user fixed effects. The dashed vertical line indicates March 13, 2020, the date that a state of national emergency was first announced in the U.S.

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



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

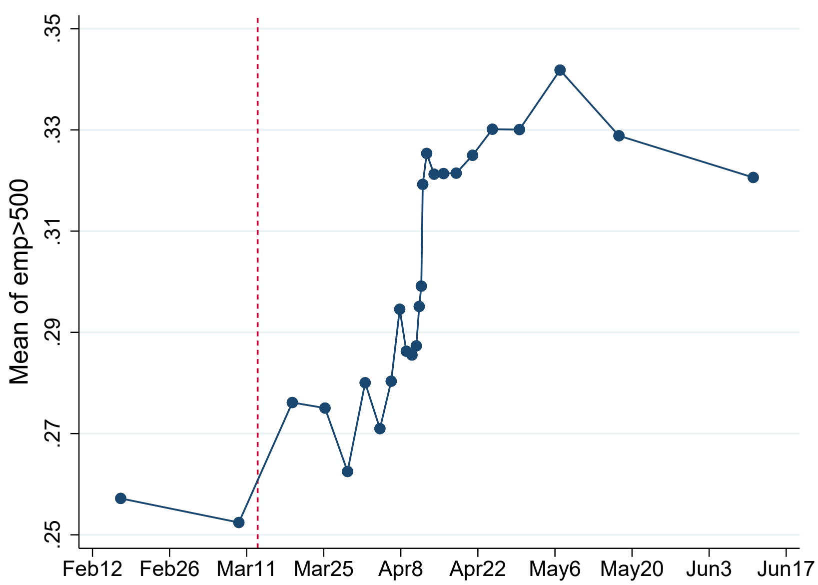
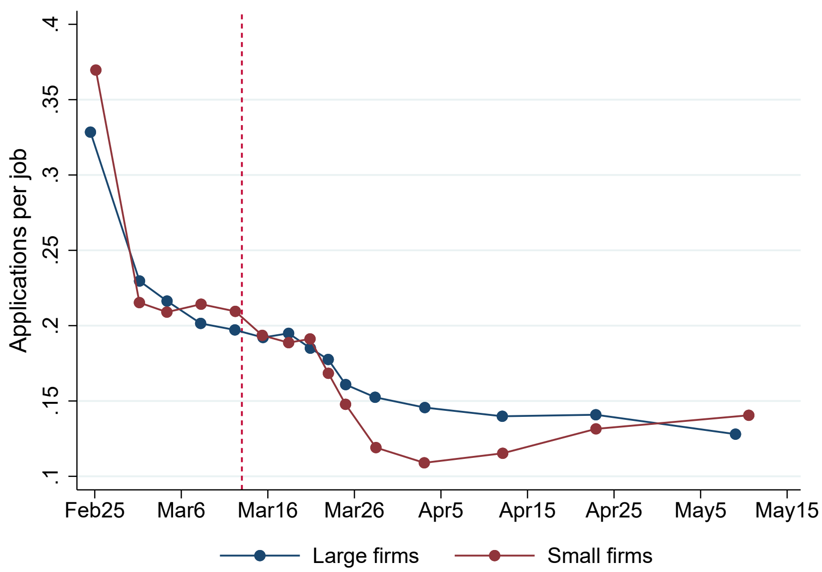


Figure 3
Changes in the Number of Applications Per Job

Panel A (Panel B) shows within-job changes in the number of applications received for that job posting from February to May 2020. The binscatter graphs remove job fixed effects and control for the log number of active job postings by a firm on a day as well as the average size of firms hiring on AngelList on a day. 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) C round at the time of application. The dashed vertical line indicates March 13, 2020, the date that a state of national emergency was first announced in the U.S.

Panel A: Changes in the number of applications per job by firm size



Panel B: Changes in the number of applicaitons per job by firm stage

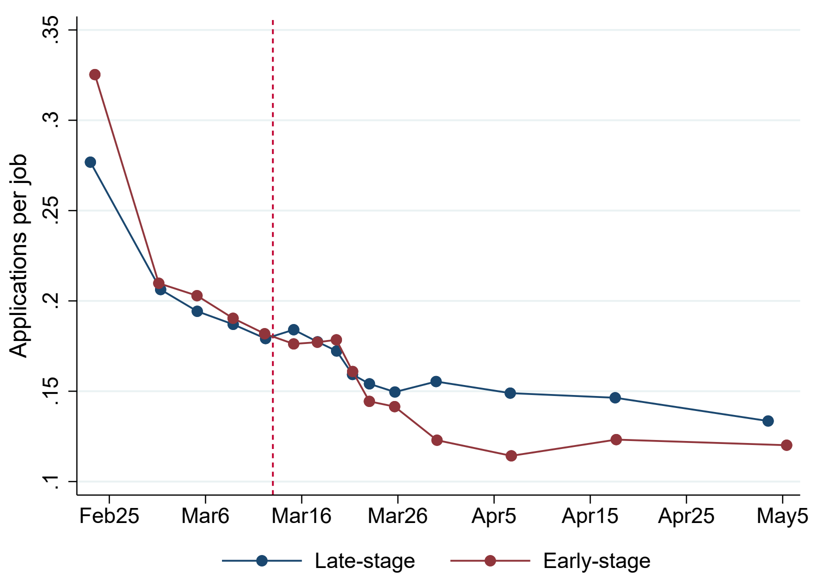
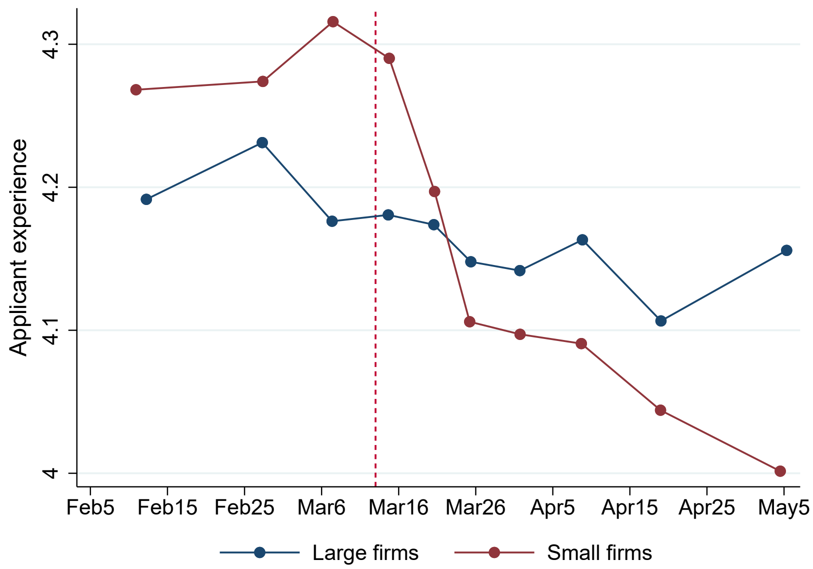


Figure 4
Changes in Applicant Quality

Panel A (Panel B) shows within-firm changes in the average experience (quality score) of job applicants from February to May 2020. The binscatter graphs remove startup fixed effects and control for the log number of active job postings by a firm on a day as well as the average size of firms hiring on AngelList on a day. Small firms are startups with no more 50 employees and large startups are those with more than 50 employees. The dashed vertical line indicates March 13, 2020, the date that a state of national emergency was first announced in the U.S.

Panel A: Changes in applicant experience by firms size



Panel B: Changes in applicant quality by firms size

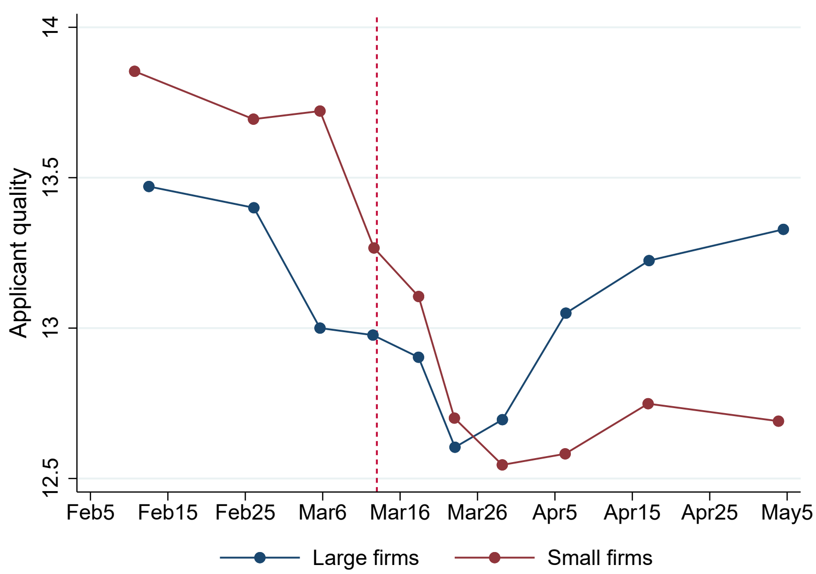


Table 1
Summary Statistics

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 job applications and control variables at the application level.

Panel A: Search level

Variable	N	Mean	Std. Dev.	Min.	Median	Max.
Ln(emp)	390,005	5.09	2.11	1.87	4.86	9.43
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	0.00	4.39	5.44
No. of roles	3,572,005	1.55	1.38	1.00	1.00	21.00
No. of markets	337,116	2.96	2.39	1.00	2.00	15.00
No. of locations	4,645,381	1.50	1.23	1.00	1.00	25.00
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	34.00

Panel B: Applications: job posting-day level

Variable	N	Mean	Std. Dev.	Min.	Median	Max.
No. of applications	1,465,942	0.18	0.77	0.00	0.00	81.00
No. of applications - high quality	1,465,942	0.09	0.44	0.00	0.00	51.00
No. of applications - low quality	1,465,942	0.09	0.43	0.00	0.00	35.00
No. of applications - experienced	1,465,942	0.09	0.48	0.00	0.00	58.00
No. of applications - inexperienced	1,465,942	0.09	0.44	0.00	0.00	41.00
Emp<50	1,465,942	0.68	0.46	0.00	1.00	1.00
Pre-C	531,164	0.73	0.45	0.00	1.00	1.00
Avg ln(emp) of recruiting firms	1,465,942	3.50	0.13	3.29	3.51	3.71
Ln(no. of active jobs by the firm)	1,465,942	1.88	1.06	0.69	1.61	5.55

Panel C: Applications: application level

Variable	N	Mean	Std. Dev.	Min.	Median	Max.
Applicant experience	400,454	4.18	3.47	0.00	3.00	10.00
Applicant quality	397,981	13.21	15.67	0.00	7.06	85.23
Emp<50	400,454	0.76	0.43	0.00	1.00	1.00
Seed	141,555	0.42	0.49	0.00	0.00	1.00
Avg ln(emp) of recruiting firms	400,454	3.51	0.13	3.29	3.51	3.71
Ln(no. of active jobs by the firm)	400,454	1.69	0.87	0.69	1.61	5.55
Ln(emp)	418,450	3.25	1.42	1.70	3.42	9.43
Late-stage	144,338	0.18	0.39	0.00	0.00	1.00
Request intro	436,198	0.07	0.26	0.00	0.00	1.00
Ln(total no. of appl. for a job)	436,198	2.60	1.26	0.69	2.48	7.35

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-19 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 employment size is larger than 500. *Post_Mar13* 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)
Post_Mar13	0.223***	0.254***	0.053***	0.052***
	(0.047)	(0.021)	(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	0.013	0.811	0.014	0.733
% change	22%	25%	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-19 from February to June 2020. The sample is at the search level. *Post_Mar13* 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)
Post_Mar13	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)	(0.008)	(0.038)	(0.007)	(0.007)	(0.063)
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 apply to around the onset of COVID-19 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. *Late stage* indicates that the firm being applied to has a financing stage later than C round (D, E, F... or exited). *Post_Mar13* 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)			Late stage		
	(1)	(2)	(3)	(4)	(5)	(6)
Post_Mar13	0.041**	-0.015	0.010	0.022***	0.013**	0.016***
	(0.019)	(0.025)	(0.023)	(0.005)	(0.005)	(0.005)
Post_Mar13 × Experienced		0.116***			0.017***	
		(0.022)			(0.003)	
Post_Mar13 × High quality			0.083***			0.013***
			(0.015)			(0.004)
Candidate state FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	418,450	418,450	418,450	144,338	144,338	144,338
Adj. R-sq	0.013	0.013	0.013	0.004	0.004	0.004
% change - worse	4.1%	-1.5%	1.0%	11.3%	6.7%	8.2%
% change - better		10.1%	9.3%		15.5%	14.9%

Panel B: With candidate FE

	Ln(emp)			Late stage		
	(1)	(2)	(3)	(4)	(5)	(6)
Post_Mar13	0.077***	0.023	0.028	0.043***	0.038***	0.036***
	(0.016)	(0.016)	(0.018)	(0.006)	(0.007)	(0.010)
Post_Mar13 × Experienced		0.109***			0.010*	
		(0.020)			(0.005)	
Post_Mar13 × High quality			0.108***			0.009
			(0.021)			(0.006)
Candidate FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	418,450	418,450	418,450	144,338	144,338	144,338
Adj. R-sq	0.144	0.144	0.145	0.037	0.037	0.038
% change - worse	7.7%	2.3%	2.8%	22.1%	19.5%	18.4%
% change - better		13.2%	13.6%		24.6%	23.0%

Table 5
Job Applications

This table examines changes in job applications received by startups around the onset of COVID-19 from February to May 2020. The sample is at the job posting-day level. The dependent variable in Panel A, *No. of applications per job,* 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. *Post_Mar13* 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-C* indicates startups with a financing stage before C round (i.e., pre-seed, seed, A and B) 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 day and the average employment size of all startups hiring on AngelList on a 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 per job					
	(1)	(2)	(3)	(4)	(5)	(6)
Post_Mar13	-0.020**	-0.006	-0.010	-0.010	-0.001	0.000
	(0.008)	(0.008)	(0.006)	(0.007)	(0.009)	(0.005)
Post_Mar13 × Emp<=50		-0.021***			-0.013*	
		(0.004)			(0.007)	
Post_Mar13 × Pre-C			-0.016***			-0.021***
			(0.004)			(0.004)
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	1,465,942	1,465,942	531,164	1,465,942	1,465,942	531,164
Adj. R-sq	0.234	0.234	0.199	0.368	0.368	0.362
% change - large/late-stage	-10.2%	-3.0%	-5.2%	-5.1%	-0.5%	0.0%
% change - small/early-stage		-13.7%	-13.5%		-7.1%	-10.9%

Table 5
(Continued)

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

	No. of applications per job							
	Experienced		Inexperienced		High-quality		Low-quality	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post_Mar13	0.001	-0.001	-0.006*	-0.008**	-0.007*	-0.005*	0.000	-0.003
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.003)	(0.002)	(0.005)
Post_Mar13 × Emp<=50	-0.017***		-0.002		-0.013***		-0.002	
	(0.003)		(0.002)		(0.003)		(0.002)	
Post_Mar13 × Pre-C		-0.012***		-0.003		-0.010***		-0.003
		(0.002)		(0.003)		(0.003)		(0.004)
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	1,465,942	531,164	1,465,942	531,164	1,465,942	531,164	1,465,942	531,164
Adj. R-sq	0.198	0.171	0.179	0.134	0.179	0.149	0.172	0.145
% change - large/late-stage	1.1%	-1.1%	-6.5%	-8.7%	-7.3%	-5.2%	0.0%	-3.0%
% change - small/early-stage	-16.8%	-13.7%	-8.7%	-12.0%	-20.8%	-15.6%	-2.0%	-5.9%

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

	No. of applications per job							
	Experienced		Inexperienced		High-quality		Low-quality	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post_Mar13	0.002	0.001	-0.003	-0.003	-0.005	-0.001	0.006	0.001
	(0.004)	(0.003)	(0.004)	(0.002)	(0.005)	(0.002)	(0.004)	(0.003)
Post_Mar13 × Emp<=50	-0.012**		-0.001		-0.009**		-0.003	
	(0.005)		(0.003)		(0.004)		(0.004)	
Post_Mar13 × Pre-C		-0.013***		-0.004		-0.011***		-0.005*
		(0.003)		(0.003)		(0.004)		(0.003)
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	1,465,942	531,164	1,465,942	531,164	1,465,942	531,164	1,465,942	531,164
Adj. R-sq	0.308	0.289	0.322	0.321	0.266	0.248	0.304	0.309
% change - large/late-stage	2.1%	1.1%	-3.3%	-3.3%	-5.2%	-1.0%	5.9%	1.0%
% change - small/early-stage	-10.5%	-12.6%	-4.3%	-7.6%	-14.6%	-12.5%	3.0%	-4.0%

Table 6
Applicant Quality

This table examines changes in applicant quality around the onset of COVID-19 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. *Post_Mar13* 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. *Seed* indicates startups at seed or pre-seed round at the time of job application. Panel A includes startup fixed effects and Panel B includes job posting fixed effects. Demand controls include the log number of active job postings by a startup on a day and the average employment size of all startups hiring on AngelList on a 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)
Post_Mar13	-0.063*	0.084	0.093**	-0.834***	-0.239	0.165
	(0.036)	(0.060)	(0.037)	(0.265)	(0.245)	(0.308)
Post _Mar13 × Emp<=50		-0.205***			-0.828***	
		(0.054)			(0.182)	
Post_Mar13 × Seed			-0.302***			-1.052***
			(0.029)			(0.236)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	400,454	400,454	140,978	397,981	397,981	141,555
Adj. R-sq	0.230	0.231	0.167	0.065	0.065	0.045
% change - large/late-stage	-1.5%	2.0%	2.3%	-6.5%	-1.9%	1.2%
% change - small/early-stage		-2.8%	-5.1%		-8.4%	-6.7%

Panel B: Within-job

	Applicant experience			Applicant quality		
	(1)	(2)	(3)	(4)	(5)	(6)
Post_Mar13	-0.088**	-0.047	-0.022	-0.812***	-0.417	-0.170
	(0.034)	(0.047)	(0.040)	(0.270)	(0.307)	(0.340)
Post_Mar13 × Emp<=50		-0.054			-0.522***	
		(0.034)			(0.169)	
Post_Mar13 × Seed			-0.086**			-0.656**
			(0.034)			(0.258)
Job FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	400,454	400,454	140,978	397,981	397,981	141,555
Adj. R-sq	0.353	0.353	0.343	0.100	0.100	0.091
% change - large/late-stage	-2.1%	-1.1%	-0.5%	-6.4%	-3.3%	-1.3%
% change - small/early-stage		-2.4%	-2.7%		-7.4%	-6.2%

Table 7
Likelihood of Requesting Intro

This table examines changes in the likelihood of a submitted job application receiving intro from the startup around the onset of COVID-19 from February to May 2020. The dependent variable *Request Intro* is a dummy equal to one if the submitted application received an intro from the startup. *Post_Mar13* 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-C* indicates startups with a financing stage before C round (i.e., pre-seed, seed, A and B) at the time of job application. Columns 1-3 control for startup fixed effects and columns 4-6 control for job posting fixed effects. All columns control for the total number of applications received for a job posting as of a given day. Standard errors are clustered by firm's state. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Request intro					
	(1)	(2)	(3)	(4)	(5)	(6)
Post_Mar13	-0.018***	-0.002	0.000	-0.012***	0.008***	0.010***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
Post_Mar13 × Emp<=50		-0.022***			-0.026***	
		(0.001)			(0.001)	
Post_Mar13 × Pre-C			-0.016***			-0.022***
			(0.001)			(0.002)
Ln(no. of applications received)	-0.019***	-0.018***	-0.011***	-0.027***	-0.026***	-0.018***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Firm FE	Yes	Yes	Yes	No	No	No
Job FE	No	No	No	Yes	Yes	Yes
N	436,198	436,198	151,196	425,623	425,623	146,934
Adj. R-sq	0.281	0.282	0.197	0.316	0.316	0.223
% change - large/late-stage	-23%	-3%	0%	-15%	10%	24%
% change - small/early-stage		-31%	-38%		-23%	-29%

Table 8
Placebo Tests Based on 2019

This table presents placebo tests for our main analysis using 2019 data. Panel A examines changes in average firm size searched by candidates. Panel B examines changes in the size and stage of firms applied to by candidates. Panel C examines within-job posting changes in the number of applications by firm size and candidate quality at the job posting-day level. *Post_Mar13* 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)
Post_Mar13	-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	-1.7%	0.9%	-3.8%	3.8%

Panel B: Size and stage of firms applied to

	Ln(emp)	Ln(emp)	Post-C	Post-C
	(1)	(2)	(3)	(4)
Post_Mar13	0.012	0.004	-0.002	-0.001
	(0.015)	(0.019)	(0.007)	(0.006)
Candidate FE	No	Yes	No	Yes
Candidate state FE	Yes	No	Yes	No
N	592,982	592,982	200,828	200,828
Adj. R-sq	0.002	0.129	0.002	0.033
% change	0.4%	0.1%	-1.2%	-0.6%

Table 8
(Continued)

Panel C: Number of applications per job

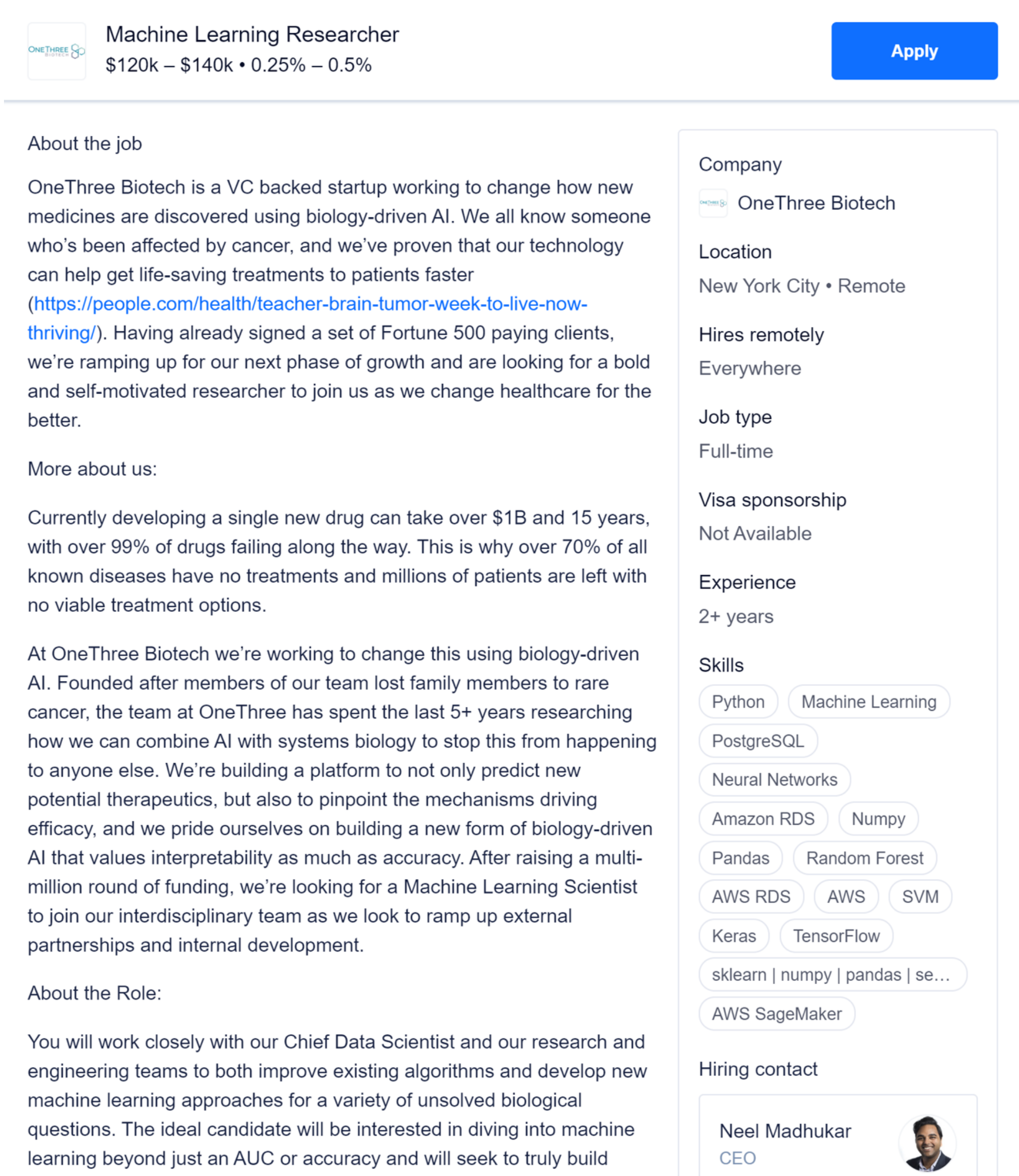
	No. of applications per job				
	All	Emp>50	Emp<=50	High quality	Low quality
	(1)	(2)	(3)	(4)	(5)
Post_Mar13	0.002	0.008**	0.000	-0.001	0.003
	(0.002)	(0.004)	(0.003)	(0.003)	(0.002)
Job FE	Yes	Yes	Yes	Yes	Yes
Days since posting FE	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
N	759,409	175,788	583,621	759,409	759,409
Adj. R-sq	0.282	0.253	0.287	0.184	0.232
% change	1.2%	6.3%	0.0%	-1.1%	3.7%

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.


Machine Learning Researcher
$120k – $140k • 0.25% – 0.5%
Apply

About the job

OneThree Biotech is a VC backed startup working to change how new medicines are discovered using biology-driven AI. We all know someone who's been affected by cancer, and we've proven that our technology can help get life-saving treatments to patients faster (https://people.com/health/teacher-brain-tumor-week-to-live-now-thriving/). Having already signed a set of Fortune 500 paying clients, we're ramping up for our next phase of growth and are looking for a bold and self-motivated researcher to join us as we change healthcare for the better.

More about us:

Currently developing a single new drug can take over $1B and 15 years, with over 99% of drugs failing along the way. This is why over 70% of all known diseases have no treatments and millions of patients are left with no viable treatment options.

At OneThree Biotech we're working to change this using biology-driven AI. Founded after members of our team lost family members to rare cancer, the team at OneThree has spent the last 5+ years researching how we can combine AI with systems biology to stop this from happening to anyone else. We're building a platform to not only predict new potential therapeutics, but also to pinpoint the mechanisms driving efficacy, and we pride ourselves on building a new form of biology-driven AI that values interpretability as much as accuracy. After raising a multi-million round of funding, we're looking for a Machine Learning Scientist to join our interdisciplinary team as we look to ramp up external partnerships and internal development.

About the Role:

You will work closely with our Chief Data Scientist and our research and engineering teams to both improve existing algorithms and develop new machine learning approaches for a variety of unsolved biological questions. The ideal candidate will be interested in diving into machine learning beyond just an AUC or accuracy and will seek to truly build

Company
OneThree Biotech

Location
New York City • Remote

Hires remotely
Everywhere

Job type
Full-time

Visa sponsorship
Not Available

Experience
2+ years

Skills
Python, Machine Learning, PostgreSQL, Neural Networks, Amazon RDS, Numpy, Pandas, Random Forest, AWS RDS, AWS, SVM, Keras, TensorFlow, sklearn | numpy | pandas | se…, AWS SageMaker

Hiring contact
Neel Madhukar
CEO

Figure A.2
Job Posting Volume

This figure shows the weekly number of job postings and the number of startups posting jobs on AngelList Talent from February to June 2020. The dashed vertical line indicates March 13, 2020, the date that a state of national emergency was first announced in the U.S.

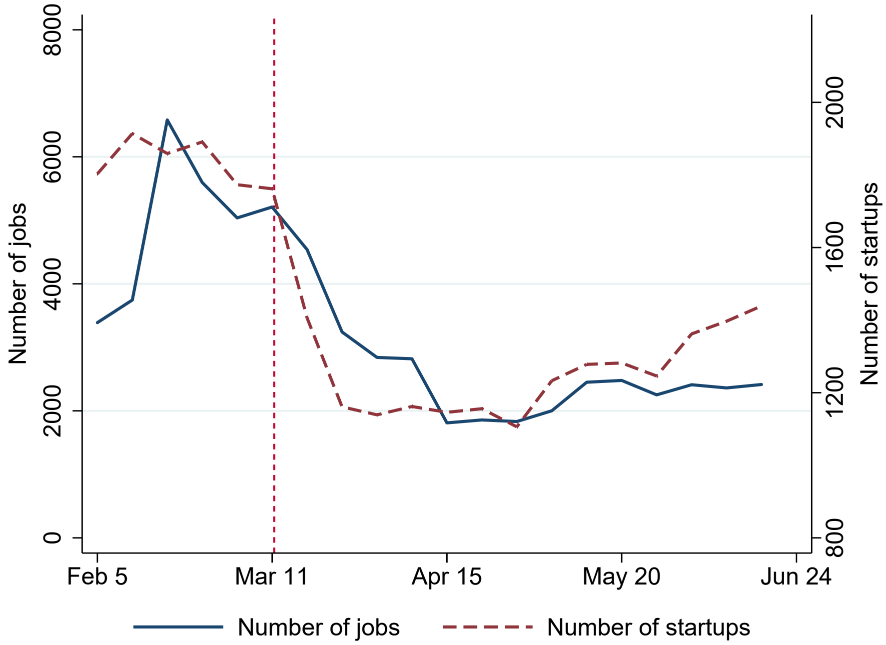


Table A.1
Size and Stage of Firms Applied by Candidates: Additional Fixed Effects

This table shows robustness of Table 4 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 apply to around the onset of COVID-19 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. *Late stage* indicates that the firm being applied to has a financing stage later than C round (D, E, F... or exited). *Post_Mar13* 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 A: Without candidate FE

	Ln(emp)			Late stage		
	(1)	(2)	(3)	(4)	(5)	(6)
Post_Mar13	0.035*	-0.020	0.004	0.021***	0.012***	0.016***
	(0.019)	(0.024)	(0.022)	(0.004)	(0.005)	(0.005)
Post_Mar13 × Experienced		0.115***			0.017***	
		(0.020)			(0.003)	
Post_Mar13 × High quality			0.083***			0.013***
			(0.014)			(0.004)
Candidate state 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	144,338	144,338	144,338
Adj. R-sq	0.044	0.044	0.044	0.004	0.018	0.017
% change - worse	3.5%	-2.0%	1.0%	10.8%	6.2%	8.2%
% change - better		9.5%	9.3%		14.9%	14.9%

Panel B: With candidate FE

	Ln(emp)			Late stage		
	(1)	(2)	(3)	(4)	(5)	(6)
Post_Mar13	0.058***	0.003	0.010	0.041***	0.035***	0.042***
	(0.016)	(0.015)	(0.017)	(0.006)	(0.007)	(0.009)
Post_Mar13 × Experienced		0.109***			0.011**	
		(0.019)			(0.005)	
Post_Mar13 × High quality			0.105***			0.007
			(0.019)			(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	144,338	144,338	144,338
Adj. R-sq	0.158	0.158	0.159	0.047	0.047	0.048
% change - worse	5.8%	0.3%	1.0%	21.0%	17.9%	21.4%
% change - better		11.2%	11.5%		23.6%	25.0%

Table A.2
Changes in the Number of Applications Per Candidate

This table examines changes in the number of applications per candidate around the onset of COVID-19 from February to May 2020. The sample is at the candidate-day level. The dependent variable is the number of job applications submitted by a user on a given day. *Post_Mar13* 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* (*Inexperienced*) indicates candidates with above (below) median number of years of experience. *High-quality* (*Low-quality*) indicates candidates with above (below) median quality score as estimated by AngelList. All columns include candidate fixed effects as well as two day-level controls: 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.

	No. of applications per candidate				
	All	Experienced	Inexperienced	High-quality	Low-quality
	(1)	(2)	(3)	(4)	(5)
Post_Mar13	0.018**	0.019**	0.019	0.015	0.026**
	(0.007)	(0.008)	(0.012)	(0.010)	(0.011)
Candidate FE	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
N	838,805	433,845	404,748	427,759	410,352
Adj. R-sq	0.102	0.103	0.103	0.088	0.13
% change	4.0%	4.5%	4.0%	3.3%	6.0%

Table A.3
Likelihood of Requesting Intro: Restrict to Jobs that Received Any Response

This table demonstrates the robustness of Table 7 to restricting to jobs that received any form of response from the startup, including reject or request into. The table examines changes in the likelihood of a submitted job application receiving intro from the startup around the onset of COVID-19 from February to May 2020. The dependent variable *Request Intro* is a dummy equal to one if the submitted application received an intro from the startup. *Post_Mar13* 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-C* indicates startups with a financing stage before C round (i.e., pre-seed, seed, A and B) at the time of job application. Columns 1-3 control for startup fixed effects and columns 4-6 control for job posting fixed effects. All columns control for the total number of applications received for a job posting as of a given day. Standard errors are clustered by firm's state. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Request intro					
	(1)	(2)	(3)	(4)	(5)	(6)
Post_Mar13	-0.027***	-0.003	0.000	-0.025***	0.006*	0.012***
	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.003)
Post_Mar13 × Emp<=50		-0.033***			-0.040***	
		(0.002)			(0.003)	
Post_Mar13 × Pre-C			-0.021***			-0.031***
			(0.003)			(0.004)
Ln(no. of applications received)	-0.032***	-0.032***	-0.019***	-0.037***	-0.037***	-0.024***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Firm FE	Yes	Yes	Yes	No	No	No
Job FE	No	No	No	Yes	Yes	Yes
N	267,761	267,761	97,129	267,761	267,761	97,129
Adj. R-sq	0.276	0.276	0.204	0.300	0.300	0.223
% change - large/late-stage	-14%	-2%	0%	-9%	6%	15%
% change - small/early-stage		-19%	-24%		-14%	-18%

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

This table examines changes in the size and financing stage of firms candidates click on around the onset of COVID-19 from February to May 2020. The sample is at the click level and includes all clicks on job postings or firms that are not 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). *Late stage* indicates that the firm being clicked (or firm associated with the job being clicked) has a financing stage later than C round (D, E, F... or exited). *Post_Mar13* 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 3 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)		Late stage	
	(1)	(2)	(3)	(4)
Post_Mar13	0.123***	0.178***	0.013***	0.030***
	(0.011)	(0.014)	(0.004)	(0.005)
Candidate FE	No	Yes	No	Yes
Candidate state FE	Yes	No	Yes	No
Controls	Yes	Yes	Yes	Yes
N	999,267	999,267	397,097	397,097
Adj. R-sq	0.015	0.228	0.007	0.146
% change	12.3%	17.8%	5.1%	11.6%

Table A.5
Robustness: Fresh Searches

This table examines changes in searched firm size around the onset of COVID-19, restricting to fresh searches that are the first searches by a user by day (columns 1-2), by week (columns 3-4), or by 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. *Post_Mar13* 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)
Post_Mar13	0.241***	0.199***	0.265***	0.205***	0.192**	0.142***
	(0.044)	(0.016)	(0.044)	(0.019)	(0.086)	(0.042)
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	24%	20%	27%	21%	19%	14%

Table A.6
Robustness: Local Number of COVID-19 Cases as Treatment

This table shows robustness of our main results using the state-level number of COVID-19 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 apply to (columns 2 and 3). Panel B examines within-job posting changes in the number of applications by firm size and candidate quality at the job posting-day level. *Ln(no. of cases)* is the logarithm of the cumulative number of COVID-19 cases reported at the state-day level obtained from the New York Times COVID-19 database. 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 4. 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 being searched or applied to

	Ln(emp)	Ln(emp)	Late-stage
	Search-level	*Application-level*	
	(1)	(2)	(3)
Ln(no. of cases)	0.037***	0.007**	0.007***
	(0.007)	(0.003)	(0.001)
Candidate FE	Yes	Yes	Yes
N	390,005	418,450	144,338
Adj. R-sq	0.811	0.144	0.037

Panel B: Number of applications per job

	No. of applications per job				
	All	Emp>50	Emp<=50	High quality	Low quality
	(1)	(2)	(3)	(4)	(5)
Ln(no. of cases)	-0.002*	0.000	-0.003**	-0.001***	0.000
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Job FE	Yes	Yes	Yes	Yes	Yes
Days since posting FE	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
N	1,465,942	463,344	1,002,598	1,465,942	1,465,942
Adj. R-sq	0.371	0.322	0.382	0.269	0.310

Panel C: Applicant quality

	Applicant experience		Applicant Quality	
	(1)	(2)	(3)	(4)
Ln(no. of cases)	-0.006	-0.003	0.095**	0.094**
	(0.007)	(0.008)	(0.044)	(0.047)
Ln(no. of cases) × Emp<=50	-0.012***		-0.072**	
	(0.003)		(0.027)	
Ln(no. of cases) × Seed		-0.019***		-0.069**
		(0.005)		(0.031)
Job FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
N	400,454	140,978	397,981	141,555
Adj. R-sq	0.353	0.343	0.100	0.091

Table A.7
Robustness: Dropping California and Massachusetts

This table shows robustness of our main results 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 apply to (columns 2 and 3). Panel B examines within-job posting changes in the number of applications by firm size and candidate quality at the job-day level. All variables and controls are defined in the same way as those in Tables 2, 4, 5, and 4. 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 being searched or applied to

	Ln(emp)	Ln(emp)	Late-stage
	Search-level	*Application-level*	
	(1)	(2)	(3)
Post_Mar13	0.227***	0.094***	0.053***
	(0.031)	(0.028)	(0.010)
Candidate FE	Yes	Yes	Yes
N	170,057	245,422	73,133
Adj. R-sq	0.718	0.139	0.033

Panel B: Number of applications per job

	No. of applications per job				
	All	Emp>50	Emp<=50	High quality	Low quality
	(1)	(2)	(3)	(4)	(5)
Post_Mar13	-0.020	-0.007	-0.026**	-0.018***	0.001
	(0.012)	(0.012)	(0.013)	(0.005)	(0.007)
Job FE	Yes	Yes	Yes	Yes	Yes
Days since posting FE	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
N	932,613	283,194	649,419	932,613	932,613
Adj. R-sq	0.389	0.350	0.397	0.286	0.333

Panel C: Applicant quality

	Applicant experience		Applicant Quality	
	(1)	(2)	(3)	(4)
Post_Mar13	-0.011	0.024	-0.106	0.078
	(0.057)	(0.048)	(0.354)	(0.439)
Post_Mar13 × Emp<=50	-0.133***		-0.779***	
	(0.040)		(0.270)	
Post_Mar13 × Seed		-0.279***		-0.957**
		(0.045)		(0.372)
Job FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
N	252,115	83,008	249,692	83,127
Adj. R-sq	0.347	0.333	0.099	0.086

Table A.8
Robustness: 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-19 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 by 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. *Post_Mar13* 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-C* indicates startups with a financing stage before C round (i.e., pre-seed, seed, A and B) 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 day and the average employment size of all startups hiring on AngelList on a 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)
Post_Mar13	-0.082***	-0.056**	0.004	-0.077***	-0.017	-0.003
	(0.019)	(0.024)	(0.023)	(0.018)	(0.023)	(0.025)
Post_Mar13 × Emp<=50		-0.040***			-0.090***	
		(0.013)			(0.024)	
Post_Mar13 × Pre-C			-0.112***			-0.103***
			(0.014)			(0.016)
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	1,465,942	1,465,942	531,164	1,465,942	1,465,942	531,164
Adj. R-sq	0.201	0.201	0.169	0.283	0.283	0.265
% change - large/late-stage	-12.0%	-8.2%	0.6%	-11.2%	-2.5%	-0.4%
% change - small/early-stage		-14.0%	-15.8%		-15.6%	-15.5%

Panel B: Total applicant quality score

	Total applicant quality score					
	(1)	(2)	(3)	(4)	(5)	(6)
Post_Mar13	-0.329***	-0.280***	-0.046	-0.233***	-0.06	-0.069
	(0.080)	(0.092)	(0.076)	(0.071)	(0.077)	(0.064)
Post_Mar13 × Emp<=50		-0.074*			-0.256***	
		(0.038)			(0.076)	
Post_Mar13 × Pre-C			-0.361***			-0.237***
			(0.033)			(0.088)
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	1,465,942	1,465,942	531,164	1,465,942	1,465,942	531,164
Adj. R-sq	0.151	0.151	0.123	0.213	0.213	0.195
% change - large/late-stage	-15.0%	-12.7%	-2.1%	-10.6%	-2.7%	-3.1%
% change - small/early-stage		-16.1%	-18.5%		-14.4%	-13.9%

Table A.9
Labor Demand: Job Postings

This table uses job postings data to examine how startups' labor demand changed around the onset of COVID-19 from February to May 2020. Panel A looks at the number of new job postings at the startup-day level. Panel B examines the number of new job postings at the day level. Panel C examines changes in job characteristics at the job posting level. Panel D provides summary statistics for the outcome variable used in Panels A to C. *Post_Mar13* 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 state in Panels A and C, and are clustered by week in Panel B. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Job posting volume: startup-day level

	No. of job postings per startup-day					
	All		Emp>50		Emp<=50	
	(1)	(2)	(3)	(4)	(5)	(6)
Post_Mar13	-0.012**	-0.025***	-0.044***	-0.071***	0.002	-0.001
	(0.005)	(0.004)	(0.009)	(0.008)	(0.003)	(0.002)
Day of week FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	Yes	No	Yes	No	Yes
N	531,855	531,855	164,042	164,042	367,813	367,813
Adj. R-sq	0.002	0.075	0.004	0.059	0.001	0.101
% change	-13%	-27%	-26%	-41%	3%	-2%

Panel B: Job posting volume: day level

	No. of job postings per day			Small firm
	All	Emp>50	Emp<=50	job share
	(1)	(2)	(3)	(4)
Post_Mar13	-211.767***	-105.686***	-106.081**	0.063**
	(61.267)	(16.732)	(49.529)	(0.023)
Day of week FE	Yes	Yes	Yes	Yes
N	168	168	168	168
Adj. R-sq	0.457	0.673	0.218	0.464
% change	-37%	-47%	-31%	10%

Table A.9
(Continued)

Panel C: Job posting characteristics

	All		Emp>50		Emp<=50	
	Ln(min. salary)	Min. experience	Ln(min. salary)	Min. experience	Ln(min. salary)	Min. experience
	(1)	(2)	(3)	(4)	(5)	(6)
Post_Mar13	-0.024	0.170***	0.018	0.273**	-0.048	0.102**
	(0.034)	(0.044)	(0.056)	(0.116)	(0.030)	(0.041)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Job type FE	Yes	Yes	Yes	Yes	Yes	Yes
Role FE	Yes	Yes	Yes	Yes	Yes	Yes
N	23,621	32,423	5,206	5,793	18,415	26,630
Adj. R-sq	0.821	0.695	0.755	0.499	0.840	0.745
% change	-0.6%	5.7%	0.4%	9.0%	-1.2%	3.4%

Panel D: Summary statistics

Variable	N	Mean	Std. Dev.	Min.	P50	Max.
	All firms					
No. of job postings per startup-day	531,855	0.09	0.76	0.00	0.00	165.00
No. of job postings per day	168	441.4	250.8	72.0	405.5	1329.0
Small firm job share	168	0.64	0.13	0.32	0.61	0.95
Ln(min. salary)	23,621	3.67	1.99	0.00	3.93	9.55
Min. experience	32,423	2.92	2.36	0.00	2.00	10.00
	Emp>50					
No. of job postings per startup-day	164,042	0.15	1.07	0.00	0.00	165.00
No. of job postings per day	168	164.6	106.4	6.0	148.5	570.0
Ln(min. salary)	5,206	4.07	2.02	0.00	4.25	8.85
Min. experience	5,793	3.30	2.40	0.00	3.00	10.00
	Emp<=50					
No. of job postings per startup-day	367,813	0.06	0.57	0.00	0.00	125.00
No. of job postings per day	168	276.8	176.6	60.0	238.0	1038.0
Ln(min. salary)	18,415	3.56	1.97	0.00	3.83	9.55
Min. experience	26,630	2.83	2.34	0.00	2.00	10.00

B Firms' Labor Demand

One of the contributions of our paper is to isolate job candidates' labor supply preferences using unique search parameter data and job fixed effects. Nevertheless, to address any remaining concerns about demand side confounding factors, we directly examine what happens to startup labor demand during COVID. Specifically, for demand side factors to explain our supply side results, we need to observe lower labor demand by small startups, as well as downskilling in their labor demand, i.e., lowering job requirements or offering lower-skilled jobs.[9] To examine these possibilities, we turn to job vacancy postings data.

Figure A.1 shows that the number of job postings by startups indeed declined overall since the onset of COVID, so did the number of startups posting jobs. This is also confirmed in Panel A of Table A.9, where we examine changes in the number of new job postings at the firm-day level. Within firms, job postings dropped by 27% overall (column 2). However, this decline masks great heterogeneity between small and large startups. When examining these two groups of firms separately, we find that the within-firm decline is concentrated among larger startups with above 50 employees. For smaller startups with fewer than 50 employees, there is almost no decline in their labor demand. We obtain similar results if we examine aggregate job posting volume at the day level. As shown in Panel B of Table A.9, aggregate job posting volume declined by 47% for large firms and by 31% for small firms after COVID; the share of small firm jobs increased by 10%. These results are consistent with Bartlett and Morse (2020), who show that larger firms have greater labor flexibility and are better able to adjust employment during COVID than smaller firms.

We further examine the experience requirement and salaries offered in job postings. Downskilling in labor demand should predict lower job experience requirement as well as lower salaries. In Panel C of Table A.9, we find no such decreases. Salaries offered by startups did not change significantly during COVID, and the minimum required years of ex-

[9] The literature has found mixed evidence on the effect of recessions on firms' skill demand (Hershbein and Kahn (2018); Campello et al. (2020b); Chiplunkar et al. (2020))

perience actually increased. These results hold for both larger and smaller startups. Taken together, these demand side results paint a picture opposite of what is happening on the supply side: Smaller startups did not see a weakened labor demand in either quantity or quality. Our main results are therefore unlikely to be driven by changes in demand side factors.