Startup labor markets and remote work: Evidence from job applications

David H. Hsu & Prasanna Tambe*
Wharton School, University of Pennsylvania

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DRAFT. Results are preliminary and incomplete.

The most recent version of this paper can be found here.

Abstract

Does offering remote work allow startup firms to attract more skilled and more diverse talent? We examine job listings and job applicant behavior on the leading platform in this space, AngelList Talent, amid the COVID-19 pandemic-induced shutdowns. We first characterize the jobs and organizations offering remote work before the shutdowns. We then leverage the context to help address the empirical confound of job design (including offering remote jobs) as co-determined with unobserved job and firm characteristics. By doing so, we estimate the change in applicant characteristics to job postings which are (exogenously shifted) to being remote. This design is a window into evaluating a managerial choice (offering remote work) which will likely become even more salient in post-pandemic job design.

Keywords: remote work; startup labor market; talent acquisition; diversity and inclusion; COVID-19; technical workforce.

*Correspondence to: dhsu@wharton.upenn.edu & tambe@wharton.upenn.edu. We are grateful for feedback from seminar audiences at the Asian Innovation and Entrepreneurship Association (AIEA), Boston College, CU Boulder, UC Berkeley, George Mason University, INSEAD, Tulane, and USC. We thank Kevin Laws and Kunal Mehta at AngelList for data access. We acknowledge research support from the Mack Center for Innovation Management at the University of Pennsylvania. Errors and omissions are ours.

1 Introduction

Remote work, also known as working-from-home (WFH), is not a new phenomenon. The 2010 US Census reported that approximately 10% of Americans in the work force conducted remote work at least one day a week, and about 5% exclusively practiced WFH. A much wider share of the world experienced remote work in 2020-21, with the COVID-19 pandemic due to government-mandated shutdowns. These behavioral changes by both employers and workers, aided by information technology platforms, gives rise to a key managerial decision as the world emerges from the pandemic: what WFH policies should firms adopt when they are no longer forced to do so?

There is a wide range of opinion on this question. At one end of the spectrum, some companies such as Twitter and Slack (before their Salesforce acquisition) announced permanent WFH policies. On the other side of the spectrum, firms like Netflix, WeWork, and JP Morgan Chase stated that they want employees back in the office as soon as it is safe (after widespread vaccine access). Other organizations, such as Facebook and Google, have taken a hybrid stance, allowing some fraction of their workers the ability to conduct all of their work remotely and/or have the flexibility to combine WFH with on-site work.

The prior academic literature in this domain concentrates on an important question informing the managerial choice of offering remote work, that of worker productivity for those randomized to a WFH condition within an organization. These field experiments mostly (though not exclusively, as we detail in a below literature review) find a positive individual productivity effect caused by remote work within the subject organizations. Left open, however, are two related issues related to the labor *market*, which in turn inform our research questions in this paper: (1) what organizational and job characteristics shape the likelihood a given job posting is listed as "remote"?, and (2) do employers attract better and more diverse (gender and race) talent when they designate a job as remote-eligible?

To study these questions, we analyze a new data set, from AngelList Talent, that covers activity from both sides of the startup labor market, collected before and after the COVID-19 induced shutdowns of March 2020. We believe this data set is unique in that it captures both supply and demand behavior in the labor market at considerable scale and granularity (prior studies using highly granular online data typically analyze one side of the market or the other). Furthermore, because the AngelList Talent platform caters to the growth-oriented, early-stage startup labor market, our sample mitigates undesirable heterogeneity (which can otherwise make statistical control more challenging). This labor market also complements the type of work and jobs featured in prior field studies on worker productivity resulting from remote work, which largely, though not exclusively, examine tasks with quite objective performance criteria such as data entry and call center performance.

Our first analysis regarding the organizations and jobs which are listed as remote-eligible centers on job listings posted prior to the COVID-19 shutdowns. We pay particular attention to portraying the descriptive patterns because we do not believe such patterns have been previously documented across a large number of organizations and jobs in the prior literature. We incorporate the detailed nature of our job listing data, such as skill requirements associated with each job. We find and characterize the empirical patterns which are associated with the likelihood a given job is listed as remote-eligible. This sets up the second analysis we conduct to address the question of whether organizations attract higher quality and more diverse talent if they designate a job as WFH. Because we know (and show in the first part of our analysis) that remote job listings are not randomly offered, analyzing job market attraction to remote job listings should ideally endogenize the job design decision to improve causal inference. We do so by analyzing applicant behavior in the midst of the COVID-19 pandemic shutdowns, which forced a quick transition to remote work conditional on hiring aspirations (and therefore made this feature of job design less of a managerial choice). This allows us to mitigate a common confound in the literature on job design, namely that job design and firm characteristics can be co-determined with the decision to offer remote work, in ways which are unmeasured and/or unobserved. We also present a separate empirical strategy centered on sample matching to triangulate results. We find that offering remote work affords organizations more applicants (and with more experience), as well as applicants drawn from more diverse gender and race backgrounds.

2 Literature

Two streams of prior work relate to our research question. While both relate to the shifting organization of work, the first domain takes the employer perspective about considerations to offer remote work. The second domain takes the employee perspective and examines drivers of their preference for/against remote work. We discuss themes within each literature in turn, especially as they relate to our empirical work, which puts together both sides of the market.

2.1 Employers and the decision to offer remote work

With the rise of a service-based (knowledge) economy, employers are rethinking the role of in-office work[1], which has implications for the possibility of decoupling the physical location of organizational offices or headquarters and where individuals conduct their work. Indeed, some employers are reconceptualizing the role and physical footprint of corporate offices and workspaces. As previously noted, as the world re-emerges from COVID-19 lockdowns in 2021, the managerial choice of whether and to what degree remote work will be allowed is likely to be a significant one shaping the future of work and job design.

Two recent studies are notable for offering direct empirical evidence on employee productivity and other impacts of remote work. Both Bloom et al. [2015], in the setting of a call center operation in China, as well as Choudhury et al. [2021], in the setting of US Patent and Trademark Office (USPTO) examiners transitioning from being allowed to "work from home" (WFH) to "work from anywhere" (WFA), document increased employee productivity. In the call center setting, the first study found a 13% increase in employee productivity, mainly due to reduced commute-, break- and sick-time, as well as a quieter work environment. The WFH employees were randomly selected from the organization's employees who indicated they would be willing to shift their work in this manner accordingly. The randomized WFH employees were 50% less likely to quit as well (though their likelihood of subsequent promotion declined). The patent examiner study found a 4.4% boost in output without need for re-work in the WFH to WFA transition (such employee status depends in part on employee seniority and request for such status). In addition, this study finds that geographically clustered WFA workers within the same technological unit experience higher productivity (though this effect does not hold for those in different units), suggesting some localization of potential peer effects. While not formally tested, this study also provides qualitative/anecdotal evidence for enhanced employee allegiance to the work organization stemming from the WFA policy.

With the caveat that the field experimental evidence is drawn from only a handful of organiza-

[1] The literature predates the COVID-19 pandemic. For example, see the work on "telecommuting" (e.g., Dutcher [2012]; Gajendran and Harrison [2007]), geographically-dispersed teams (Hinds and Mortensen [2005]; Gibson and Gibbs [2006]), and more generally, alternative job arrangements (e.g., Mas and Pallais [2020])

tions, one puzzle which arises is: if offering remote work increases employee productivity, why do all employers not offer it? A possible explanation involves career concerns in which employees may be wary of remote work's impact on their promotion possibilities, even if they prefer the flexibility, and employers benefit via enhanced employee productivity. In a call center work setting before and after the COVID-19 shutdown, Emanuel and Harrington [2020] find more productive workers do not want to pool with (latently) less productive ones (resulting in lower promotion rates, which they also find, consistent with Bloom et al. [2015]). Barrero et al. [2020] argue that the COVID-19 shutdowns and widespread experience with remote work has a potential destigmatizing effect and a reason to expect remote work persistence after the COVID-19 pandemic lifts. Beyond mere stigma, in a field experiment of on-the-job market consequences of summer interns' virtual social interaction with top managers (in the summer of 2020), Bojinov et al. [2020] find that randomization into informal social interactions ("water cooler" interactions) with senior managers improves prospects of being offered a subsequent full-time position at the firm. These results suggest both that social interactions in the workplace are important for career advancement outcomes, and that it is possible, even in a remote context, to design such interactions (though they are perhaps less likely to occur by happenstance in the virtual as compared to onsite setting).

Another explanation to the puzzle challenges the premise that remote work increases employee productivity in the first place. In a field experiment of data-entry work in India where performance and error rates can be precisely measured, Atkin et al. [2020] find a *positive* onsite treatment effect, and evidence that the most capable employees sort into formal office settings (in the prior studies finding a positive WFH treatment effect, the pool from which randomization for the treatment is drawn reflects a prior employee opt-in to the possibility of the treatment condition). The possibility of unobserved employee sorting is also strongly implied by the Emanuel and Harrington [2020] study as well (in the post COVID-19 shutdown period, call center workers hired into remote jobs were 18% less productive than those hired into on-site jobs). These findings are consistent with recent remarks by JP Morgan Chase's CEO Jamie Dimon that remote work does not work well "for those who want to hustle" (Benoit [2021]) and WeWork's CEO Sundeep Mathrani commented: "those who are uberly engaged with the company would want to go to the office at least two-thirds of the time, at least" (Dill [2021]). The negative WFH productivity effect could also arise from behavioral origins, in that workers may not wish to shirk when working remotely, but because of self control issues (Kaur et al. [2015]), managerial oversight in an on-site capacity can help impose worker self-discipline.

While there is considerable focus in the literature on worker productivity effects of remote work, less discussed is the ability of firms to manage a WFH and remote workforce. This relates to the degree of managerial intensity and skills required to manage in the virtual environment. The managerial infrastructure of the organization may therefore be an important driver of the likelihood of offering remote work. Intertwined with this is job characteristics and the nature of the work demanded: for some types of work which are highly interdependent among individuals or work teams, the degree of managerial intensity and coordination may be higher; conversely, if work is relatively modular, managerial intensity may be lower (for empirical evidence, see e.g., Tambe and Hitt [2012] on information technology jobs most likely to be offshored). Not only does the degree of managerial oversight depend on the nature of the work and job, it may depend on employee characteristics such as tenure at the organization in an on-site capacity (which may relate to employee knowledge of organizational norms and culture, degree of trust, etc.). Finally, there may be a competitive element to offering remote work if, for example, local competitors are offering such "non-traditional" work arrangements. Note that these and other factors are difficult to observe and measure, especially at scale, which presents a host of empirical challenges we will discuss at more length in the data section.

2.2 Employees and the decision to engage in remote work

Here, we discuss the employee perspectives which have not yet been mentioned in shaping preferences for remote work. One large theme is that certain demographic groups, such as women with young children and families (e.g., Mas and Pallais [2017]; Atkin et al. [2020]) disproportionately value job flexibility, including the ability to conduct remote work. A second theme is that infrastructure preparedness, both with regard to space in the home as well as computing resources, including access to a stable broadband internet connection, is an important precondition to remote work. Indeed, Barrero et al. [2020] argue that one of the reasons WFH is likely to persist in the long term is because of the sunk infrastructure arrangements many made in these resources during the course of the COVID-19 pandemic. A third theme is employee psychological and social considerations (such as isolation, mental health, and well-being) associated with remote work (e.g., [Gajendran and Harrison, 2007]). The total effect of these considerations is not straightforward, though, because remote work can act asymmetrically on employees' relations with their family as compared to their co-workers.

On balance, employees seem to value flexible work arrangements such as remote work, but how much? In an experimental setting, Mas and Pallais [2017] estimate that workers on average accept compensating wage differentials (20% of wages to avoid a schedule set by an employer on short notice and 8% for the option to WFH) for work flexibility, though the average is skewed by outlier preferences.

An open set of issues relate to labor market dynamics (attracting talent, especially with racial and gender diversity) aligned with the managerial decision of making jobs remote-work eligible. There are two empirical difficulties of addressing this managerial problem. First, there are a number of unobserved and unmeasured factors on both sides of the marketplace identified in the literature which make a typical observational study difficult. Second, the methodology of many of the recent studies in this literature rely on field experiments, which enhance causal interpretation, but have the drawback of being unable to generalize across field sites (organizations) and are not suited to studying labor *markets*.

3 Data

Note that there are unobserved and unmeasured factors on both sides of the marketplace (the likelihood of offering remote jobs and labor supply (including family) conditions) which make a typical observational study difficult. In this section, we describe the data and empirical strategy we use to examine the correlates and consequences of offering remote work.

3.1 Overview

We analyze data from AngelList Talent, a leading online platform for startup labor market activity for entrepreneurial ventures. This job marketplace is part of a larger AngelList platform catering to the startup ecosystem (AngelList Venture, for example, is a financial capital marketplace). Although not exclusive to technical occupations, most of the activity on AngelList Talent is for positions in technical or technical-adjacent positions, such as machine learning engineers, data scientists, or product managers, together with associated management and sales/marketing positions.[2]

AngelList Talent has since its inception in 2012 attracted some 62,000 companies to post over 215,000 jobs. The site has had approximately 3.6M unique job candidates upload profiles to their platform, and has connected about 1M applicants to jobs. While we do have further information about the applicants, including their applications to job postings from within the platform, we do not have direct information through the platform of any hiring offers or applicant mobility events (such activities take place outside of the platform).

The AngelList Talent data span historical job postings since the platform's inception since 2012, but our access to daily site activity from job *applicants* runs from February 5 to June 18, 2020, and so we use this time window for our job listings analysis. These dates book-end the adoption of employers' pandemic policies. From this platform, we have job listing data on all of the job postings employers made to the platform including a description of the firm, open position titles, remote work designation, skills required, and compensation details (wages & equity) for a subset of the jobs. From the applicant data, we have information on users' platform activity (e.g., searches, clicks, applications) such as listings viewed and applied to, and whether employers indicated interest in meeting with the applicant. To engage on the platform, job candidates had previously filled in their profile information (such as resume data, including educational history, skills, prior employers and LinkedIn page). They are then able to search for positions (and can filter their searches by role, compensation, location, skills required, startup size, etc.) and can apply for a position from within the platform. Examining both the labor demand and supply sides of this market together allows us to: (1) characterize organizational and job characteristics associated with remote-eligible job listings, and (2) analyze how a shift in the characteristics of job listings (remote-eligible) induced by the pandemic is met by a change in applicant composition.

[2]The COVID-19 induced recession of 2020 has affected workers unequally, with demand for technology workers, such as those working for venture capital-backed startups, remaining very robust (e.g., Gompers et al. [2020]), while the economic situation for all small businesses on average characterized as much more precarious and financially fragile (e.g., [Bartik et al., 2020a]). This mirrors the findings of Dingel and Neiman [2020] that while approximately 37% of jobs in the US can be conducted remotely (which favorably compares to other countries), the comparable figures for jobs in management and computing in the US (those closest to the jobs on the AngelList Talent platform) are greater than 80%.

3.2 Data description and variables

In this section, we provide a high-level description of (a) job listings, and (b) applicant characteristics. Before doing so, however, we would like to characterize the types of organizations listing on the AngelList Talent platform (not just in our sample window). As an overview, consider the following information about the top four employers in the overall data: SpaceX (849 job listings), Slack (452), Twilio (374), and DoorDash (372). In total, of the approximately 62,000 organizations posting jobs on the platform, about 63% of the organizations have an employee headcount of less than 501 people, with 19% of organizations on the platform belonging to the larger than 50 but less than 201 employee category. The remaining 37% of the overall sample of organizations are larger than 500 employees, with the largest segment (almost 22%) within that being the over 1,000 but less than 5,001 category.[3]

Table 1 shows the overall size distribution of firms by headcount on the platform, as well as the top five locations of firms. While AngelList Talent's platform covers job listings from around the world (we exclude international locations in an effort to stem heterogeneity in our sample), the top two locations are San Francisco and New York City, which together comprise over half of the total job listings on the platform since 2011. This may not be surprising given both the locus of venture capital backed startup activity (and potential home bias in AngelList's headquarters, which is located in San Francisco).

We examine two areas empirically: (1) factors shaping the likelihood a job is listed as remote-eligible (before the COVID-related shutdowns in the US, which we take to be March 13, 2020 in accordance with U.S. federal government designation of a national emergency and associated quarantine orders), and (2) how WFH job status influences job applicant characteristics to job listings (quantity, quality, and gender & racial diversity).

3.2.1 Variables and description of remote listings

For the first analysis, the level of analysis is at the job listing level, with the outcome of interest that a job is listed as remote-eligible. We examine several groups of explanatory variables: (1) organizational factors, such as size (proxied by employee headcount), funding stage, and location;

[3]Table 1 also contains information about the distribution of companies organized by stage of highest attained funding round. The top two attained stages are Series A, with about 24% of the sample, and seed stage (16%).

and (2) job characteristics as proxied by job titles and required skills. In the job listings dataset, the top four job titles are: software engineer (321), senior software engineer (294), product manager (233), and sales development representative (177), while the top four skills most requested in job postings are: *javascript* (1366), *python* (1273), *sales* (1204), and *react.js* (1141). More generally, Figure 1 provides information about the distribution of job postings by employee headcount (left panel) and by highest attained funding round (right panel), both disaggregated between onsite (denoted in acqua-colored bars) and remote-eligible jobs (salmon-colored bars). Taken as a whole, smaller and earlier funding round stage companies are the ones most actively listing jobs, and these type of firms are also the ones disproportionately listing their jobs as WFH.

We begin describing factors associated with remote-eligible jobs.[4] In Table 2, we present descriptive organizational characteristics, separated by remote as compared to on-site jobs. A final column reports the difference in the average values of the conditional means. We see that the difference between onsite and remote jobs increases with organizational headcount and attained financing milestones, and is slightly more prevalent outside of Silicon Valley.[5] Salary compensation is higher for on-site relative to remote jobs, though we observe the opposite pattern with regard to equity (these descriptive statistics likely reflect the fact that smaller firms are more likely to offer remote work, and these smaller firms are the ones which are also more likely to compensate based on equity).

3.2.2 Variables and empirical design examining the consequences of remote listings

To get a sense of the type of organizations (by employee headcount) which are shifting their jobs to remote work after the COVID-19 shutdowns, consider Figure 3. The smallest companies (those under 50 employees) seem to offer remote work less frequently relative to before the shutdowns, while those organizations at the larger end of the size distribution (1000+ employees) are offering

[4]The sample comprises jobs listed on the AngelList platform from February 5, 2020 and running through the period just before the COVID-19 shutdowns (March 13, 2020). While we have job listings on the AngelList platform since its inception in 2011, because our second analysis on the consequences of remote listings is constrained by applicant data (which, because it is "clickstream" data and much more detailed, is very large). We currently have access to about 4.5 months of applicant beginning February 5, 2020. The time series since 2011 of the percentage of jobs listed in AngelList Talent which are remote-eligible peaks in 2013 and 2017, when over 30% of the jobs are designated WFH. Since 2017, the fraction of remote-eligible jobs has been declining. Of course, the absolute number of jobs listed on the platform has been increasing over time as well.

[5]The Silicon Valley designation includes the following cities: San Francisco, San Jose, Fremont, Santa Clara, Sunnyvale, Oakland, Berkeley, Santa Monica, and San Mateo.

remote work more frequently after the shutdowns. On the applicant side, the descriptive pattern of fraction of applications sent to remote-eligible jobs pre- and post-shutdown is dramatic. Figure 5 demonstrates that before the shutdowns, the fraction of applications sent to remote job listings as a share of all applications is essentially flat and stable, at approximately 50%. After the shutdowns, the corresponding percentage is rising with the elapsed weeks since the shutdowns, and ending at approximately 90% by the end of our observation window.

For the second analysis, we examine how a host of job applicant characteristics relate to (and are induced by) the managerial decision to make jobs remote-eligible. In this analysis, our outcome variables center on applicant reactions to job postings, and span the following: (1) *Application count* is the count of number of applications sent to a job listing (mean in sample=3.6 for jobs receiving at least one job application); (2) *Applicant experience* is the number of years of work experience years among applicants to a job; (3) *Applicant quality* is a score AngelList assigns to job candidates based on their own proprietary algorithm, the components of which include experience, education, skills, and within-AngelList platform activities (we do not know the exact weights placed on each of the components; the mean value is 14.5); (4) *Percent female applicants* is the fraction of applications sent by female applicants to job postings (average is 9%), which we infer using the popular *gender-guesser* package that infers gender from name; and (5) *Percent applicant URM status* is the fraction of applicants to a given job which are likely to belong to an underrepresented minority group (mean=9%), using the *wru* package in R (see Imai and Khanna [2016]; Crabtree and Chykina [2018]; Grumbach and Sahn [2020] for applications of this package in social science research). Table 3 contains the summary statistics for these variables. The explanatory variables are *Post-closure*, an indicator for after the COVID-induced shutdowns (mean=0.81); and *Remote* is a dummy variable for whether a job is listed as remote-eligible (mean=0.21).

To characterize the evolving job listing and application landscape before and after the shutdowns, consider the following figures. Figure 2 shows the dramatic shift in the fraction of new job listings designated remote-eligible by week before and after the shutdowns (designated by the vertical red line) in the AngelList Talent job listings. The figure indicates volatility around the middle weeks of March 2020. As the transition was occurring to the pandemic economy, employers trying to fill local positions may have refrained from posting, driving the fraction of remote listings higher, but this volatility settles within a few weeks. By May, listings experienced a slow but unmistakable shift towards remote listings.

A complication of interpreting these descriptive applicant patterns is that we know from our analysis that *remote job listings* are not randomly determined. We have two empirical strategies to improve our inference. Since we will explain details of the operationalization below, we give a high-level overview of our approaches here. Our first technique is to implement a (propensity score) matching (PSM) procedure in which we balance the "treated" (remote) observations to the "control" observations on key observable variables such as job title. This approach allows us to sharpen the sample to eliminate undesirable heterogeneity (if the treatment and control groups are unbalanced on key observable variables, the threat of unobserved third factors could generate spurious results). This matching approach helps improve inference attributed to the *remote* job effect on applicant characteristics.

Of course the PSM (or any matching) strategy can only match on observable variables, and there is still the possibility that unobserved variables could correlate with *remote* listings. We therefore leverage the exogenous COVID-19 government-mandated shutdowns in which the decision to offer remote work was largely taken away from managers. We employ prediction models of on-site jobs in the pre-shutdown regime and compare them to job listings we would have predicted to be also on-site in the post-COVID regime, but are instead remote as a result of the COVID-19 shutdowns. In this manner, we estimate the change in applicant characteristics (quantity, quality, and diversity) stemming from the exogenous switch to remote work. This allows us to estimate a *remote, post-shutdown* effect on applicant characteristics.

4 Results

4.1 Correlates of remote job listings

In Table 5, we use an OLS regression framework to regress *remote* on organizational categorical variables which proxy for size (employee headcount) in column 1, attained external funding status in column 2, location (*in Silicon Valley?*) in column 3, and all of the above in column 4.[6] Several patterns emerge, which are consistent with the patterns documented in the descriptive statistics: relative to the smallest organizational size category (employee headcount of one to ten),

[6] These results are also robust to a probit or logit model. We present OLS here to compare a model fit statistic with another table with a different estimation strategy we introduce shortly.

as the organizational size category increases, there appears to be a progressively lower likelihood of remote job listings. This rough pattern (though noisier) also appears true for higher funding round attainment (proxying organizational development), relative to the base category of pre-seed funding. Finally, Silicon Valley jobs are less likely to be remote-eligible relative to jobs listed in other locations (column 3). Of particular note, however, is that even with all organizational factors included in the regression (column 4), the overall variance the model explains (R-squared statistic) is approximately 8.5%.

Relating job characteristics, such as job title, to remote work is not straightforward. We first examine in Table 4 the frequency with which job titles are designated as remote-eligible. We show the job titles which are associated with the most and least likelihood of a remote job listing by regressing *remote* on job titles and sorting the resulting estimates of each job title fixed effect. The left hand side of the table shows the job titles most associated with remote listings, such as "DevOps engineer" and "senior java developer", while the right hand side shows the 10 job titles least likely to be associated with remote listings, such as "service technician" and "subscriber sales representative".[7]

The second panel of Table 4 shows an analogous list for requisite skills which are most (least) associated remote job listings on the left (right) hand of the panel, using the same methodology as before (except replacing skills for job titles). Because of the large number of skills listed in the data, we confine our attention to the 250 most frequent skills in the data. The skills most associated with remote jobs are: "firebase" (an app development environment for Google's mobile platform) and "blockchain"; the skills least associated with remote jobs are "embedded systems" and "scala" (a coding language useful for big data and machine learning).

We present two approaches to estimate how technical and managerial skills relate to *remote* in a multivariate framework. In Table 6, we manually sort classes of skills into a variety of categories. In general, "high-end" technical skills (labeled as "DemandTechnical" in the table) are negatively related to *remote*, whereas run-of-the-mill technical skills flip from being positively associated with remote jobs (without job title fixed effects) to negatively related (with job title fixed effects). On the business skill side, marketing skills are positively related to *remote*, whereas management and

[7] This heterogeneity is consistent with broader surveys regarding cross-industry variation in remote work adoption in the face of COVID-19 [Bartik et al., 2020b] and how variation in the nature of work (particularly information work) correlates with remote work [Brynjolfsson et al., 2020].

finance skills are negatively related. In contrast with this manual categorization method, in Table 7, we specify 200 candidate skills ex-ante (the 200 most frequently appearing skill in the database), and employ a LASSO regression with a lambda value of 0.01. The top 30 skills with significant coefficient values (sorted in descending value) related to *remote* are listed, with the remaining 170 skills receiving no weight (we use the output of the LASSO model as inputs to skill-level fixed effects in our next empirical table).

Finally, in Table 8, we present an estimation approach which successively employs job title FEs (column 1), startup (organizational) FEs (column 2), week FEs (column 3), location FEs (column 4), skill FEs (column 5), and all FEs (column 6). The principle behind this approach is that comparing organizations of a given size, for example, with regard to the likelihood of offering remote jobs could be difficult because of, for example, unobserved managerial quality or structure. The overall model fit in explaining *remote* improves substantially relative to regression specifications which estimate the parameters, ranging from a low adjusted R-squared of 0.002 to a high of 0.652.

4.2 Talent attracted to remote job listings

We begin our analysis in this section with descriptive patterns of the applicants pre- and post-shutdowns. Consider Figure 5, in which we plot the mean number of applications, their quality (measured by AngelList Talent's quality score and industry experience), and diversity (fraction female applicants and fraction URM applicants) over time (again, the dashed red vertical line denotes the closure boundary). The mean for on-site job listings is marked in a solid black line, while the remote job listing mean is marked by a dotted black line throughout the figure.

With regard to applications, at the aggregate level, we see that while applications sent to onsite job listings are higher than those sent to remote jobs in the weeks leading up to the shutdowns, this pattern reverses in the post shutdown period. The level of applications being sent to job listings in the post-shutdown period diminishes relative to the pre-period. As to quality, while there does not appear to be substantial differences in the AngelList "quality" score between on-site and remote jobs either before or after the shutdowns, the difference in the applicant (industry) experience variable shows a clear pattern: experience is higher across both time periods for remote-eligible listings as compared to on-site listings. As is true for all patterns shown in this table, no statistical or empirical strategy has yet been employed, and so should be interpreted as purely descriptive.

Finally, on the diversity front, while the fraction of female applicants to job listings appears to be approximately equal between remote and on-site jobs before closures (around 10% of applicants), it appears that remote listings after the closures are associated with a higher percentage of female applicants. For the fraction of applicants with URM status, in the pre-period, remote job listings appear higher (about 11% of applicants) than on-site listings. There does not seem to be a clear pattern after the closures, however.

Our next step is to examine these results in an OLS regression framework in which we do not yet tackle the issue of endogenous remote job listings. In Table 9, we examine the correlates of number of applications received to job listings. In each specification, we include fixed effects for startup, job title, job type (part time or full time), location, and week. Across the five applicant composition outcomes, we see that *remote* is positively related with all of the outcomes with the exception of *percent female applicants*.

The analysis in the prior table carries the implicit assumption that remote listings are exogenously determined. However, a significant confound to this interpretation is that remote listings are more likely shaped by factors associated with the firm and the job position itself. To fix ideas, consider a simple example of the top five job titles for pre-seed companies in the data: software engineer, account executive, product manager, senior software engineer, and sales development representative. By contrast, for firms which recruit on the platform but which are post-IPO, the corresponding job titles are: enterprise account executive, senior software engineer, solutions consultant, customer success manager, and account executive. This suggests that there is considerable across-firm variation in offering remote work at all (likely related to unobserved managerial capabilities in managing a remote work force), and furthermore, that there is a dispersion of jobs (and associated skills) which are more or less amenable to the remote work environment. The critical empirical challenge for inference is now clear: there is likely self-selection in firms offering remote work listings in ways which may be unobserved and/or unmeasured. In order to move beyond correlating applicant characteristics with offering remote work, we adopt two complementary empirical strategies, a PSM approach and a quasi-experimental approach, which we discuss in turn.

Our first empirical strategy of addressing the endogenous nature of remote job listings is through a PSM matching strategy, in which we exactly match "treated" and "control" observations by job title and full-time versus part-time job status. Pre-processing the sample in this way helps to mitigate undesirable heterogeneity which could be associated with unobserved or unmeasured third factors which might lead to spurious results. Table 10 presents the results, which uses the matched sample. We run regression specifications of applicant characteristics in response to job listings. In Table 10, the *remote* coefficient is positive and significant across the applicant characteristic outcome variables (all at the 1% level with the exception of the relation with *Applicant quality*, which is weakly significant at the 10% level). In comparing the estimated economic effects in Table 10 relative to the estimates in Table 9 (in which we treat remote jobs as exogenously-given), we see that the estimates in Table 10 are smaller in magnitude, though perhaps more realistic in effect (a discrete change in remote status corresponds to a 4-5% increase in female and URM applications, etc.).

The unanticipated COVID-19 shutdowns afford us a separate quasi-experimental empirical strategy to address the endogeneity of remote job listings. In Table 11, we fit a model using the pre-closure sample to predict whether a given job listing is remote-eligible. We use that model on the post-closure data to categorize such jobs into one of four groups: (1) predicted remote & actually remote; (2) predicted remote & actually onsite; (3) predicted onsite & actually onsite; and (4) predicted onsite & actually remote. We define the "treated" group as category (4) [these are job-listings which are predicted to be onsite, but because of the COVID shutdowns, are instead observed as remote), with the other groups being "control". In Table 11, the baseline category is (3), and the focal coefficients of interest are in the first row. The *remote* coefficient is positive and significant in all of the columns with the exception of the *applicant quality* variable, and with economic magnitudes similar to the PSM regressions in Table 10.

5 Discussion

While the basic technological infrastructure ingredients enabling remote work may have been in place prior to the COVID-19 pandemic, the added behavioral shift (on the part of both employees and employers) facilitated by the prolonged work-from-home environment gave direct WFH experience. As the US emerges from the pandemic, a salient managerial decision is job design, including the scale and scope of remote work. This paper is a window into what might happen in the startup labor market, particularly on the applicant quantity, quality and diversity sides, should employers elect to make jobs remote-eligible. We start by characterizing the organizational and job-level correlates of remote work. Since offering remote work is not random, we take advantage of the exogenous nature of the COVID-19 shutdowns to address the endogeneity of offering remote jobs. By doing so, we document the positive effects of offering WFH on a number of applicant characteristics.

Of course, our empirical work cannot capture the full dynamic equilibrium of labor market adjustments on both sides, which may occur in the aftermath of the 2019-2021 pandemic. An additional inference issue is the extent to which potentially hiring firms decide to wait out the COVID shutdowns and forestall their hiring activities. If such behavior were randomly distributed among hiring firms, this would not present a problem. However, if such firms' job posting behavior is systematically related to their beliefs about their ability to successfully manage remote work and/or the job skills they are recruiting for, our results may be biased.[8]

A third interpretational point is that we do not measure productivity or other worker-level output measures. Ideally, an overall evaluation of remote work would compare the quality of talent recruited as well as the productivity and creativity of employees. The prior literature on remote work focuses on worker productivity output, and in this small literature, there are varying estimated effects and explanations, ranging from productivity increases as a result of fewer distractions and more flexibility associated with remote work (Bloom et al. [2015]; Choudhury et al. [2020]) to less productivity as a result of poor individual self-control (Kaur et al. [2015]). The typical empirical context in this area of research is one in which output can be measured fairly objectively (such as data entry rates, misspelling rates, and number of minutes spent with customers). However, especially in knowledge work, it may be difficult to quantify the output in the same manner. Ideally future work in this domain would examine both labor market mobility and output measures related to innovation and creativity. Doing so would provide greater insight into potential broader impact of the shifting applicant behavioral patterns we document.

A final interpretation point relates to boundary conditions of remote work and the future of

[8]We are considering two empirical strategies to explore this domain. First, with the assumption that firms which have (recently) raised venture capital funding are under more pressure to deploy their financial resources in hiring, we could test if our core results are overturned once we confine our sample to this smaller set of firms. Second, with the assumption that as the pandemic unfolded over time, the time scale of disruption became more apparent, we confine our sample to time intervals comparing the pre-event time period (before March 13, 2020) to two different post-event time periods: March 14 through April 30 (comparison sample "A") and May 1 through June 18 (comparison sample "B"). These two post-event time samples bisect the post period in an attempt to capture shifting sentiment about the duration of the COVID shutdown. There are ex-ante arguments to be made for both samples as a comparison set to the pre-COVID regime with respect to urgency of hiring (more ambiguity in the sample A about expected duration versus more clarity about the protracted nature of the shutdowns in sample B).

organizing and managing work, especially as related to competitive (startup) labor markets. We capitalize on the sudden shift in the work environment stemming from the COVID-19 shutdowns as part of our empirical strategy. However, future research in this domain would benefit from exploring the variety of jobs which can be made remote (not necessarily taking this as given) by managerial techniques, perhaps aided by (digital) technology. We suspect that the concept of "jobs which can be effectively performed remotely" is not exogenously-given and fixed; rather, the evolution of the category may be a labor-driven one, as surveys have repeatedly suggested that worker interest in remote work post-COVID outpaces the intention of employers to offer such work (Barrero et al. [2020]). In addition, given the prolonged change in work habits associated with COVID-19, such research may address topics of likely managerial policy in a post-COVID world, such as how to organize interdependent (as compared to modular) remote team work, and the degree to which newly-hired versus existing employees are eligible for certain configurations of remote work.

We end with one concrete arena for future exploration. The notion of remote-eligible jobs go hand-in-hand with the prospect of decoupling worker's residence location with the physical location of her workplace. As such, there may be implications for the geography of innovation, a long-standing topic of interest in the social sciences (e.g., Marshall [1890]; Saxenian [1996]). As suggestive patterns, consider Figure 6. In panel (a), for the sample of applicants living within Silicon Valley, we can see a very clear positive slope of applicants from this sample sent to job listings in "second-tier" tech hubs outside of Silicon Valley, especially after the closures. In panel (b), when the applications are decomposed between remote and onsite listings for these same Silicon Valley applicants, it is clear that the applications driving the overall effect is to remote-eligible jobs, perhaps suggesting the intent of workers to exit Silicon Valley. More generally, consider Figure 7 which plots cumulative job applications against city rank (higher numbers correspond to more job listings). The red dots plot the pre-closure trend, while light blue plots the post-closure trend. In both cases, there is considerable concentration in that the top two cities garner approximately 60% of the overall job applications. After the closures, however, the concentration of applications to the top cities becomes more diffuse. We therefore suspect that the future of organizing work will also have implications for the geography of innovation.

To conclude, we suspect that the entire category of "alternative" work and job design is going to be the subject of much experimentation going forward, probably in ways much more subtle than that which much of the world experienced in the COVID-19 shutdowns. As a result, we hope that the work presented here is a window to understanding remote work and the startup labor market, but recognize there is much work to be done to understand this aspect of the future of organizing work.

References

Atkin, D., Schoar, A., and Shinde, S. (2020). Worker sorting, work discipline and development. Technical report, MIT Sloan working paper.

Barrero, J. M., Bloom, N., and Davis, S. J. (2020). Why working from home will stick. *University of Chicago, Becker Friedman Institute for Economics Working Paper*, (2020-174).

Bartik, A. W., Bertrand, M., Cullen, Z., Glaeser, E. L., Luca, M., and Stanton, C. (2020a). The impact of COVID-19 on small business outcomes and expectations. *Proceedings of the National Academy of Sciences*, 117(30):17656–17666.

Bartik, A. W., Cullen, Z. B., Glaeser, E. L., Luca, M., and Stanton, C. T. (2020b). What jobs are being done at home during the COVID-19 crisis? evidence from firm-level surveys. Technical report, National Bureau of Economic Research.

Benoit, D. (2021). Jamie dimon on booming economy and finally getting off zoom. *Wall Street Journal*.

Bloom, N., Liang, J., Roberts, J., and Ying, Z. J. (2015). Does working from home work? Evidence from a chinese experiment. *The Quarterly Journal of Economics*, 130(1):165–218.

Bojinov, I., Choudhury, P., and Lane, J. N. (2020). A field experiment on virtual social interactions and performance of remote workers. Technical report, Harvard mimeo.

Brynjolfsson, E., Horton, J. J., Ozimek, A., Rock, D., Sharma, G., and TuYe, H.-Y. (2020). Covid-19 and remote work: an early look at US data. Technical report, National Bureau of Economic Research.

Choudhury, P., Foroughi, C., and Larson, B. (2021). Work-from-anywhere: The productivity effects of geographic flexibility. *Strategic Management Journal*, 42(4):655–683.

Choudhury, P., Foroughi, C., and Larson, B. Z. (2020). Work-from-anywhere: The productivity effects of geographic flexibility. In *Academy of Management Proceedings*, volume 2020, page 21199. Academy of Management Briarcliff Manor, NY 10510.

Crabtree, C. and Chykina, V. (2018). Last name selection in audit studies. *Sociological Science*, 5:21–28.

Dill, K. (2021). Wework ceo says least engaged employees enjoy working from home. *Wall Street Journal*.

Dingel, J. I. and Neiman, B. (2020). How many jobs can be done at home? *Journal of Public Economics*, 189:104235.

Dutcher, E. G. (2012). The effects of telecommuting on productivity: An experimental examination. the role of dull and creative tasks. *Journal of Economic Behavior & Organization*, 84(1):355–363.

Emanuel, N. and Harrington, E. (2020). 'working' remotely?: Selection, treatment and the market provision remote work". Technical report, Harvard mimeo.

Gajendran, R. S. and Harrison, D. A. (2007). The good, the bad, and the unknown about telecommuting: meta-analysis of psychological mediators and individual consequences. *Journal of applied psychology*, 92(6):1524.

Gibson, C. B. and Gibbs, J. L. (2006). Unpacking the concept of virtuality: The effects of geographic dispersion, electronic dependence, dynamic structure, and national diversity on team innovation. *Administrative Science Quarterly*, 51(3):451–495.

Gompers, P. A., Kaplan, S. N., and Mukharlyamov, V. (2020). Private equity and COVID-19. Technical report, National Bureau of Economic Research.

Grumbach, J. M. and Sahn, A. (2020). Race and representation in campaign finance. *American Political Science Review*, 114(1):206–221.

Hinds, P. J. and Mortensen, M. (2005). Understanding conflict in geographically distributed teams: The moderating effects of shared identity, shared context, and spontaneous communication. *Organization Science*, 16(3):290–307.

Imai, K. and Khanna, K. (2016). Improving ecological inference by predicting individual ethnicity from voter registration records. *Political Analysis*, pages 263–272.

Kaur, S., Kremer, M., and Mullainathan, S. (2015). Self-control at work. *Journal of Political Economy*, 123(6):1227–1277.

Marshall, A. (1890). *Principles of Economics, by Alfred Marshall.* Macmillan and Company.

Mas, A. and Pallais, A. (2017). Valuing alternative work arrangements. *American Economic Review*, 107(12):3722–59.

Mas, A. and Pallais, A. (2020). Alternative work arrangements. *Annual Review of Economics*, 12:631–658.

Saxenian, A. (1996). *Regional advantage.* Harvard University Press.

Tambe, P. and Hitt, L. M. (2012). Now it's personal: Offshoring and the shifting skill composition of the us information technology workforce. *Management Science*, 58(4):678–695.

Table 1: Characteristics of startup firms participating on AngelList Talent

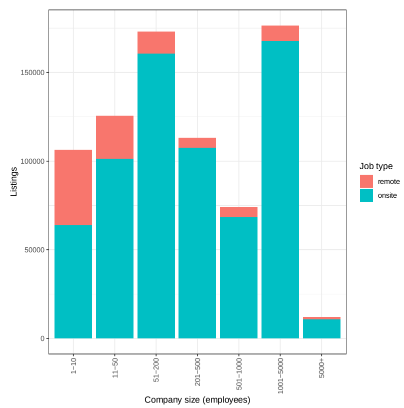
Funding	Counts	Size	Counts	City	Counts
1-10	9792	Pre-Seed	593	San Francisco	3731
11-50	8699	Seed	$5,554$	New York City	3685
51-200	11535	Series A	$8,347$	Los Angeles	1797
201-500	9205	Series B	$7,098$	Chicago	1295
501-1000	7868	Series C	$5,507$	Boston	1176
1001-5000	13488	Series D	$3,227$	Austin	984
5000+	1398	Series E	$1,667$		
		Series F	974		
		Series G	190		
		IPO	898		
		Closed	91		

Table 2: Comparing remote and onsite job listings

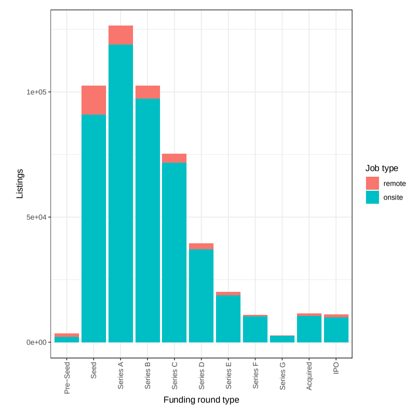
	Remote	Onsite	Difference
1-10	0.320	0.680	0.360
11-50	0.164	0.836	0.672
51-200	0.085	0.915	0.830
201-500	0.067	0.933	0.866
501-1000	0.095	0.905	0.810
1001-5000	0.061	0.939	0.878
5000+	0.073	0.927	0.854
Pre-Seed	0.415	0.585	0.170
Seed	0.093	0.907	0.814
Series A	0.071	0.929	0.858
Series B	0.067	0.933	0.866
Series C	0.061	0.939	0.878
Series D	0.078	0.922	0.844
Series E	0.091	0.909	0.818
Series F	0.045	0.955	0.910
Series G	0.012	0.988	0.976
IPO	0.111	0.889	0.778
Acquired	0.051	0.949	0.898
Outside SV	0.112	0.888	0.776
In SV	0.098	0.902	0.804
Min salary	73.084	98.286	25.202
Max salary	100.275	116.250	15.975
Min equity	0.164	0.115	-0.049
Max equity	0.488	0.273	-0.215

Table notes: This table compares how remote and onsite listings appear in firms with different characteristics. For the first three sections, the first two columns are the fraction of remote and onsite listings for firms in each category, and the third column is the difference between the two. The last four rows compare salary and equity figures between remote and onsite listings for firms in these categories.

Figure 1: What types of employers issue listings for remote jobs?



(a) Employer size



(b) Funding round type

Figure notes: These charts report listings posted both pre and post COVID shutdown.

Table 3: Applicant characteristics for job listings in sample

	Mean	Std. Dev.	Maximum	Minimum
Number apps	3.626	97.921	17,916	1
Mean Experience	4.351	3.065	10	0
Mean Quality	14.518	12.834	70	0
Frac female apps	0.089	0.122	0.333	0
Frac URM apps	0.090	0.235	1	0

Table notes: This table shows application statistics for job listings in the sample. The first row is average number of applications for job listings that received at least one application. The second is average experience of applicants. The third is average quality of applicants, where quality is a proprietary score used by the platform. The fourth row is the fraction of female applicants to each listing. The fifth row is the fraction of URM applicants to each listing.

Figure 2: Remote listings posted before and after COVID shutdowns

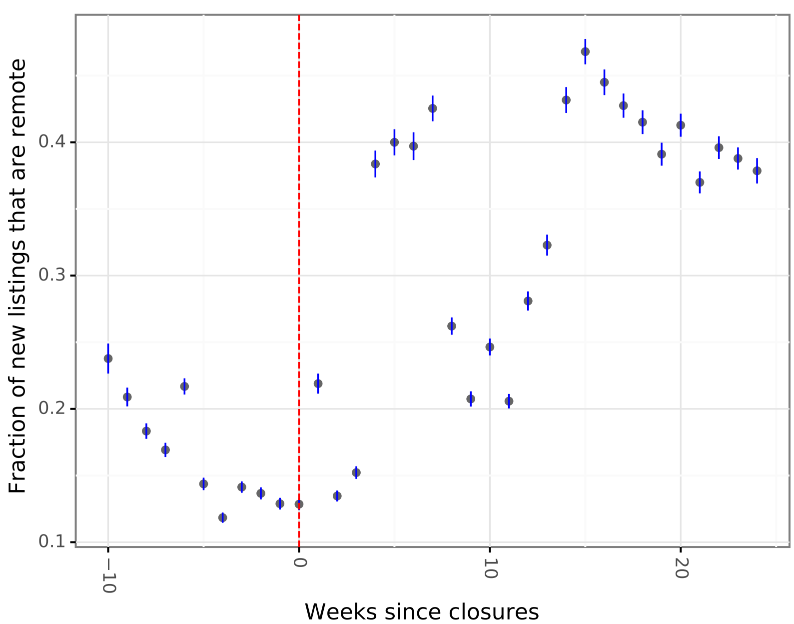


Figure Notes: This chart illustrates mean values and standard error of the mean bars for the fraction of job listings in each week that are remote work opportunities. The top panel is for all markets and the bottom panel separates the figures into Silicon Valley and all other markets.

Figure 3: How does COVID shift which firms issue remote listings?

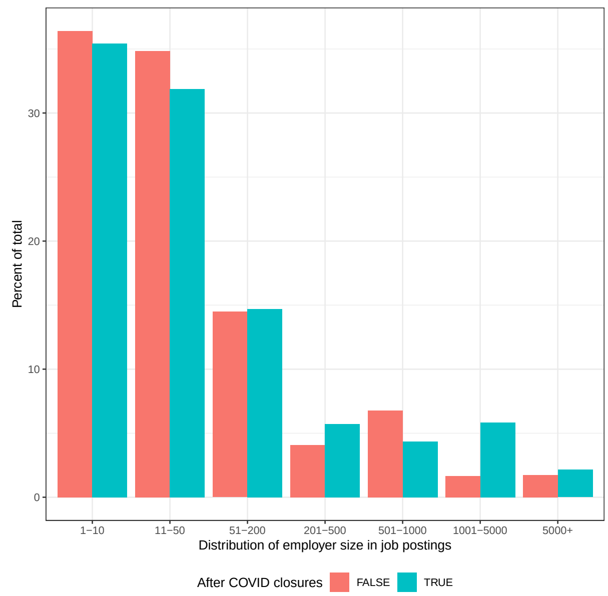


Figure 4: Fraction of applications sent to remote openings

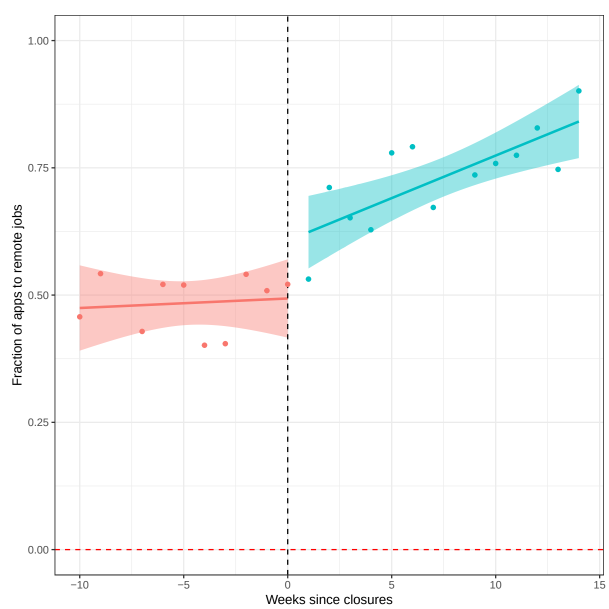


Figure Notes: This chart illustrates changes in the fraction of applications to listings allowing remote work. The x-axis ticks denotes the number of weeks since the COVID closures. The y-axis the fraction of applications sent to remote listings.

Table 4: Job skills, titles, and remote listings

Most remote titles	Least remote titles
DevOps Engineer (Remote / Work from h	Service Technician
Senior Java Developer (Remote)	Subscriber Sales Representative (Part
Co-Founder	Automotive Technician
Social Media Intern	MuleSoft Architect
Business Development	Caregiver
CTO	Quality Engineer
Technical Co-Founder	Physician Assistant
Remote(Customer Service Representativ	RUST Software Engineer
Marketing Intern	Associate, Technical Account Manageme
Growth Hacker	Coordinator

Most remote skills	Least remote skills
Firebase	Embedded Systems
Blockchain	Scala
Spring	Analytics and Reporting
Wordpress	Operations
Creative Writing	Event Management
Selenium	Microsoft .NET
Back-End Development	Microservices
Community Management	Software
Copywriting	Java J2EE
Test Automation	Jenkins

Table notes: This table lists the skills that are most and least likely to appear in remote listings. "Pct remote" signifies the fraction of occurences for each of these skills for which they can be found in remote jobs. Only skills that appear at least 250 times in the data set are used for this analysis.

Table 5: Predicting WFH listings using organizational characteristics

	Dependent variable:			
	remote			
	Headcount	Funding	Location	All
	(1)	(2)	(3)	(4)
11-50	−0.208*** (0.006)			−0.191*** (0.006)
51-200	−0.292*** (0.005)			−0.269*** (0.006)
201-500	−0.304*** (0.006)			−0.286*** (0.006)
501-1000	−0.160*** (0.006)			−0.149*** (0.006)
1001-5000	−0.329*** (0.006)			−0.318*** (0.006)
5000+	−0.343*** (0.012)			−0.297*** (0.014)
Seed		−0.241*** (0.012)		−0.123*** (0.011)
Series A		−0.291*** (0.012)		−0.139*** (0.012)
Series B		−0.303*** (0.012)		−0.140*** (0.012)
Series C		−0.299*** (0.012)		−0.134*** (0.012)
Series D		−0.279*** (0.012)		−0.108*** (0.012)
Series E		−0.214*** (0.013)		−0.045*** (0.013)
Series F		−0.339*** (0.014)		−0.144*** (0.014)
Series G		−0.351*** (0.021)		−0.192*** (0.021)
IPO		−0.322*** (0.015)		−0.162*** (0.015)
Acquired		−0.284*** (0.013)		−0.162*** (0.013)
in Silicon Valley			−0.054*** (0.002)	−0.049*** (0.002)
Constant	0.348*** (0.005)	0.363*** (0.011)	0.101*** (0.001)	0.476*** (0.011)
Observations	74,567	74,567	74,567	74,567
R^2	0.073	0.018	0.008	0.086
Adjusted R^2	0.073	0.018	0.008	0.085

Table notes: This table reports OLS regressions on whether a listing is remote. All listings are from the pre-COVID sample. The omitted variable in col (1) is 1-10, in col (2) is pre-seed, and in col (3) is outside SV. Standard errors are shown in parentheses, with *, **, and *** denoting significance at the 10%, 5%, and 1% level, respectively.

Table 6: Major skill categories and remote status

	Dependent variable:	
	remote	
	(1)	(2)
Technical	0.024^{***}	-0.020^{***}
	(0.005)	(0.006)
Marketing	0.071^{***}	0.064^{***}
	(0.005)	(0.007)
DemandTechnical	-0.027^{***}	-0.022^{***}
	(0.005)	(0.005)
Creative	0.013^{**}	0.014^{*}
	(0.006)	(0.008)
Sales	-0.006	-0.007
	(0.006)	(0.009)
Business	-0.011^{*}	-0.0003
	(0.006)	(0.007)
Communication	0.015^{**}	0.008
	(0.006)	(0.006)
Finance	-0.051^{***}	-0.014
	(0.015)	(0.019)
Management	-0.070^{***}	-0.019^{**}
	(0.006)	(0.007)
Customer	-0.053^{***}	0.001
	(0.008)	(0.010)
Baseline	-0.078^{***}	-0.041^{***}
	(0.008)	(0.009)
Constant	0.290^{***}	0.042
	(0.005)	(0.145)
Job title FE	No	Yes
Observations	61,753	61,730
R^2	0.010	0.104
Adjusted R^2	0.010	0.096

Table notes: This table reports the results of coefficient estimates from a regression with skills divided into major categories.

Table 7: Lasso regression of skills on remote status

Skill.name	Coefs
Spring	0.535
Shell Scripting	0.485
Selenium	0.351
Social Media Marketing	0.239
Blockchain	0.220
Closing Deals	0.139
Content Creation	0.115
Sales and Marketing	0.110
Data Science	0.065
PostgreSQL	0.056
Social Media	0.054
React Native	0.043
Financial Services	0.036
Customer Service	0.033
Email Marketing	0.028
AWS Lambda	0.025
Test Automation	0.018
Firebase	0.013
MySQL	0.010
Full-Stack Web Development (Node/Redux/React)	0.010
Design	0.009
Digital Marketing	0.002
Product Development	-0.013
Data Warehouse	-0.034
SaaS	-0.046
Consulting	-0.047
Embedded Systems	-0.100
SQL	-0.133
Marketing Automation	-0.133
Sourcing	-0.134
Office Administration	-0.188
Technical Recruiting	-0.230
Jenkins	-0.272
Product Launch	-0.274
Spring Boot	-0.469

Table notes: This table reports the results of coefficient estimates from a regression of major skill categories on remote status. Only the top 200 skills were classified, and the value for each major skill is the number of time a skill in that category appears in the job listing.

Table 8: Predicting WFH listings using firm and job characteristics on the pre-COVID sample

	Dependent variable:					
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	−0.000	0.000	0.018***	0.733***	0.129***	0.048
	(0.157)	(0.092)	(0.004)	(0.039)	(0.006)	(0.143)
Startup FE		✓				✓
Title FE	✓					✓
Location FE				✓		✓
Weeks FE			✓			✓
Skill FE					✓	
Observations	21,888	21,893	21,893	21,893	3,129	21,888
R^2	0.281	0.502	0.003	0.309	0.321	0.688
Adjusted R^2	0.252	0.483	0.002	0.288	0.308	0.652

Table notes: This table reports OLS regressions on whether a listing is remote. All listings are from the pre-COVID sample. Column (1) includes only title FE. Column (2) includes only startup FE. Column (3) includes time. Column (4) includes location FE. Column (5) is skill FE and column (6) includes firm, title, time, and location FE. Standard errors are shown in parentheses, with *, **, and *** denoting significance at the 10%, 5%, and 1% level, respectively.

Figure 5: Applicant attributes by remote status

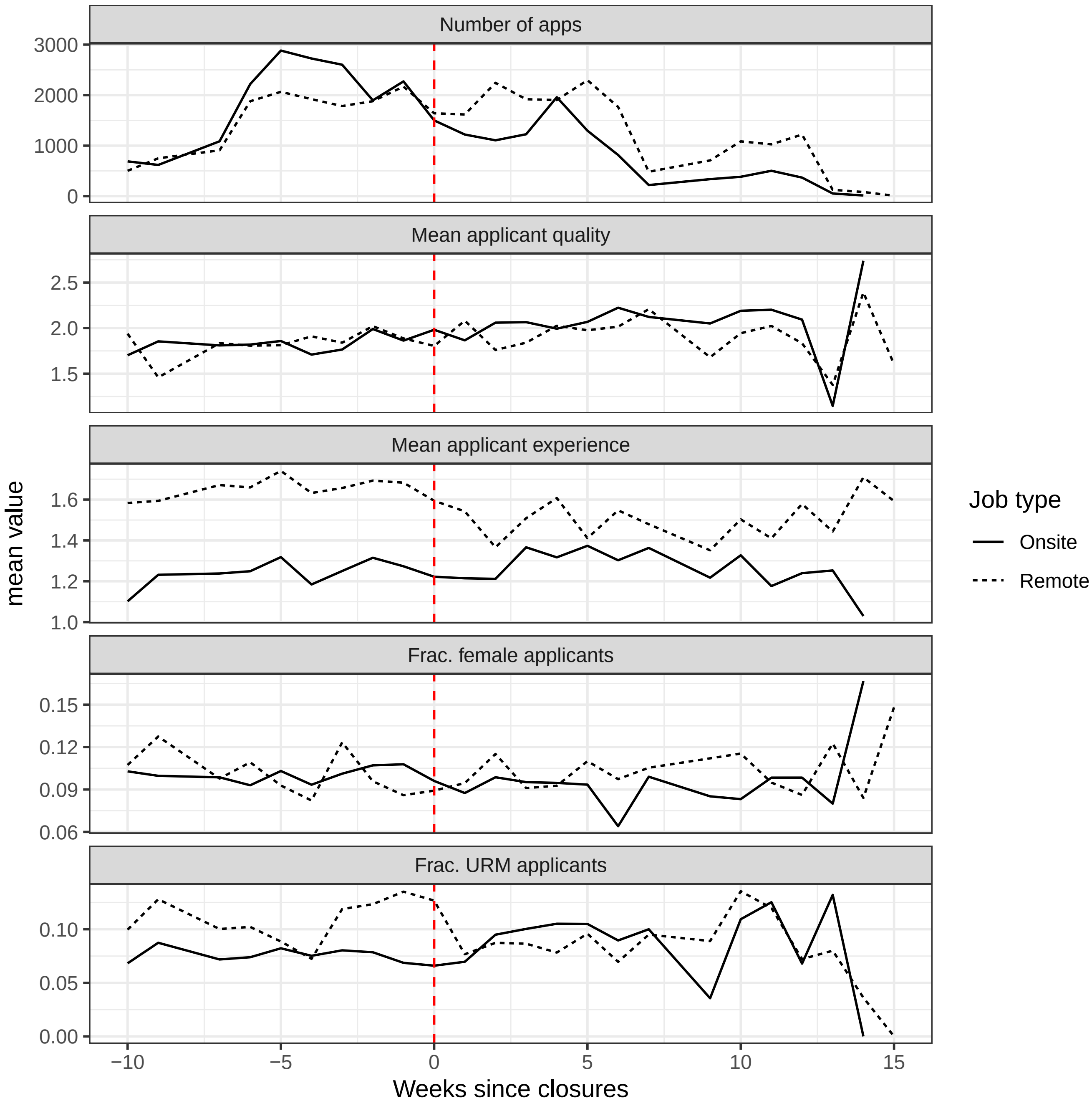


Figure Notes: The top panel plots average number of applicants against week in panel. The second panel is the average applicant quality against week in panel (quality is a proprietary score created by the platform). The third panel is the average experience of applicants against week in panel (experience measured as years of experience in their latest role). The fourth panel is the fraction of applicants to the listing that are female. The fifth panel is the fraction of applicants to a panel that are URM candidates.

Table 9: Characteristics of applicants to remote job listings

	Dependent variable:				
	Log apps	Log quality	Log exp	Log female apps	Log URM apps
	(1)	(2)	(3)	(4)	(5)
Remote	0.623***	0.926**	0.770***	0.093	0.188**
	(0.049)	(0.363)	(0.189)	(0.212)	(0.090)
Constant	0.090	−4.221**	2.966***	1.334*	−0.414
	(0.335)	(2.014)	(1.066)	(0.754)	(0.494)
Job title FE	Yes	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes	Yes
Job type FE	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes
Startup FE	Yes	Yes	Yes	Yes	Yes
Observations	5,996	1,002	903	780	1,080
R^2	0.617	0.855	0.916	0.913	0.813
Adjusted R^2	0.433	0.494	0.656	0.570	0.400

Table notes: This table reports OLS regressions on the numbers and types of applications sent to job listings. Standard errors are shown in parentheses, with *, **, and *** denoting significance at the 10%, 5%, and 1% level, respectively.

Table 10: Matching estimator output

	Dependent variable:				
	Log apps	Log quality	Log exp	Log fem apps	Log URM apps
	(1)	(2)	(3)	(4)	(5)
Remote	0.308***	0.115*	0.233***	0.036***	0.051***
	(0.036)	(0.069)	(0.010)	(0.004)	(0.003)
Constant	1.555***	2.038***	0.097***	0.095***	0.023***
	(0.070)	(0.128)	(0.022)	(0.010)	(0.007)
Observations	2,260	2,278	21,253	21,253	21,253
R^2	0.197	0.194	0.125	0.062	0.055
Adjusted R^2	0.186	0.182	0.123	0.060	0.053

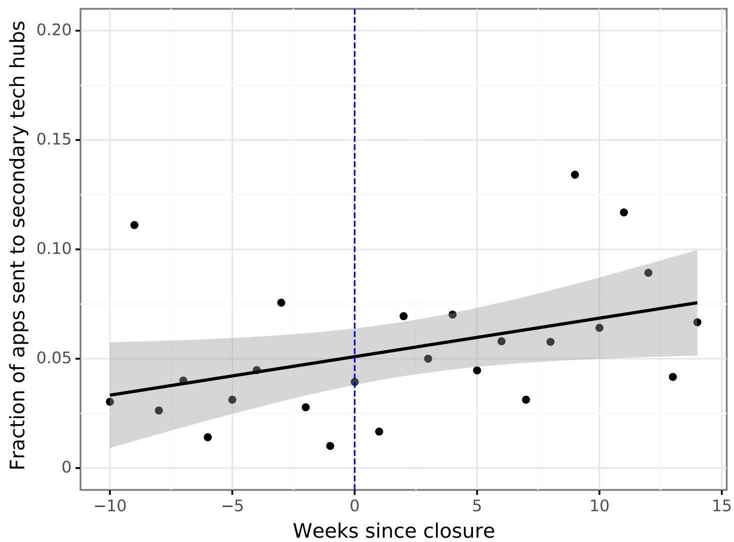
Table notes: This table reports OLS regressions on the types and counts of applications sent to job listings. The DV in all columns is logged number of applications. Standard errors are shown in parentheses, with *, **, and *** denoting significance at the 10%, 5%, and 1% level, respectively.

Table 11: Quasi-experimental comparisons

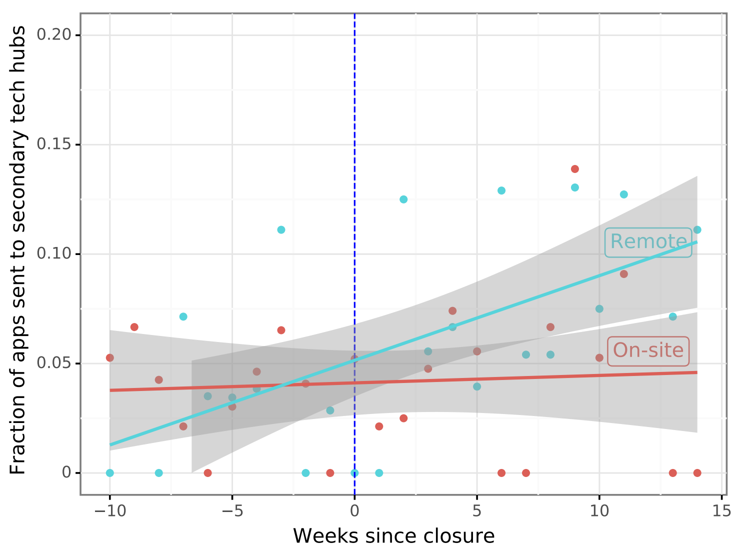
	Dependent variable:				
	Log apps	Log quality	Log exp	Log female apps	Log URM apps
	(1)	(2)	(3)	(4)	(5)
Remote, predicted onsite	0.211***	0.053	0.315***	0.054***	0.037***
	(0.006)	(0.077)	(0.038)	(0.002)	(0.002)
Onsite, predicted remote	0.120***	1.395***	0.039	−0.017	0.046***
	(0.045)	(0.420)	(0.216)	(0.018)	(0.014)
Remote, predicted remote	−0.325***	−0.807	0.119	−0.035*	−0.063***
	(0.048)	(0.524)	(0.260)	(0.019)	(0.016)
Constant	0.433***	1.965***	1.152***	0.058***	0.046***
	(0.015)	(0.103)	(0.055)	(0.006)	(0.005)
Week FE	Yes	Yes	Yes	Yes	Yes
Observations	26,950	1,280	1,394	26,950	26,950
R^2	0.139	0.044	0.072	0.042	0.040
Adjusted R^2	0.138	0.032	0.061	0.042	0.040

Table notes: This table reports OLS regressions on the types and counts of applications sent to job listings on a matched set of observations. The *MatchIt* package is used in R for the matching. Matching is done without replacement and matches are 1:1. The DV in all columns is logged number of applications. Standard errors are shown in parentheses, with *, **, and *** denoting significance at the 10%, 5%, and 1% level, respectively.

Figure 6: Fraction of applications sent to "second tier" tech hubs



(a) From SV applicants



(b) From SV applicants

Figure Notes: Cities in the second-tier city set include Austin, Washington, Seattle, Denver, Atlanta, Santa Monica, San Diego, Cambridge, Philadelphia, and Washington DC.

Figure 7: Cumulative applications by city rank for US applicants

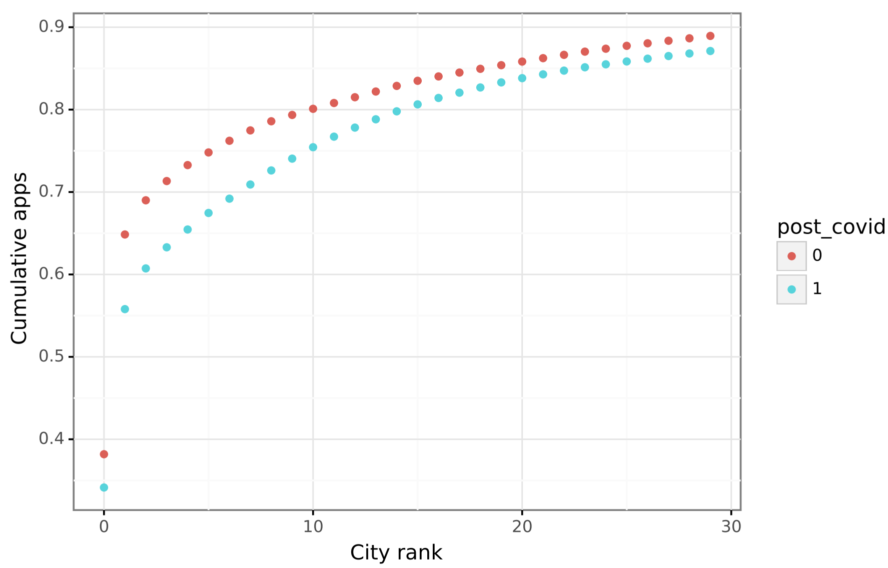


Figure Notes: This chart plots log market size (according to number of listings in the market) against the fraction of listings in the market that are classified as remote. Markets with less than 250 listings are excluded from the analysis.