NBER WORKING PAPER SERIES

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LABOR MARKET CONCENTRATION, DOWNSKILLING, AND INCOME INEQUALITY

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Working Paper 27208
http://www.nber.org/papers/w27208

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
May 2020

We are grateful to Tom Ashenmacher at LinkUp for data access and support. All errors are our own. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

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NBER Working Paper No. 27208
May 2020
JEL No. E24,G31,J23

ABSTRACT

Big data on job-vacancy postings reveal several dimensions of the impact of COVID-19 on the U.S. job market. Firms have cut back on postings for high-skill jobs more than for low-skill jobs, with small firms nearly halting their new hiring altogether. New-hiring cuts and downskilling are most pronounced in local labor markets lacking depth (where employment is concentrated within a few firms), in low-income areas, and in areas with greater income inequality. Cuts are deeper in industries where workers are more unionized and in the non-tradable sector. Access to finance modulates corporate hiring, with credit-constrained firms curtailing their job postings the most. Our study shows how the early-2020 global pandemic is shaping the dynamics of hiring, identifying the firms, jobs, places, industries, and labor markets most affected by it. Our results point to important challenges to the scale and speed of a recovery.

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1 Introduction

The COVID-19 pandemic has brought about the largest economic dislocation since the Great Depression. The ongoing crisis hit the corporate sector in a unique fashion. While prior shocks to business activity came through channels such as the supply of capital (the Financial Crisis) or technology (digitalization and automation), COVID-19 hit the human capital component of the production process. No machines were destroyed or became obsolete, no banks failed, and access to credit did not collapse — instead, human capital was threatened by a global health crisis. The consequences to labor markets are likely deep and long lasting. While aggregate data point to unprecedented labor market disruptions, understanding and addressing the forces driving aggregate movements will require identifying the firms, jobs, places, industries, and the skill level of workers most directly affected by the pandemic.

We present an assessment of the impact of the COVID-19 pandemic on the hiring decisions of U.S. companies. Hiring represents a costly, forward-looking investment in human capital and the decision to accelerate or scale back hiring reflects managers' expectations about their companies' future. We are able to track these decisions during the COVID-19 pandemic using *big data* on firms' job postings from LinkUp, a leading labor market research firm. The LinkUp data comprise job postings sourced from company hiring boards and websites of over 50,000 employers, encompassing public and private firms across all industries and regions of the U.S. The data are continuously updated and provide information on the employer, position sought, desired worker skill-level, and location of each job posting. These detailed records enable us to match the job postings data with a number of firm-specific information, allowing us to gauge how various margins of corporate hiring respond to the 2020 pandemic in real time.

Job postings by American companies have been dramatically altered by COVID-19; see Figure 1. An abnormal drop begins in the first week of March 2020, coinciding with the very beginning of the pandemic spread in the U.S.[1] The drop in hiring leads the unprecedented spike in initial jobless claims by almost two weeks. It also predates the first local stay-at-home

[1] At the time, the first U.S. death officially attributed to COVID-19 by the Centers for Disease Control and Prevention (CDC) was recorded on February 29$^{\text{th}}$, 2020. Subsequent reports suggest that deaths that occurred earlier in February in Santa Clara County, California were potentially attributable to COVID-19.

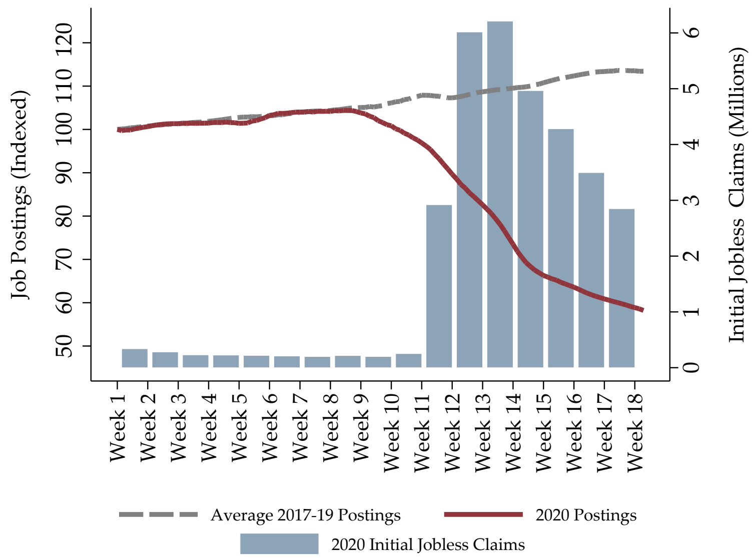
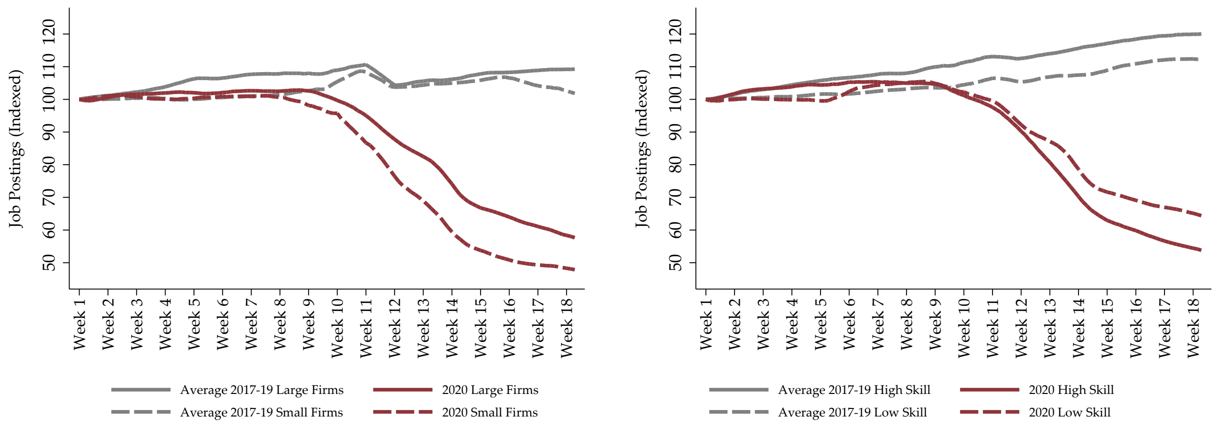


Figure 1. Job Posting Dynamics. This figure plots the 7-day rolling average of total active job postings across the first 18 weeks of 2017–2019, contrasting it to the level of total active job postings over the same period of 2020. The series are indexed such that they take the value of 100 for the first week of January (on the left y-axis). On the right y-axis, we show the weekly level of initial jobless claims (in millions).

orders, as well as state and federal emergency declarations by one week. The magnitude of the decline in new hiring ads is striking, with the level of active job postings as of the first week of May 2020 dropping 40% below the average level of postings as of the same week in 2017–2019.

A key benefit of our data is that they contain critical *firm-specific* information, allowing us to track corporate hiring patterns at a great level of detail. Doing so reveals significant disparities in both the types of firms curtailing their hiring and hiring cuts across job skill levels. Figure 2 depicts these dynamics as the pandemic unfolds. The decline in active job postings by small firms substantially exceeds that of large firms, with small firms reducing their hiring by over 50% and large firms reducing hiring by some 30–40% (see Panel A). Panel B shows that hiring cuts among high-skill jobs (e.g., CEOs, lawyers, post-secondary teachers, statisticians, and physicians) exceed those among low-skill jobs (agricultural, food services, landscaping, garment, and timber logging workers). The differential effects of COVID-19 on firms and jobs may determine which policy responses are likely to be effective in re-establishing a well-functioning labor market. They can inform us about the extent and speed of a potential recovery.



(A) Postings by Firm Size

(B) Postings by Job Skill Levels

Figure 2. Weekly Job Postings by Firm Size and Job Skill Levels. This figure plots the 7-day rolling average of active job postings across the first 18 weeks of 2017–2019, contrasting it to the job postings over the same period in 2020. Data are partitioned by firm size (Panel A) and job skills (Panel B). Large firms are public firms in the top tercile of the asset distribution in the preceding quarter and small firms are those in the bottom tercile. High-skill jobs are those whose O*NET codes map to Job Zone 5 and low-skill jobs are those whose O*NET codes map to Job Zone 1 (1–5 Job Zone scale). The series are indexed such that they take the value of 100 for the first week of January (on the left y-axis).

Our analyses go deeper into the granular nature of hiring cuts by way of assembling a firm-ZIP-week panel of job posting activity. As we detail below, our empirical testing simultaneously accounts for unobserved heterogeneity at the firm, ZIP, and week levels, also accounting for various local labor market characteristics. Under this setup, we contrast and compare hiring changes within firms and geographical areas over time. Our baseline tests show that firms cut their new job postings in local labor markets on a *weekly basis* by 9% of the 2017–2019 average level with the onset of the pandemic. This estimate translates to a 57% ($=1-(1-0.09)^9$) cumulative 9-week decline. Panel A of Figure 2 points to firm size playing an important role in modulating firms' reactions to the pandemic. Our regression analyses confirm this, with results showing that small firms cut job postings significantly more than large firms. In effect, small firms reduced their weekly new postings by a striking 59% of the 2017–2019 average level more than their larger counterparts.

We further characterize the nature of hiring cuts by categorizing job postings according to skill levels. Within-firm analyses show that hiring cuts are more pronounced at the high end of the worker-skill spectrum. In the first nine weeks of the pandemic, the ratio of high-to-low-skills new job postings declined by 5 percentage points; one-sixth of the ratio for the same time window in 2017–2019. This result is in contrast to literature pointing to new-hire upskilling in the aftermath of the Financial Crisis (e.g., Hershbein and Kahn (2018)). It is, however, consistent with reports of accelerated hiring into low-skill occupations during the pandemic and research showing association between unemployment and downskilling (Modestino et al. (2016)).[2]

We verify that COVID-19 is *dynamically driving* our results by conditioning our tests on local-area exposure to the spread of the coronavirus. Location–time-specific estimations show that declines in new job postings are progressively more pronounced in labor markets that became more affected by the COVID-19 contagion. As the virus spreads, firms cut weekly job postings by 10% of the 2017–2019 average in counties at the top of the weekly distribution of COVID-19 cases relative to those at the bottom. Geographical analyses, too, reveal a dramatic, ongoing curtailment in new hiring in areas that became most exposed to COVID-19.

Our study also shows how various labor market characteristics modulate firms' responses to the pandemic. We consider the role played by unionization and find that declines in job postings are more acute for highly unionized jobs. This is consistent with unionization translating into higher *ex ante* labor adjustment costs. We also show that firms in the non-tradable sector cut their job postings the most. This reflects the fact that this sector has been most affected by restrictions on in-person economic activity imposed since COVID-19 began spreading.

The next feature we study is local labor market depth, or the extent to which hiring is concentrated in the hands of a small number of local employers. Employers in a competitive labor market may not reduce their hiring as much as those in more concentrated markets do. This is because employers in a competitive labor market face the risk of being unable to rehire their workers when conditions improve. In line with this argument, within-firm estimates show that firms cut their job postings more aggressively in less competitive labor markets. Subsequently, we examine the role of firm geographic concentration. Controlling for size, firms whose operations are widely diversified across different areas of the country reduce their hiring less pronouncedly than firms whose operations are concentrated. Geographical diversification

[2] *New York Times*, March 22nd, 2020, *"Help Wanted: Grocery Stores, Pizza Chains and Amazon Are Hiring."*

appears to enhance firms' ability to withstand negative shocks to their workforce (see also Giroud and Mueller (2019)).

Our subsequent set of analyses investigates the role played by credit access. Credit constraints shaped firms' hiring decisions in the aftermath of the Financial Crisis (Campello et al. (2010) and Chodorow-Reich (2014)). While the COVID-19 crisis originated outside the financial system, the availability of financing has been viewed as an important buffer for firms hit by the pandemic (Granja et al. (2020) and Fahlenbrach et al. (2020)). Accordingly, economic policy responses such as the Paycheck Protection Program (PPP) and other elements of the Coronavirus Aid, Relief, and Economic Security (CARES) Act have targeted firms with infusions of capital. We consider a number of metrics capturing firms' *ex ante* access to financing, such as their private or public status, credit ratings, access to outstanding credit lines, and cash holdings. Across all proxies, we find that credit constraints intensify the cuts in job postings. For instance, firms without bank credit lines cut their weekly job postings by 13% of the 2017–2019 average, relative to firms with at least one credit line available. Firms in the latter group have between 2 and 3 credit lines outstanding, on average, representing up to $780 million in available facilities (24% of their total assets). In a final set of tests, we evaluate the effectiveness of the PPP by comparing the hiring decisions of public firms receiving funding under the program with those of a matched group of control firms. We show that PPP recipient firms cut their job postings by more than other firms in the days after receiving funding. Our findings highlight side effects of stimulus policies designed to preserve *existing* employment on firms' *new* hiring.

A granular examination of the location of job postings indicates that the decline in high-skill postings is particularly pronounced in (often-depressed) rural and exurban areas of the U.S. In addition, we find that firms cut back on job postings the most in low-income areas and areas with greater income inequality. The patterns we observe raise concerns about whether jobs lost to the pandemic are likely to return even when overall economic conditions improve. One of the likely consequences of COVID-19 is that of aggravating regional economic inequalities.

Our study contributes to a growing and important body of work on the economic impact of COVID-19 by providing a granular analysis of *firm-specific* recruitment activities during the pandemic.[3] It also contributes to the understanding of how the pandemic may affect recent developments in labor markets, including upskilling and downskilling (Autor and Dorn (2013), Modestino et al. (2016), Hershbein and Kahn (2018), and Campello et al. (2020)), job polarization (Autor (2014) and Jaimovich and Siu (2020)), as well as increasing market concentration (Azar et al. (2017) and Benmelech et al. (2018)). Our results carry policy implications. They suggest that economic recovery may be hindered by the fact that hiring cuts have been particularly severe in concentrated local labor markets, among high-skill jobs, and across smaller firms with limited access to capital. The pandemic also brought about particularly deleterious effects to the hiring of workers in poorer areas and places where income inequality was already high. Economic stimuli focusing on ameliorating the impact of COVID-19 should consider these labor market dynamics.

2 Data and Empirical Methodology

2.1 Job Postings Data

The core of our data is obtained from LinkUp, a leading provider of job market data and analytics. LinkUp assembles a comprehensive database of job openings sourced directly from over 50,000 employers, starting from 2007. These data are continuously updated by crawling company websites, capturing information on, among other things, job posting creation, modification, and deletion dates. The data for each posting also contain information on the job title, firm identifier, and geographical tracking to the ZIP code level. LinkUp attributes an O*NET occupation code to each posting based on a natural language processing algorithm. LinkUp has made available to us their entire database consisting of raw records and other processed fields.

[3]Examples include Alfaro et al. (2020), Ding et al. (2020), and Ramelli and Wagner (2020) on stock market reactions to COVID-19, Coibion et al. (2020) who survey household labor force participation, Baker et al. (2020a) on uncertainty surrounding the pandemic, Hassan et al. (2020) on measuring firm exposures to COVID-19, Bartik et al. (2020) and Granja et al. (2020) on small business responses, Baker et al. (2020b) on household spending reactions to the pandemic, Kahn et al. (2020) on the aggregate decline in job vacancies and spike in unemployment insurance claims, and Cajner et al.'s (2020) evidence on employment contraction based on firm-anonymized payroll records.

Our sampling runs from January 1st, 2017 through May 5th, 2020. We restrict our attention to American firms and job postings. We use LinkUp's linking tables to map each firm's internal identifier to its ticker, NAICS industry code, and then to its Compustat GVKEY. We link these data to other firm-level data sources using tickers and GVKEYs. To gauge the required skill level of a job posting, we map the posting's O*NET code to a Job Skill Zone (1 to 5 scale) based on the O*NET Skill Zone linking table.[4]

2.2 Other Data Sources

Our analysis uses additional data on firm fundamentals and operations, labor markets, credit conditions, and various geography-level information. We obtain firm financial data from Compustat's Quarterly and Annual files. For information on the geographical location of firms' operations, we use the Your-economy Time-Series (YTS) database, maintained by the Business Dynamics Research Consortium at the University of Wisconsin. The YTS database is compiled from Infogroup's historical business files and are linked longitudinally to track location, employment, and sales information at the establishment-year level for public and private firms. Information on firms' credit ratings come from Compustat's Ratings files. Data on outstanding credit lines are from WRDS-Reuters DealScan. Data on unionization are from the Bureau of Labor Statistics (BLS). County-level data on income inequality are obtained from the U.S. Census Bureau's American Community Survey (ACS). Monthly state-level unemployment and labor force figures are obtained from the BLS. We obtain statistics on daily recorded COVID-19 cases in each county from the New York Times.

2.3 Variable Construction and Measurement

2.3.1 Job Postings and Skills

Our base data come from 26,414 firms (both public and private). We collapse the job posting-level data into a firm–week–ZIP code panel, consisting of 49,385,544 observations. We compute

[4] The O*NET classification of Job Skill Zones is based upon the Specific Vocational Preparation required for an occupation as per the Dictionary of Occupational Titles (see Autor et al. (2003) and Donangelo (2014)).

our tests' dependent variables using this panel as follows. *New Job Postings* is the logarithm of one plus the total number of new job postings *created* by a given firm in a given week in a given 3-digit ZIP code.[5] As an alternative metric of corporate hiring, we also track the number of active job postings *maintained* by a firm in a week in a ZIP code. Using the number of active job postings, we compute Δ*Active Job Postings* as the percentage change in job postings (relative to the same firm, same ZIP, and same week in the previous year). The benefit of Δ*Active Job Postings* is that it incorporates both the creation of new job postings and the deletion of postings.

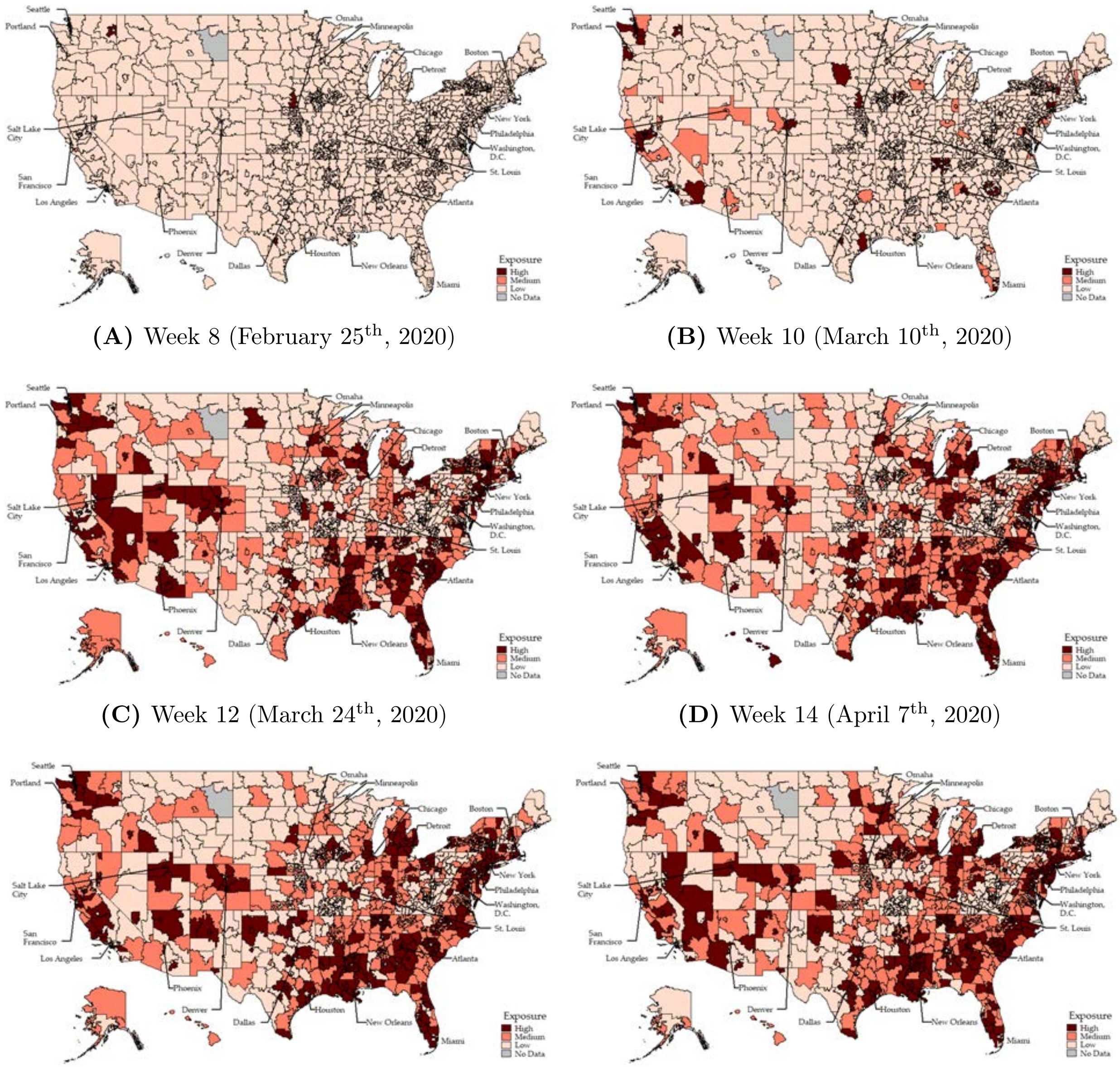
Our next set of dependent variables gauges heterogeneity in the skill level of job postings. Δ*Low Skill Postings* is the percentage change in job postings (relative to the same firm, same ZIP, and same week in the previous year) for occupations with O*NET codes corresponding to Job Zone 1. Δ*High Skill Postings* is measured analogously for occupations with O*NET codes corresponding to Job Zone 5. The total number of low-skill job postings created in our sample is 2,355,279, while the number of high-skill postings is 3,127,187.[6] Additionally, we compute the *High-to-Low-Skills Postings Ratio* as the number of job postings created in Job Zone 5 divided by the number of job postings created in Job Zone 1 for a given firm–week–ZIP triple. Through this ratio, we can measure whether hiring activity *within a firm and labor market* is skewed towards low-skill (if the ratio is <1) or high-skill (if the ratio is >1) positions.

2.3.2 Conditioning Variables

Several dynamics may modulate firm responses to the COVID-19 pandemic, and we proxy for these forces using a number of conditioning variables. The first variable captures the intensity of the pandemic at a local-area level; that is, the locality where a firm seeks to hire. *High COVID Exposure* is an indicator that takes the value of 1 for each county-week

[5] We follow Chetty et al. (2013) in defining the relevant area boundaries of our geographical analysis. There are 899 3-digit ZIP codes in the U.S. and they provide for more granular mapping than commuting zones (709) or MSAs (392), yet allow for more precise estimations than 5-digit ZIP codes (oftentimes arbitrarily assigned to large buildings or university campuses). The average (median) population of a 3-Digit ZIP code is 349,490 (212,964) based on the 2010 U.S. Census.

[6] See Appendix A for the complete listing of occupations included under the low- and high-skill categories. Our results are robust to alternate definitions of low- and high-skill jobs, including defining low-skill (high-skill) jobs as those in as Job Zones 1 and 2 (4 and 5).



(A) Week 8 (February 25th, 2020) **(B)** Week 10 (March 10th, 2020)

(C) Week 12 (March 24th, 2020) **(D)** Week 14 (April 7th, 2020)

(E) Week 16 (April 21st, 2020) **(F)** Week 18 (May 5th, 2020)

Figure 3. COVID-19 Exposure. This figure illustrates the distribution of cumulative COVID-19 cases per capita at the ZIP code level at two-week intervals, beginning on Week 8 (Panel A, February 25th) and ending on Week 18 (Panel F, May 5th) of 2020. ZIP codes belonging to the highest tercile of cumulative confirmed COVID-19 cases per capita are colored in the darkest shade, ZIP codes belonging to the second tercile are colored in the intermediate shade, and ZIP codes in the lowest tercile are colored in the lightest shade.

belonging to the highest tercile of the number of confirmed COVID-19 cases per capita in the United States and 0 for the lowest tercile.[7] Figure 3 depicts the time-series evolution of the exposure of counties based on total recorded number of COVID-19 cases per capita since

[7]We map ZIP codes to counties using the HUD-USPS ZIP Code Crosswalk. While we partition and rank areas into terciles for convenience, we demonstrate our results are robust to conditioning on various alternative cutoff points along the COVID-19 case distribution, including quartiles, quintiles, and deciles.

February 25^{th}, 2020. In Week 8 of 2020 (Panel A) there was relatively little human exposure to the coronavirus, with only a handful of cases reported across the country. By Week 10 (Panel B), there were noticeable outbreaks on the West Coast (Seattle and San Francisco Bay Area) and evidence of community contagion in cities throughout the U.S. By Week 12 (Panel C), the coronavirus outbreak appeared to have spread across the country, notably in the Northeast (New York, New Jersey, and Massachusetts). Exposure as of Week 18 (Panel F) shows the widespread presence of COVID-19 cases across the U.S., with urban centers being most affected.

The next set of conditioning variables relates to firm size. They are computed using data on firm assets and employees for public firms in our sample. *Small Firm* (*Assets*) is an indicator variable that takes the value of 1 for firms in the bottom tercile of the total assets distribution (measured in December 2019) and 0 for firms in the top tercile. In analogous fashion, *Small Firm* (*Employees*) is an indicator that takes the value of 1 for firms in the bottom tercile of total employees and 0 for firms in the top tercile.

We also condition our tests on variables capturing local labor market characteristics and firm geographical diversification. *High Unionization* is an indicator variable that takes the value of 1 for firms in the top tercile of the labor unionization rate in 2019 (at the 4-digit SIC industry level) and 0 for firms in the bottom tercile.[8] *Non-Tradables* is an indicator that takes the value of 1 for firms in the non-tradable sector and 0 for firms in the tradable sector (cf. Mian and Sufi (2014)).[9] *Low Local Labor Market Depth* takes the value of 1 for ZIP codes in the top tercile of the Herfindahl–Hirschman Index (HHI) of active job postings and 0 for ZIP codes in the bottom tercile. The HHI is calculated within a ZIP code across all employers with active job postings in that ZIP code for the year 2019. *High Firm Geographic Concentration* takes the value of 1 for firms in the top tercile of the HHI of their operations and 0 for firms in the bottom tercile. The HHI of a firm's operations is calculated by taking the sum of the squared employment shares across all ZIP codes a firm operates in, based on 2018 establishment-level data from YTS. *Low Local Household Income* is an indicator that takes the value of 1 for

[8]Examples of highly unionized industries include airlines, shipping, telecommunications, healthcare, steel, coal, and motion pictures.

[9]Examples of the non-tradable sector businesses include supermarkets, restaurants, office supplies, car dealerships, food service, and clothing.

counties in the bottom tercile of the median household income distribution as of 2018 and 0 for counties in the top tercile. *High Local Income Inequality* is an indicator that takes the value of 1 for counties in the top tercile of the income inequality distribution (measured by the 2018 5-year Gini coefficient) and 0 for counties in the bottom tercile of that distribution.

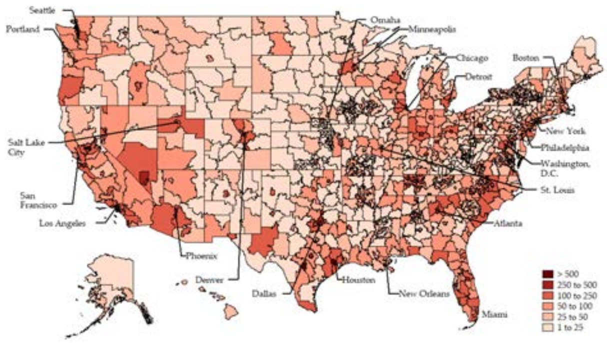
The final set of conditioning variables captures a firm's ability to raise financing. *Private Firm* is an indicator variable that takes the value of 1 for private firms and 0 for public firms. *Speculative Grade* is an indicator that takes the value of 1 for firms with an S&P issuer rating of less than BBB– (or unrated) as of 2019 and 0 otherwise. *No Credit Lines* is an indicator that takes the value of 1 for firms with no active lines of credit and 0 for firms with at least one line of credit as of the end of 2019. *Low Cash Holdings* is an indicator variable that takes the value of 1 for firms in the lowest tercile of the corporate cash-to-asset distribution and 0 for firms in the highest tercile of cash (measured in December 2019).

2.3.3 Control Variables

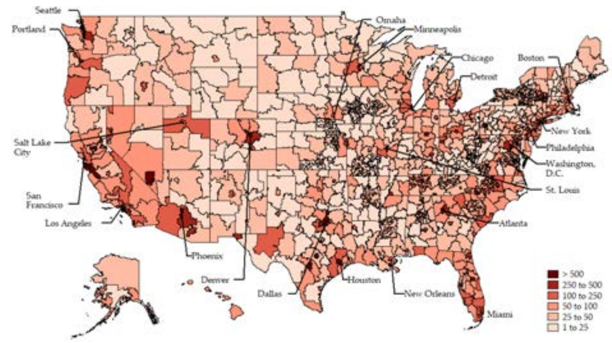
We account for several additional variables that are likely to influence firm hiring. At the state-month level, we control for the logarithm of the total labor force and the unemployment rate. At the firm-quarter level, we control for the logarithm of total assets, profitability (net income divided by lagged assets), cash (divided by lagged assets), financial leverage (total short- and long-term debt divided by lagged assets), Q (market-to-book ratio of assets), and investment (capital expenditures divided by lagged assets); all measured using pre-COVID-19 data.

2.4 Data Coverage and Validation

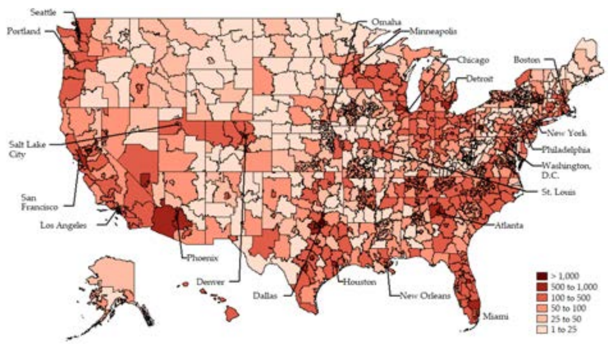
It is important to verify the quality of our job postings data both in terms of geographical representativeness and correspondence with overall job creation in the economy. Figure 4 showcases the geographical coverage of the LinkUp data. It does so using pre-COVID-19 data from years 2017 through 2019. Panels A and B depict job posting activity by large and small firms. Based on these panels, it appears that hiring across small and large firms were similarly



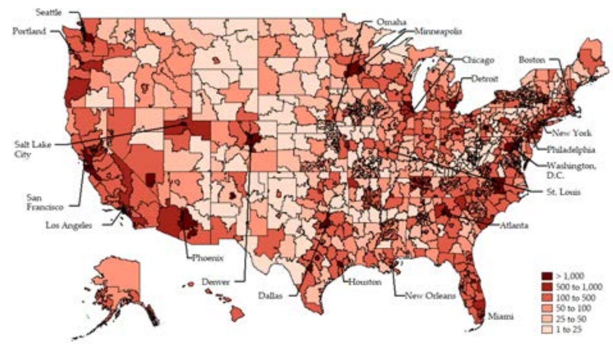
(A) Postings by Small Firms



(B) Postings by Large Firms



(C) Low-Skill Postings

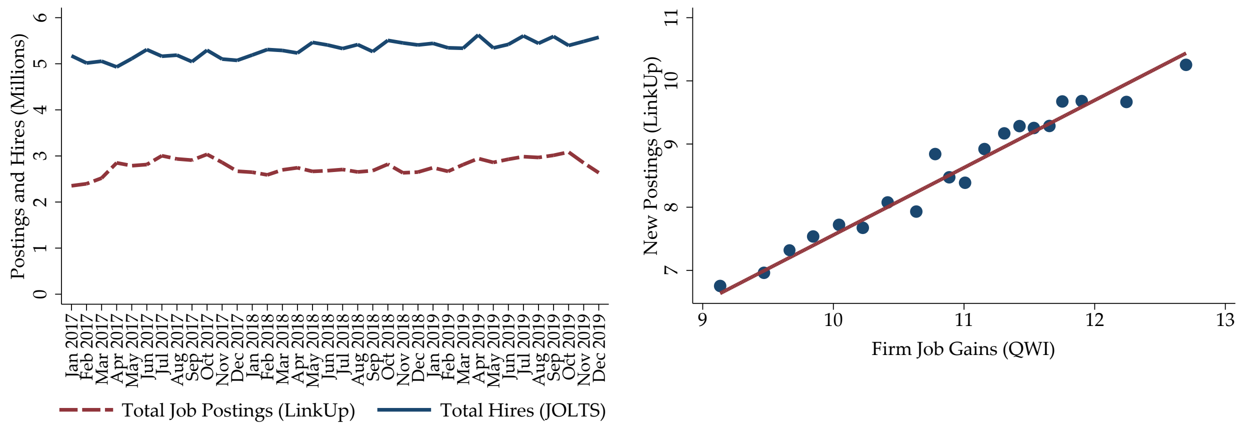


(D) High-Skill Postings

Figure 4. Geographical Distribution of Job Postings (2017–2019). This figure depicts the distribution of the number of active job postings at the ZIP code level, averaged over 2017–2019. Panel A (B) shows total active postings by small (large) firms defined as firms in the bottom (top) tercile of total assets. Panel C (D) shows total active postings for low (high) skill jobs defined as jobs whose O*NET codes map to Job Zone 1 (5).

geographically distributed prior to the 2020 pandemic. High-skill job postings (Panel D) seemed more prevalent in urban centers and on the coasts, compared to low-skill job postings (Panel C).

We compare our job postings data with administrative data on employment in Figure 5. Panel A shows that the total number of job postings in LinkUp consistently captures around 50% of total private-sector hires in the BLS Job Openings and Labor Turnover Survey (JOLTS). Panel B shows the relation between total new postings calculated from LinkUp data and firm job gains from the U.S. Census Bureau's Quarterly Workforce Indicators (QWI) data. The plot suggests a close link between job posting activity and job gains recorded at firms. The LinkUp data appear to provide a reasonable representation of corporate hiring.



(A) JOLTS

(B) QWI

Figure 5. Data Validation. Panel A depicts total job postings (from LinkUp data) and total private-sector hires (seasonally adjusted) from the BLS Job Openings and Labor Turnover Survey (JOLTS). Panel B plots the average state-level relation between total new postings (from LinkUp data) and firm job gains from the U.S. Census Bureau's Quarterly Workforce Indicators (QWI) data. Data in Panel B are in logs and represented in the form of 20 equal-sized bins based on the cross-sectional distribution of the depicted variables.

2.5 Summary Statistics

Table 1 reports descriptive statistics for the key variables used in our analysis. The average number of new postings by a firm in a given ZIP per week over the 2017–2020 period is 1.36 (or, expressed in log terms, 0.31). The average for the pre-COVID-19 period (1.48 postings, or 0.39 in log terms) is higher than the 2020 average of 1.34 (or 0.30 in log terms). The average percentage change in active postings by a firm–ZIP–week is 12% over the entire 2017–2020 period. As with new postings, the average percentage change in active postings is 14% over 2017–2019, consistent with the expansion of economic activity and hiring in the last few years. The average percentage change in active postings is a much lower 3.5% in 2020 (this includes the pre-pandemic months of January and February). Firms in our sample tend to post 2.8 high-skill jobs for every 10 low-skill jobs, reflected in an average *High-to-Low-Skills Postings Ratio* of 0.28. The reported summary statistics for firm-level control variables suggest that the public firms in our sample are representative of the Compustat universe of firms (see, e.g., Barrot and Sauvagnat (2016)).

Table 1 about here.

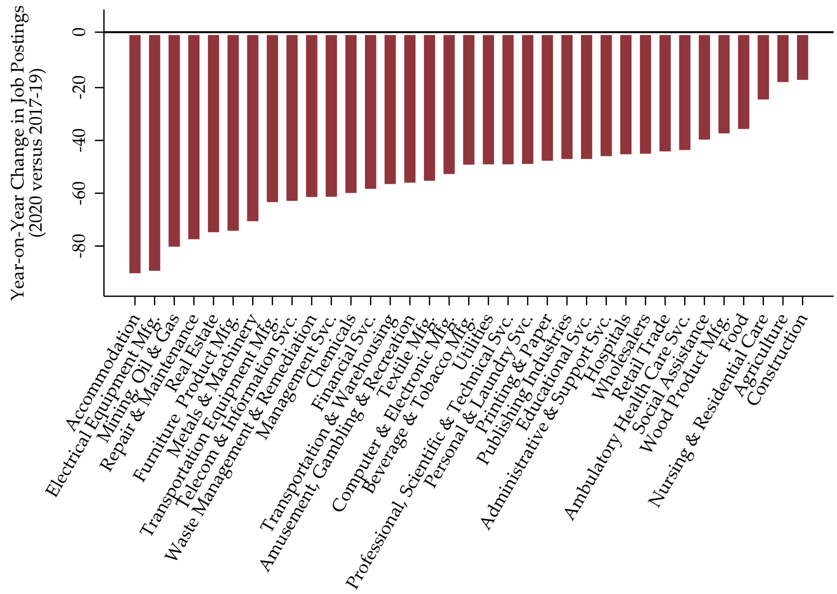


Figure 6. Industry Distribution of Post-COVID Declines in Job Postings. This figure plots the industry distribution of the cumulative percentage change in the number of active job postings for the post-COVID period (relative to the average number of active job postings in the same weeks of 2017–2019). Firms are assigned to industries based on their 3-digit NAICS codes (see Appendix B).

We showcase the existence of business-sector heterogeneity in the way COVID-19 affects the economy in Figure 6. Firms in the accommodation and electrical equipment manufacturing industries posted the greatest decline in hiring activity, nearly 90%. This is almost five times as large as that of the least affected industries. Industries in the latter category include construction, agriculture, and nursing & residential care facilities, whose services and goods have been deemed essential, and consequently have been in high demand since the onset of the pandemic. This variation suggests the inclusion of firm-by-time–fixed effects (subsuming industry-by-time–fixed effects) in our analysis, thereby alleviating concerns that our results may be driven by industry dynamics.

2.6 Empirical Specification

As a baseline, we empirically estimate a model that relates firms' job postings with a time indicator variable that captures the onset of the pandemic. We additionally interact that time indicator with several conditioning variables, while controlling for other drivers of firms' postings. Our specification takes the following form:

$$Y_{i,j,t} = \beta_1 Post\ COVID_t + \beta_2 X_{i,j,t} + \beta_3 Post\ COVID_t \times X_{i,j,t} \qquad (1)$$
$$+ \theta \boldsymbol{Controls}_{i,j,t} + FEs + \epsilon_{i,j,t},$$

where $Y_{i,j,t} \in$ {*New Postings, ΔActive Postings, ΔLow-Skill Postings, ΔHigh-Skill Postings, High-to-Low-Skills Postings Ratio*} for firm i in ZIP code j in week t. $Post\ COVID$ is a dichotomous variable that takes the value of 1 for each week after February 29$^{\text{th}}$, 2020 and 0 otherwise. $X_{i,j,t} \in$ {*High COVID Exposure, Small Firm (Assets), Small Firm (Employees), High Unionization, Non-Tradables, Low Local Labor Market Depth, High Firm Geographic Concentration, Low Local Household Income, High Local Income Inequality, Private Firm, Speculative Grade, No Credit Lines, Low Cash Holdings*} refers to a relevant conditioning variable. ***Controls*** is a vector of variables described in Section 2.3.3. Our baseline specification accounts for unobserved heterogeneity with the inclusion of dynamic firm–, ZIP–, and week–fixed effects. Standard errors are triple–clustered by firm, ZIP, and week.[10]

3 Base Results

3.1 Job Posting Activity

We first estimate Eq. (1) without conditioning variables to gauge the baseline impact of COVID-19 on job postings. We then assess whether firm responses are heightened in areas with more severe exposure to COVID-19, as the pandemic spreads. The results are reported in Table 2.

TABLE 2 ABOUT HERE.

[10]In light of the large number of observations in our sample, we adopt a stringent, multi-dimensional clustering scheme. It simultaneously allows for arbitrary cross-correlation of standard errors within the firm, geographical, and time dimensions. Our estimated t-statistics would be larger by one order of magnitude otherwise (see Cameron et al. (2011)).

The estimate in column (1) points to the pandemic imposing a negative and highly significant toll on firm hiring. The economic magnitude is striking. The coefficient of –0.035 implies that firms cut their average weekly postings in a ZIP code area by 9% (= 0.035 / 0.39) of the 2017–2019 average, following the start of the pandemic. The magnitude of this effect increases as we condition on the local level of exposure to the coronavirus contagion. In particular, the estimate in column (2) implies that firms have been curtailing their weekly new job posting activity within areas with highest levels of confirmed COVID-19 cases by 1.14 $(= -0.040 \, / - 0.035)$ times the unconditional effect, relative to those areas with fewer cases.[11]

The next metric of corporate hiring activity that we consider is the change in active job postings. In particular, the percentage change in active postings maintained by a firm in a ZIP code, relative to the same week in the prior year (this reflects both the addition and deletion of postings). The results in columns (3) and (4) are statistically significant and consistent in sign with those reported in columns (1) and (2). Recall, the average change in active postings over the last 3 years was 14%. The coefficient in column (3) indicates that in the weeks following February 29th, 2020, this rate has declined by 14.7 percentage points. In effect, COVID-19 reversed the growth in active job postings observed over the 2017–2019 period.

3.2 Worker Skill

Next, we assess whether the quality of human capital that firms seek to hire has been affected by the pandemic. We do so by comparing changes in active postings for high-skill positions relative to low-skill positions by the same firm in the same locality over time. The results obtained from estimating Eq. (1) using Δ*Low-Skill Postings*, Δ*High-Skill Postings*, and *High-to-Low-Skills Postings Ratio* as dependent variables are reported in Table 3.

Table 3 about here.

The estimates in columns (1) through (4) show a decline in both low- and high-skill job postings. Critically, the decline is more pronounced among high-skill postings. In columns (5)

[11] The uninteracted *Post COVID* and *High COVID Exposure* regression terms are subsumed by dynamic fixed effects.

and (6) we report the effects on the *High-to-Low-Skills Postings Ratio*. That ratio declines significantly as the pandemic spreads. The number of high-skill postings made by a firm in a given ZIP–week declines disproportionately relative to the number of low-skill postings previously made by the *same* firm in that *same* ZIP–week. The drop of –0.051 (column (5)) in this ratio represents 17% (= 0.051 / 0.30) of the 2017–2019 average *High-to-Low-Skills Postings Ratio*.[12] Likewise, in the regions most exposed to COVID-19, this ratio declines by 21.3% of the pre-COVID-19 average. Our tests account for the local unemployment rate, and imply that the pandemic drives a spike in downskilling over and above the previously reported association between the two in the U.S. (see Modestino et al. (2016)). These results provide unique insights into the emergence of downskilling dynamics in local labor markets under COVID-19. They signify a reversal of the upskilling trend observed since the Financial Crisis (Hershbein and Kahn (2018)).

3.3 Firm Size

Our analysis considers several characteristics that modulate firms' hiring responses. The first dimension we study is firm size. The stimulus programs enacted in response to the pandemic, such as the Paycheck Protection Program (PPP), have focused on providing support to small businesses. These policies are predicated on the notion that small businesses have been the hardest hit. We verify that this is the case by re-running the baseline specification in Eq. (1) conditioning on firm size. Our classification of small firms is based on balance sheet data reported by public firms, which tend to be larger than private firms. Our results would likely form the upper bound for the universe of small private firms, which are likely to be cutting back on their hiring even more than our estimates imply. The results are reported in Table 4.

TABLE 4 ABOUT HERE.

Regardless of whether firms are classified based on assets or employees, small firms cut their job posting activity substantially (relative to large firms) following the onset of the pandemic. The decline in new postings of –0.231 (see column (1)) is 59.2% of the 2017–2019 average

[12] See Table C.1 for evidence that our inferences are robust to alternative definitions of high- and low-skill jobs. Table C.2 shows that they are robust to considering alternative cutoffs along the COVID-19 case distribution.

weekly job posting rate of 0.39. Notably, small firms appear to skew their job postings away from high-skill jobs relative to large firms under the pandemic (columns (3) and (4)). Our findings show that small firms are bearing the brunt of COVID-19, justifying the targeting of economic stimulus towards such firms as a way to minimize the loss of jobs in the economy.

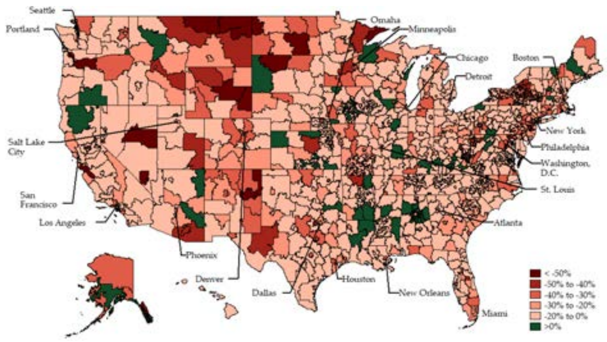
3.4 Mapping Firm Hiring Responses

We provide geographical context for the results in Tables 3 and 4 by plotting the post-COVID cuts in job postings by location in Figure 7. Across all figure panels, we statistically reject the null of spatial randomization ($p < 0.01$) based on Moran's I test statistics. A comparison between Panels A and B highlights that small firms have more acutely reduced their job postings relative to large firms.[13] The disproportionate cuts in high-skill job postings relative to low-skill job postings is evident from Panels C and D.

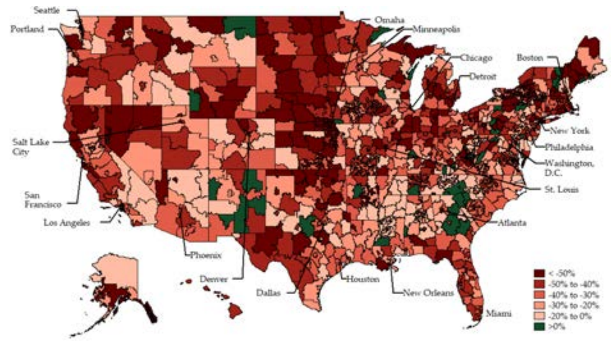
Our geography-based approach is particularly useful in illustrating the interactive effects of firm size and job skills on the extent of COVID-19-induced hiring cuts. Panel E shows relatively mild declines in low-skill postings by large firms across the country, with some regions experiencing growth.[14] Panel F paints a dramatically different picture in showing that small firms have made deep cuts to their hiring for high-skill positions. Notably, cuts in high-skill postings appear to be most severe in exurban and rural areas. This heightens concerns about the economic impact of COVID-19 on these particular regions, and their potential for recovery. These labor markets were unlikely to have been particularly active in the pre-pandemic period. With the spread of COVID-19, they run the risk of experiencing a large contraction in high-skill hiring as small local firms are disproportionately impacted by the pandemic.

[13] This happens despite the geographical distribution of job postings being virtually identical across small and large firms before the pandemic (see Panels A and B of Figure 4).

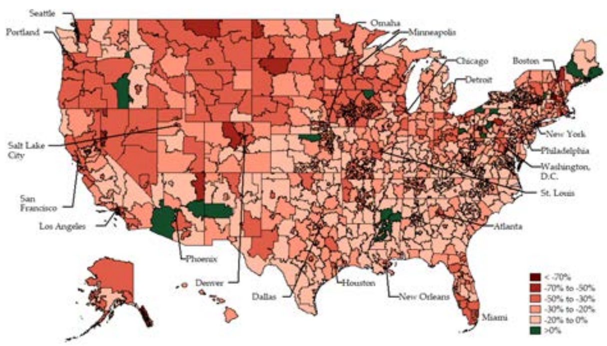
[14] This is consistent with widespread reports of certain large firms continuing to hire into low-skill positions.



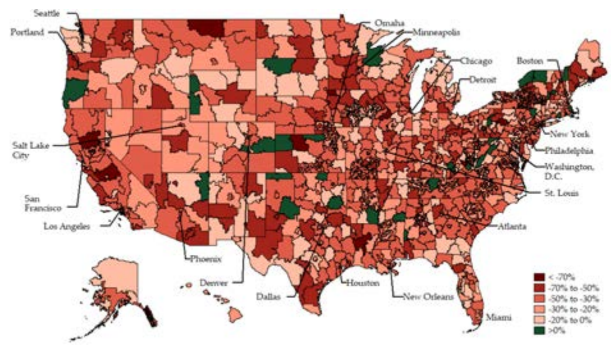
(A) Postings by Large Firms



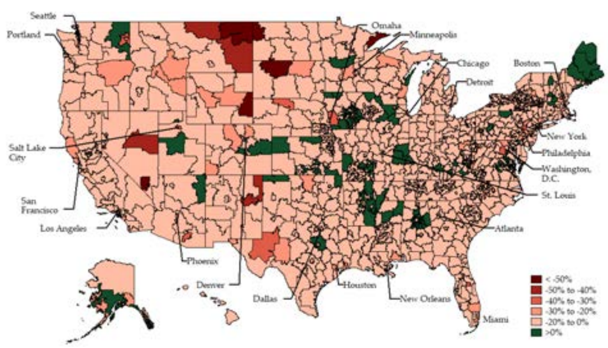
(B) Postings by Small Firms



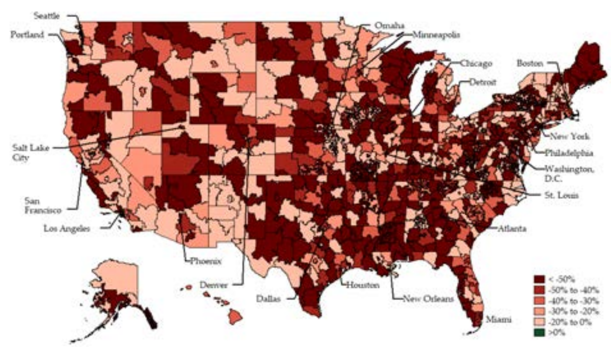
(C) Low-Skill Postings



(D) High-Skill Postings



(E) Low-Skill Postings by Large Firms



(F) High-Skill Postings by Small Firms

Figure 7. Geographical Distribution of Post-COVID Declines in Job Postings. This figure depicts the distribution of the change in the number of job postings at the ZIP code level for the post-COVID period (relative to the average number of job postings in the same weeks of 2017–2019). Panel A (B) shows the percentage change in postings by large (small) firms defined as firms in the top (bottom) tercile of total assets. Panel C (D) shows the percentage change in postings for low (high) skill jobs defined as jobs whose O*NET codes map to Job Zone 1 (5). Panel E shows the percentage change in postings for low-skill jobs by large firms, while Panel F shows the percentage change in postings for high-skill jobs by small firms.

4 Labor Markets, Credit Access, and Income Distribution

4.1 Labor Market and Geographical Characteristics

In our next set of tests, we estimate the baseline specification in Eq. (1) conditioning on labor market and geographical characteristics that are likely to shape hiring. The characteristics we consider are unionization, tradability, labor market depth, and geographic concentration. The results are reported in Table 5.

Table 5 about here.

Firms in highly unionized industries curtail their new postings more than those in less unionized industries under the pandemic (see column (1)). This is consistent with such firms facing higher labor adjustment costs. Accordingly, they may prefer adopting a "wait-and-see" approach before entering into rigid labor contracts during uncertain economic conditions. The coefficient estimate of –0.022 implies that firms in highly unionized industries cut their job postings by 5.6% of the 2017–2019 new posting creation rate more than firms in less unionized industries. Similarly, firms operating in the non-tradable sector cut their job posting activity more than firms operating in the tradable sector (column (2)). Non-tradable firms are highly exposed to local economic conditions as they rely more heavily on foot traffic, which has declined precariously with the pandemic. These firms also disproportionately reduce their hiring into high-skill positions relative to low-skill positions (see columns (5) and (6)).

We next consider labor market depth, measured as the concentration of employers in a local labor market. The logic underlying this test is that labor markets dominated by a small set of employers may experience more substantial cuts in hiring in bad times. This is because dominant local employers run a lower risk of having to compete with other employers when conditions improve.[15] Results in columns (3) and (7) of Table 5 show that concentrated labor markets experience greater declines in new job postings, particularly high-skill postings, with COVID-19. These results are particularly striking as they are estimated *within firms*, that is,

[15] For theoretical reviews on labor market concentration, see Boal and Ransom (1997), Bhaskar et al. (2002), and Manning (2011), and for empirical evidence see Azar et al. (2017) and Benmelech et al. (2018).

they compare the new job posting intensity by the same firm across local labor markets that are more versus less concentrated. This phenomenon is likely to be of concern to policymakers. Such markets may become even more concentrated in the future as marginal employers may not survive the downturn, leading to a potentially slower labor market recovery.

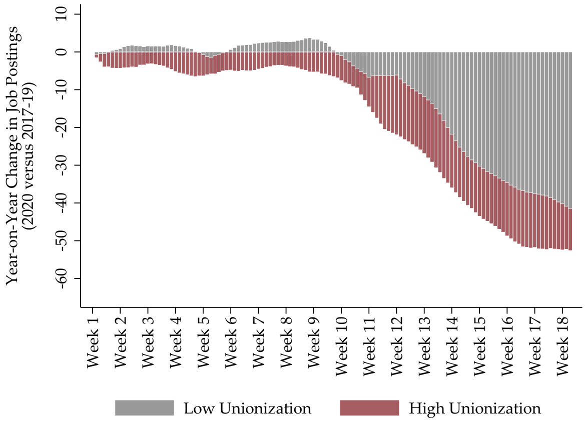
Finally, we look at firm geographic concentration. The estimates in columns (4) and (8) of Table 5 suggest that (controlling for firm size) firms whose footprints are concentrated in fewer regions cut back on their hiring more than firms with geographically dispersed operations. Geographical dispersion appears to confer an advantage to firms in withstanding the current pandemic-led crisis.

We provide economic interpretation and dynamics for the results in Table 5 by plotting various indicators of job posting activity in Figure 8. Panel A shows that firms in highly unionized industries cut their active job postings substantially more, and earlier, than firms in low unionization industries. Panel B shows similar patterns of hiring cuts among firms in the non-tradable sector relative to the tradable sector. The disproportionate decline in job postings in the non-tradable sector points to this sector being relatively hard hit as the pandemic spreads and social distancing orders are put in place (hiring cuts are higher starting from mid-March). Panel C shows that local labor markets with "lower depth" (more concentrated) have experienced cuts in job postings that are 5 percentage points higher than labor markets that are less concentrated. Panel D stresses that firms with more concentrated operations reduce their active job postings by almost twice as much as do firms with a more diversified geographic footprint.

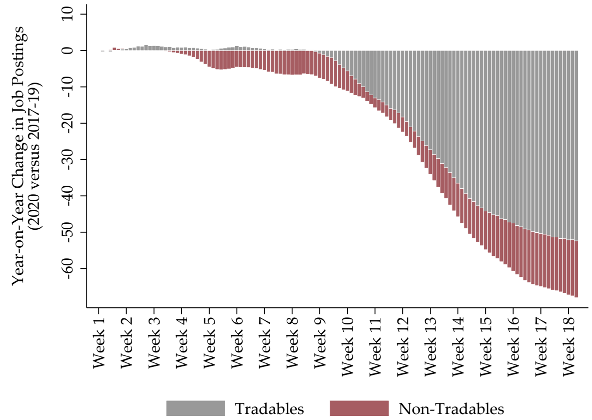
4.2 Access to Finance and Credit

Our subsequent set of analyses concerns firms' access to financing. We condition our baseline specification in Eq. (1) on four proxies of financing constraints: a firm's private or public status, whether it is rated as speculative or investment grade, whether it has an outstanding credit line to tap into, and whether it holds a large cash buffer. The results are presented in Table 6.

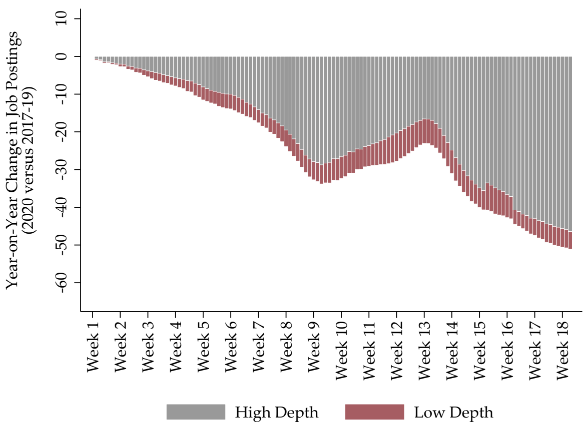
TABLE 6 ABOUT HERE.



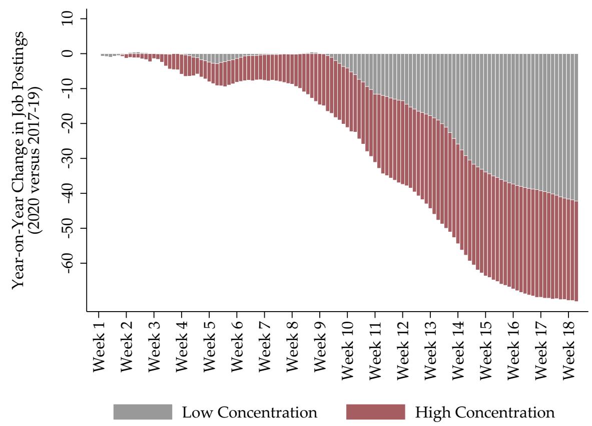
(A) Postings by Low versus High Unionization



(B) Postings by Tradables versus Non-Tradables



(C) Postings by Local Labor Market Depth



(D) Postings by Firm Geographic Concentration

Figure 8. Job Posting Dynamics by Labor Market and Geographical Characteristics. This figure depicts the prior 7-day rolling average percentage change in total active postings on each day of 2020 relative to the same day averaged across 2017–2019. Panel A shows the changes in postings for firms in low versus high unionization industries (based upon BLS data). Panel B shows the changes in postings for firms in the tradable and non-tradable sectors as per the classification in Mian and Sufi (2014). Panel C shows the change in postings for ZIP codes in the lowest versus highest tercile of local labor market depth. Panel D shows the change in postings for firms in the highest versus lowest tercile of geographical concentration of operations.

Across all four metrics, financially constrained firms cut back on job postings — particularly postings for high-skill jobs — by more than other firms in the wake of the pandemic. The associated economic magnitudes are large. The estimate in column (3) implies that firms without access to liquidity in the form of credit lines reduced their weekly job postings by 13.1% of the 2017–2019 average as compared to firms with at least one credit line outstanding. The latter set of firms, on average, had 2.4 facilities outstanding amounting to $780 million of available liquidity. Our results suggest that bank credit lines work as a buffer during the pandemic, preventing more severe declines in hiring. The coefficient in column (4) implies that cash savings perform a similar function. Firms in the bottom tercile of the cash distribution cut their weekly postings by 12.6% of the pre-COVID-19 average more than firms with large cash buffers. The cash-constrained firms had an average of $562 million in cash holdings (1.3% of assets) while firms in the highest tercile of cash holdings had $5.2 billion in cash reserves (30.5% of assets) at the end of 2019. Unlike the Financial Crisis of 2008-09, the COVID-19 crisis did not originate in the financial system, yet lack of access to financing has substantially hampered firms' hiring activity.

Among the many policies aimed at mitigating the economic impact of COVID-19, the Paycheck Protection Program (PPP) administered by the SBA as part of the CARES Act has garnered substantial attention. The PPP provides loans to small businesses and repayment is forgiven if these businesses utilize the funds to retain their existing employees. The effectiveness of the program has been questioned, with reports highlighting that funds have been allocated towards firms with pre-existing access to external financing (e.g., public firms).[16] We conduct a test of the labor market consequences of the PPP by examining its impact on recipient firms' job posting activity. We do so focusing on the subset of public firms receiving funds under the PPP.

Figure 9 tracks job postings by PPP recipient firms around the date on which they submitted relevant regulatory filings.[17] We contrast the job posting activity of these firms with a control group of public firms in the same industry selected by propensity-score matching (based on firm characteristics such as size, profitability, cash holdings, and financial leverage). PPP recipient firms and control firms display statistically indistinguishable hiring trends prior to filing. Recipient firms show a declining trend in job postings up to ten days prior to filing, nonetheless. This is indicative of the time lag between these firms receiving funding and having to file the required regulatory disclosures to notify investors. The differential decline in postings becomes statistically significant five days post-filing, and persists for at least ten days thereafter. Notably, loan forgiveness under the PPP is conditional upon recipient firms not laying off their

[16] See *Wall Street Journal*, April 26$^{\text{th}}$, 2020, *"At Least 13 Public Companies Give Back $170 Million in Small-Business Stimulus Money. Others Say They'll Keep It."* Granja et al. (2020) find that funds from the PPP have not been disbursed to areas most adversely affected by the pandemic.

[17] A total of 140 public firms in our sample submitted regulatory filings (8-Ks) to the SEC as of May 5$^{\text{th}}$, 2020 stating they had received PPP funding. Among these, 80 firms have complete data for the days surrounding the filing date, did not report returning the funds, and were matched to at least one control firm.

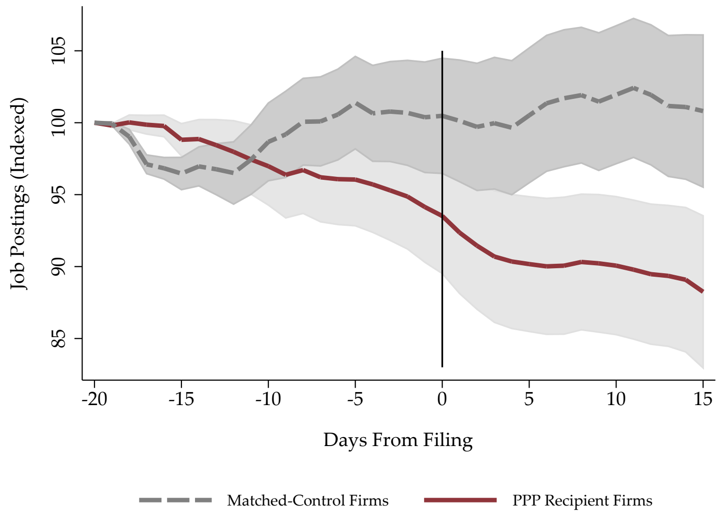


Figure 9. Paycheck Protection Program and Job Posting Dynamics. This figure illustrates the 7-day rolling average of total active job postings around the dates public firms reported receiving PPP funding in 8-K filings submitted to the U.S. Securities and Exchange Commission (SEC). Control firms are selected among public firms in the same industry by estimating propensity scores as a function of firm size, profit, cash holdings, financial leverage, Q, and investment. For each PPP recipient firm, we identify the nearest-neighbor non-recipient firm (with replacement) and include it in the control group. Confidence intervals are calculated as ± 1.5 standard deviations from the mean active postings for each day. Postings are indexed to 100 at the 20^{th} day prior to firms reporting receiving PPP funding.

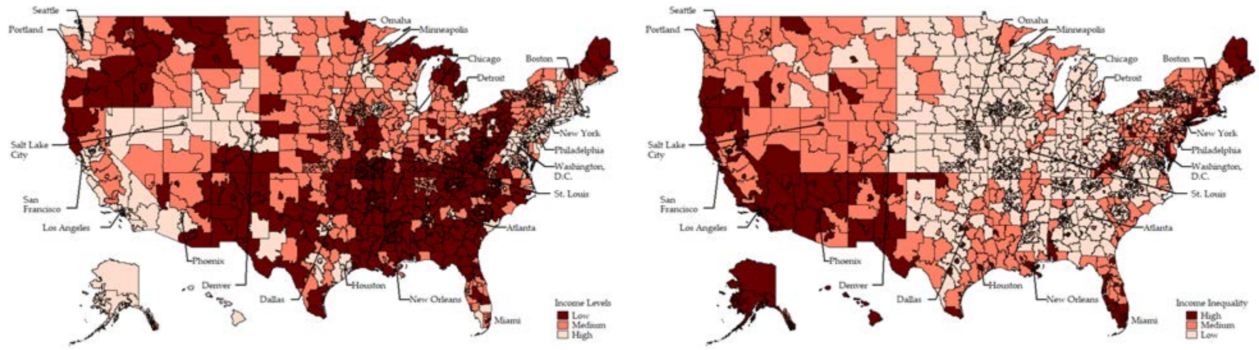
existing workforce. This regulatory-induced reduction in workforce turnover is associated with an ostensibly unintended decline in *new* hiring among recipient firms. Our results highlight the challenges faced by policy makers in promoting *job creation* in a post-pandemic recovery.

4.3 Income Levels and Inequality

Our final set of tests considers the role played by regional economic characteristics in modulating firms' hiring responses to the pandemic. We condition our baseline specification in Eq. (1) on two relevant metrics: household income (county-level median) and income inequality (county-level 5-year Gini coefficient). The results are reported in Table 7.

TABLE 7 ABOUT HERE.

Firms appear to cut back on new job postings — particularly high-skill postings — substantially more in low income regions (columns (1) and (3)) and regions with greater income disparity (columns (2) and (4)). Figure 10 provides geographical context for these results by



(A) Median Household Income Terciles **(B)** Gini Coefficient Terciles

Figure 10. Distribution of Income Levels and Inequality. This figure illustrates the distribution of median household income (Panel A) and Gini coefficient (Panel B) as of 2018, based on data from the U.S. Census Bureau American Community Survey (ACS).

mapping the distribution of income levels and income inequality across the country. Our results imply that local job markets most negatively affected by COVID-19 lie in the intersection of low household income and high income inequality. Examples include rural areas of Maine, Mississippi, New Mexico, Texas, and Northern California, as well as certain urban centers and exurban areas surrounding New Orleans, Detroit, and St. Louis. The COVID-19-induced weakening of labor markets in such regions is likely to exacerbate within- and across-regional inequalities. This could render the eventual recovery even more precarious due to the aggravation of pre-existing disparities.

5 Conclusion

This study provides an early account of the labor market effects of the COVID-19 pandemic based on real-time, granular, firm-level job posting data. We report sharp declines in corporate hiring across the board, but with meaningful heterogeneity along the lines of firm size, various labor market characteristics, and credit access. A particularly concerning trend is that firms are disproportionately cutting back on high-skill hiring ("downskilling") and on hiring in areas outside the major cities. This is likely to be detrimental to local government revenues in the near term as reduced hiring into higher wage jobs spells lower income-based tax collections. In the longer term, this may harm local recovery prospects as the re-hiring costs for high-skill positions will likely be high. This suggests that additional stimulus may be warranted targeting firms who hire for high-skill positions in rural and exurban areas. Regional disparities may also be amplified by the abnormal hiring cuts across low-income, high-inequality areas of the country.

While our analyses provide timely insights into the initial impact of the COVID-19 pandemic, conditions continue to evolve and may shape some of our findings. Uncertainty still looms large over the disease's spread and its impact on the U.S. economy. We plan to continue tracking the effects of the COVID-19 pandemic on corporate hiring, helping with the assessment of current and proposed policy interventions and measuring signs of a recovery.

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Table 1. Descriptive Statistics

This table presents descriptive statistics for the main variables used in our empirical analyses over the 2017–2020 period. The dependent variables are *New Job Postings*, Δ*Active Job Postings*, Δ*Low-Skill Postings*, Δ*High-Skill Postings*, and *High-to-Low-Skills Postings Ratio*. The unit of observation is a firm–ZIP–week, where ZIP is the three-digit ZIP-code of a job posting. *New Job Postings* is the logarithm of one plus the total number of job postings created. Δ*Active Job Postings* is the percentage change (relative to the same week in the previous year) in total active job postings. Δ*Low-Skill* (*High-Skill*) *Postings* postings is the percentage change, relative to the same week in the previous year, in job postings for occupations with O*NET occupation codes corresponding to Job Zone 1 (5). *High-to-Low-Skills Postings Ratio* is the total number of job postings created for occupations with O*NET occupation codes corresponding to Job Zone 5 divided by the total number of job postings created for occupations with O*NET occupation codes corresponding to Job Zone 1. *Post COVID* is an indicator variable that takes the value of 1 for each week after February 29th, 2020 and zero otherwise. *High COVID Exposure* is an indicator variable that takes the value of 1 for each county-week belonging to the highest tercile of the number of confirmed COVID cases per capita and 0 for each county-week belonging to the lowest tercile of the number of confirmed COVID cases per capita. *Small Firm* (*Assets*) is an indicator variable that takes the value of 1 for firms in the bottom tercile of total assets (measured in the last available quarter) and 0 for firms in the top tercile. *Small Firm* (*Employees*) is an indicator variable that takes the value of 1 for firms in the bottom tercile of total employees (measured in the last available year) and 0 for firms in the top tercile. *High Unionization* is an indicator variable that takes the value of 1 for firms in the top tercile of the labor unionization rate (at the industry level) and 0 for firms in the bottom tercile. *Non-Tradables* is an indicator variable that takes the value of 1 for firms in the non-tradable sector and 0 for firms in the tradable sector. *Low Local Labor Market Depth* is an indicator variable that takes the value of 1 for ZIP codes in the top tercile of the Herfindahl–Hirschman Index of active job postings and 0 for ZIP codes in the bottom tercile of the HHI of active job postings. The HHI is calculated within a ZIP across all employers with active job postings in that ZIP. *High Firm Geographic Concentration* is an indicator variable that takes the value of 1 for firms in the top tercile of the HHI of their operations and 0 for firms in the bottom tercile of the HHI of their operations. The HHI of a firm's operations is calculated by taking the sum of the squared employment shares across all ZIP codes a firm operates in. *Low Local Household Income* is an indicator variable that takes the value of 1 for counties in the bottom tercile of median household income as of 2018 and 0 for counties in the top tercile. *High Local Income Inequality* is an indicator variable that takes the value of 1 for counties in the top tercile of Gini coefficient and 0 for firms in the bottom tercile. *Private Firm* is an indicator variable that takes the value of 1 for private firms and 0 for public firms. *Speculative Grade* is an indicator variable that takes the value of 1 for firms with a speculative grade rating and 0 for firms with an investment grade rating. *No Credit Lines* is an indicator variable that takes the value of 1 for firms with no outstanding lines of credit and 0 for firms with at least one outstanding line of credit. *Low Cash Holdings* is an indicator variable that takes the value of 1 for firms in the lowest tercile of cash (scaled by lagged assets) and 0 for firms in the highest tercile of cash. State controls are the unemployment rate and the logarithm of the labor force. Firm controls are the quarterly logarithm of total assets, profitability (net income divided by lagged assets), cash (divided by lagged assets), leverage (total short- and long-term debt divided by lagged assets), Q (market-to-book ratio), and investment (capital expenditures divided by lagged assets).

Variable	N	Mean	SD	Median	IQR
Dependent Variables					
New Job Postings (Log)	49,385,544	0.31	0.60	0.00	0.69
Δ*Active Job Postings*	26,928,778	0.12	3.80	–0.24	1.17
Δ*Low-Skill Postings*	2,692,847	–0.06	2.02	0.00	1.00
Δ*High-Skill Postings*	3,652,180	–0.20	2.27	–0.67	1.00
High-to-Low-Skills Postings Ratio	567,440	0.28	2.19	0.00	0.00
COVID-19 Exposure					
High COVID Exposure	32,994,411	0.79	0.41	1.00	0.00
Firm Size					
Small Firm (Assets)	14,501,393	0.04	0.19	0.00	0.00
Small Firm (Employees)	15,676,115	0.01	0.10	0.00	0.00
Labor Market Characteristics					
High Unionization	10,942,649	0.37	0.48	0.00	1.00
Non-Tradables	13,267,100	0.50	0.50	0.00	1.00
Low Local Labor Market Depth	35,198,194	0.21	0.41	0.00	0.00
High Firm Geographic Concentration	9,603,235	0.50	0.50	0.00	1.00
Low Local Household Income	32,570,048	0.28	0.45	0.00	1.00
High Local Income Inequality	33,817,979	0.67	0.47	1.00	1.00
Financial Constraints Measures					
Private Firm	49,385,544	0.52	0.50	1.00	1.00
Speculative Grade	20,175,698	0.55	0.50	1.00	1.00
No Credit Lines	49,385,544	0.64	0.48	1.00	1.00
Low Cash Holdings	10,656,009	0.79	0.41	1.00	0.00
State Controls					
State Unemployment Rate (%)	11,404,003	3.93	0.70	4.00	1.00
State Labor Force (Log)	11,404,003	15.38	0.90	15.40	1.19
Firm Controls					
Size	19,853,663	9.11	1.83	9.07	2.54
Cash	19,560,335	0.09	0.13	0.05	0.09
Leverage	19,816,521	0.39	1.08	0.33	0.31
Profitability	19,702,080	0.02	0.04	0.01	0.02
Q	19,578,570	1.99	1.48	1.78	1.10
Investment	19,552,052	0.03	0.04	0.02	0.03

Table 2. The Impact of COVID-19 on Job Postings: Baseline

This table reports output from Eq. (1). The dependent variables are *New Job Postings* and Δ*Active Job Postings*. The unit of observation is a firm–ZIP–week, where ZIP is the three-digit ZIP-code of a job posting. *New Job Postings* is the logarithm of one plus the total number of job postings created. Δ*Active Job Postings* is the percentage change (relative to the same week in the previous year) in total active job postings. *Post COVID* is an indicator variable that takes the value of 1 for each week after February 29th, 2020 and zero otherwise. *High COVID Exposure* is an indicator variable that takes the value of 1 for each county-week belonging to the highest tercile of the number of confirmed COVID cases per capita and 0 for each county-week belonging to the lowest tercile of the number of confirmed COVID cases per capita. State controls are the unemployment rate and the logarithm of the labor force. Firm controls are the quarterly logarithm of total assets, profitability (net income divided by lagged assets), cash (divided by lagged assets), leverage (total short- and long-term debt divided by lagged assets), Q (market-to-book ratio), and investment (capital expenditures divided by lagged assets). Firm×quarter–, ZIP–, and week–fixed effects are included as indicated. All regressions are estimated over a sample of private and public firms over the January 1st, 2017 to May 5th, 2020 period. Robust standard errors, reported in parentheses, are triple–clustered by firm, ZIP, and week.

	New Job Postings		Δ*Active Job Postings*	
	(1)	(2)	(3)	(4)
Post COVID	–0.035***		–0.147***	
	(0.011)		(0.034)	
Post COVID × *High COVID Exposure*		–0.040***		–0.155***
		(0.013)		(0.045)
Controls	Yes	Yes	Yes	Yes
Fixed Effects				
Firm × Quarter	Yes	Yes	Yes	Yes
ZIP	Yes	Yes	Yes	Yes
Week	No	Yes	No	Yes
Observations	11,387,645	7,841,929	25,989,424	17,458,249
R-squared	0.385	0.386	0.267	0.287

Statistical significance is indicated as follows: *** p <0.01, ** p <0.05, * p <0.1.

Table 3. The Impact of COVID-19 on Job Postings: Worker Skills

This table reports output from Eq. (1). The dependent variables are Δ*Low-Skill Postings*, Δ*High-Skill Postings*, and *High-to-Low-Skills Postings Ratio*. The unit of observation is a firm–ZIP–week, where ZIP is the three-digit ZIP-code of a job posting. Δ*Low-Skill* (*High-Skill*) *Postings* postings is the percentage change, relative to the same week in the previous year, in job postings for occupations with O*NET occupation codes corresponding to Job Zone 1 (5). *High-to-Low-Skills Postings Ratio* is the total number of job postings created for occupations with O*NET occupation codes corresponding to Job Zone 5 divided by the total number of job postings created for occupations with O*NET occupation codes corresponding to Job Zone 1. *Post COVID* is an indicator variable that takes the value of 1 for each week after February 29th, 2020 and zero otherwise. *High COVID Exposure* is an indicator variable that takes the value of 1 for each county-week belonging to the highest tercile of the number of confirmed COVID cases per capita and 0 for each county-week belonging to the lowest tercile of the number of confirmed COVID cases per capita. State and firm controls are as defined in Table 2. Firm×quarter–, ZIP–, and week–fixed effects are included as indicated. All regressions are estimated over a sample of private and public firms over the January 1st, 2017 to May 5th, 2020 period. Robust standard errors, reported in parentheses, are triple–clustered by firm, ZIP, and week.

	Δ*Low-Skill Postings*		Δ*High-Skill Postings*		*High-to-Low-Skills Postings Ratio*	
	(1)	(2)	(3)	(4)	(5)	(6)
Post COVID	–0.088**		–0.112***		–0.051**	
	(0.033)		(0.038)		(0.020)	
Post COVID × *High COVID Exposure*		–0.091***		–0.117***		–0.064***
		(0.029)		(0.029)		(0.017)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects						
Firm × Quarter	Yes	Yes	Yes	Yes	Yes	Yes
ZIP	Yes	Yes	Yes	Yes	Yes	Yes
Week	No	Yes	No	Yes	No	Yes
Observations	2,622,347	1,736,534	3,499,555	2,458,596	544,138	397,951
R-squared	0.164	0.162	0.261	0.248	0.621	0.593

Statistical significance is indicated as follows: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 4. The Impact of COVID-19 on Job Postings: Firm Size

This table reports output from Eq. (1). The dependent variables are *New Job Postings* and *High-to-Low-Skills Postings Ratio*. The unit of observation is a firm–ZIP–week, where ZIP is the three-digit ZIP-code of a job posting. *New Job Postings* is the logarithm of one plus the total number of job postings created. *High-to-Low-Skills Postings Ratio* is the total number of job postings created for occupations with O*NET occupation codes corresponding to Job Zone 5 divided by the total number of job postings created for occupations with O*NET occupation codes corresponding to Job Zone 1. *Post COVID* is an indicator variable that takes the value of 1 for each week after February 29th, 2020 and zero otherwise. *Small Firm* (*Assets*) is an indicator variable that takes the value of 1 for firms in the bottom tercile of total assets (measured in the last available quarter) and 0 for firms in the top tercile. *Small Firm* (*Employees*) is an indicator variable that takes the value of 1 for firms in the bottom tercile of total employees (measured in the last available year) and 0 for firms in the top tercile. State and firm controls are as defined in Table 2. Firm×quarter–, industry×quarter–, ZIP–, and week–fixed effects are included as indicated. All regressions are estimated over a sample of public firms over the January 1st, 2017 to May 5th, 2020 period. Robust standard errors, reported in parentheses, are triple–clustered by firm, ZIP, and week.

	New Job Postings		*High-to-Low-Skills Postings Ratio*	
	(1)	(2)	(3)	(4)
Post COVID × *Small Firm* (*Assets*)	–0.231***		–0.183***	
	(0.042)		(0.048)	
Post COVID × *Small Firm* (*Employees*)		–0.234***		–0.162***
		(0.066)		(0.037)
Controls	Yes	Yes	Yes	Yes
Fixed Effects				
Industry × Quarter	Yes	Yes	Yes	Yes
ZIP	Yes	Yes	Yes	Yes
Week	Yes	Yes	Yes	Yes
Observations	3,570,023	3,911,149	137,621	176,172
R-squared	0.175	0.164	0.113	0.110

Statistical significance is indicated as follows: *** p <0.01, ** p <0.05, * p <0.1.

Table 5. The Impact of COVID-19 on Job Postings: Labor Market and Geographical Characteristics

This table reports output from Eq. (1). The dependent variables are *New Job Postings* and *High-to-Low-Skills Postings Ratio*. The unit of observation is a firm–ZIP–week, where ZIP is the three-digit ZIP-code of a job posting. *New Job Postings* is the logarithm of one plus the total number of job postings created. *High-to-Low-Skills Postings Ratio* is the total number of job postings created for occupations with O*NET occupation codes corresponding to Job Zone 5 divided by the total number of job postings created for occupations with O*NET occupation codes corresponding to Job Zone 1. *Post COVID* is an indicator variable that takes the value of 1 for each week after February 29th, 2020 and zero otherwise. *High Unionization* is an indicator variable that takes the value of 1 for firms in the top tercile of the labor unionization rate (at the industry level) and 0 for firms in the bottom tercile. *Non-Tradables* is an indicator variable that takes the value of 1 for firms in the non-tradable sector and 0 for firms in the tradable sector. *Low Local Labor Market Depth* is an indicator variable that takes the value of 1 for ZIP codes in the top tercile of the Herfindahl–Hirschman Index of active job postings and 0 for ZIP codes in the bottom tercile of the HHI of active job postings. The HHI is calculated within a ZIP across all employers with active job postings in that ZIP. *High Firm Geographic Concentration* is an indicator variable that takes the value of 1 for firms in the top tercile of the HHI of their operations and 0 for firms in the bottom tercile of the HHI of their operations. The HHI of a firm's operations is calculated by taking the sum of the squared employment shares across all ZIP codes a firm operates. State and firm controls are as defined in Table 2. Firm×quarter–, industry×quarter–, ZIP–, and week–fixed effects are included as indicated. All regressions are estimated over a sample of private and public firms (except column (4) which is estimated over public firms) over the January 1st, 2017 to May 5th, 2020 period. Robust standard errors, reported in parentheses, are triple–clustered by firm, ZIP, and week.

	New Job Postings			
	(1)	(2)	(3)	(4)
Post COVID × *High Unionization*	–0.022**			
	(0.010)			
Post COVID × *Non-Tradables*		–0.007**		
		(0.003)		
Post COVID × *Low Local Labor Market Depth*			–0.073**	
			(0.029)	
Post COVID × *High Firm Geographic Concentration*				–0.067***
				(0.015)
Controls	Yes	Yes	Yes	Yes
Fixed Effects				
Firm × Quarter	Yes	Yes	Yes	No
Industry × Quarter	No	No	No	Yes
ZIP	Yes	Yes	Yes	Yes
Week	Yes	Yes	Yes	Yes
Observations	2,592,686	2,997,243	8,324,025	2,309,688
R-squared	0.388	0.255	0.331	0.211

	High-to-Low-Skills Postings Ratio			
	(5)	(6)	(7)	(8)
Post COVID × High Unionization	–0.015***			
	(0.002)			
Post COVID × Non-Tradables		–0.009**		
		(0.004)		
Post COVID × Low Local Labor Market Depth			–0.016**	
			(0.007)	
Post COVID × High Firm Geographic Concentration				–0.029*
				(0.016)
Controls	Yes	Yes	Yes	Yes
Fixed Effects				
Firm × Quarter	Yes	Yes	Yes	No
Industry × Quarter	No	No	No	Yes
ZIP	Yes	Yes	Yes	Yes
Week	Yes	Yes	Yes	Yes
Observations	128,638	122,037	344,106	160,312
R-squared	0.440	0.482	0.614	0.110

Statistical significance is indicated as follows: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 6. The Impact of COVID-19 on Job Postings: Access to Finance and Credit

This table reports output from Eq. (1). The dependent variables are *New Job Postings* and *High-to-Low-Skills Postings Ratio*. The unit of observation is a firm–ZIP–week, where ZIP is the three-digit ZIP-code of a job posting. *New Job Postings* is the logarithm of one plus the total number of job postings created. *High-to-Low-Skills Postings Ratio* is the total number of job postings created for occupations with O*NET occupation codes corresponding to Job Zone 5 divided by the total number of job postings created for occupations with O*NET occupation codes corresponding to Job Zone 1. *Post COVID* is an indicator variable that takes the value of 1 for each week after February 29th, 2020 and zero otherwise. *Private Firm* is an indicator variable that takes the value of 1 for private firms and 0 for public firms. *Speculative Grade* is an indicator variable that takes the value of 1 for firms with a speculative grade rating and 0 for firms with an investment grade rating. *No Credit Lines* is an indicator variable that takes the value of 1 for firms with no outstanding lines of credit and 0 for firms with at least one outstanding line of credit. *Low Cash Holdings* is an indicator variable that takes the value of 1 for firms in the lowest tercile of cash (scaled by lagged assets) and 0 for firms in the highest tercile of cash. State and firm controls are as defined in Table 2. Firm×quarter–, industry×quarter–, ZIP–, and week–fixed effects are included as indicated. All regressions are estimated over a sample of private and public firms (except columns (2) through (4) which are estimated over public firms) over the January 1st, 2017 to May 5th, 2020 period. Robust standard errors, reported in parentheses, are triple–clustered by firm, ZIP, and week.

	New Job Postings			
	(1)	(2)	(3)	(4)
Post COVID × *Private Firm*	–0.027**			
	(0.013)			
Post COVID × *Speculative Grade*		–0.038**		
		(0.014)		
Post COVID × *No Credit Lines*			–0.051***	
			(0.011)	
Post COVID × *Low Cash Holdings*				–0.049***
				(0.015)
Controls	Yes	Yes	Yes	Yes
Fixed Effects				
Firm × Quarter	Yes	No	No	No
Industry × Quarter	No	Yes	Yes	Yes
ZIP	Yes	Yes	Yes	Yes
Week	Yes	Yes	Yes	Yes
Observations	11,387,645	4,649,078	10,486,090	2,454,872
R-squared	0.385	0.144	0.080	0.118

	High-to-Low-Skills Postings Ratio			
	(5)	(6)	(7)	(8)
Post COVID × *Private Firm*	–0.080**			
	(0.036)			
Post COVID × *Speculative Grade*		–0.024**		
		(0.010)		
Post COVID × *No Credit Lines*			–0.054***	
			(0.009)	
Post COVID × *Low Cash Holdings*				–0.069**
				(0.034)
Controls	Yes	Yes	Yes	Yes
Fixed Effects				
Firm × Quarter	Yes	No	No	No
Industry × Quarter	No	Yes	Yes	Yes
ZIP	Yes	Yes	Yes	Yes
Week	Yes	Yes	Yes	Yes
Observations	544,138	185,686	538,114	70,405
R-squared	0.603	0.101	0.122	0.224

Statistical significance is indicated as follows: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 7. The Impact of COVID-19 on Job Postings: Income Levels and Inequality

This table reports output from Eq. (1). The dependent variables are *New Job Postings* and *High-to-Low-Skills Postings Ratio*. The unit of observation is a firm–ZIP–week, where ZIP is the three-digit ZIP-code of a job posting. *New Job Postings* is the logarithm of one plus the total number of job postings created. *High-to-Low-Skills Postings Ratio* is the total number of job postings created for occupations with O*NET occupation codes corresponding to Job Zone 5 divided by the total number of job postings created for occupations with O*NET occupation codes corresponding to Job Zone 1. *Post COVID* is an indicator variable that takes the value of 1 for each week after February 29th, 2020 and zero otherwise. *Low Local Household Income* is an indicator variable that takes the value of 1 for counties in the bottom tercile of median household income as of 2018 and 0 for counties in the top tercile. *High Local Income Inequality* is an indicator variable that takes the value of 1 for counties in the top tercile of Gini coefficient and 0 for firms in the bottom tercile. State and firm controls are as defined in Table 2. Firm×quarter–, industry×quarter–, ZIP–, and week–fixed effects are included as indicated. All regressions are estimated over a sample of private and public firms (except columns (2) and (3) which are estimated over public firms) over the January 1st, 2017 to May 5th, 2020 period. Robust standard errors, reported in parentheses, are triple–clustered by firm, ZIP, and week.

	New Job Postings		*High-to-Low-Skills Postings Ratio*	
	(1)	(2)	(3)	(4)
Post COVID × *Low Local Household Income*	–0.025**		–0.008**	
	(0.010)		(0.003)	
Post COVID × *High Local Income Inequality*		–0.033***		–0.019**
		(0.011)		(0.007)
Controls	Yes	Yes	Yes	Yes
Fixed Effects				
Firm × Quarter	Yes	Yes	Yes	Yes
ZIP	Yes	Yes	Yes	Yes
Week	Yes	Yes	Yes	Yes
Observations	7,596,947	7,774,418	329,495	346,391
R-squared	0.344	0.377	0.579	0.553

Appendix A O*NET Job Zone Classification

Table A.1. List of Low Skill Jobs

This table reports the list of low skill jobs with O*NET occupation codes corresponding to Job Zone 1.

Low Skill Occupations
Cooks, Fast Food
Food Preparation Workers
Combined Food Preparation and Serving Workers, Including Fast Food
Counter Attendants, Cafeteria, Food Concession, and Coffee Shop
Baristas
Food Servers, Nonrestaurant
Dining Room and Cafeteria Attendants and Bartender Helpers
Dishwashers
Landscaping and Groundskeeping Workers
Amusement and Recreation Attendants
Models
Door-To-Door Sales Workers, News and Street Vendors, and Related Workers
Graders and Sorters, Agricultural Products
Agricultural Equipment Operators
Farmworkers and Laborers, Crop
Fishers and Related Fishing Workers
Hunters and Trappers
Fallers
Logging Equipment Operators
Cement Masons and Concrete Finishers
Plasterers and Stucco Masons
Helpers–Painters, Paperhangers, Plasterers, and Stucco Masons
Septic Tank Servicers and Sewer Pipe Cleaners
Derrick Operators, Oil and Gas
Rock Splitters, Quarry
Roustabouts, Oil and Gas
Fabric Menders, Except Garment
Meat, Poultry, and Fish Cutters and Trimmers
Laundry and Dry-Cleaning Workers
Pressers, Textile, Garment, and Related Materials
Sewing Machine Operators
Grinding and Polishing Workers, Hand
Cutters and Trimmers, Hand
Painting, Coating, and Decorating Workers
Bridge and Lock Tenders
Conveyor Operators and Tenders

Table A.2. List of High Skill Jobs

This table reports the list of high skill jobs with O*NET occupation codes corresponding to Job Zone 5.

High Skill Jobs	
Chief Executives	Sociologists
Chief Sustainability Officers	Urban and Regional Planners
Treasurers and Controllers	Anthropologists
Education Administrators, Elementary and Secondary School	Archeologists
Education Administrators, Postsecondary	Geographers
Distance Learning Coordinators	Historians
Architectural and Engineering Managers	Political Scientists
Medical and Health Services Managers	Substance Abuse and Behavioral Disorder Counselors
Natural Sciences Managers	Educational, Guidance, School, and Vocational Counselors
Investment Fund Managers	Marriage and Family Therapists
Management Analysts	Mental Health Counselors
Financial Quantitative Analysts	Rehabilitation Counselors
Computer and Information Research Scientists	Healthcare Social Workers
Mathematicians	Mental Health and Substance Abuse Social Workers
Operations Research Analysts	Clergy
Statisticians	Lawyers
Biostatisticians	Judicial Law Clerks
Environmental Engineers	Administrative Law Judges, Adjudicators, and Hearing Officers
Human Factors Engineers and Ergonomists	Arbitrators, Mediators, and Conciliators
Fuel Cell Engineers	Judges, Magistrate Judges, and Magistrates
Microsystems Engineers	Business Teachers, Postsecondary
Nanosystems Engineers	Computer Science Teachers, Postsecondary
Animal Scientists	Mathematical Science Teachers, Postsecondary
Soil and Plant Scientists	Architecture Teachers, Postsecondary
Biologists	Engineering Teachers, Postsecondary
Biochemists and Biophysicists	Agricultural Sciences Teachers, Postsecondary
Microbiologists	Biological Science Teachers, Postsecondary
Zoologists and Wildlife Biologists	Forestry and Conservation Science Teachers, Postsecondary
Bioinformatics Scientists	Atmospheric, Earth, Marine, and Space Sciences Teachers, Postsecondary
Molecular and Cellular Biologists	Chemistry Teachers, Postsecondary
Geneticists	Environmental Science Teachers, Postsecondary
Epidemiologists	Physics Teachers, Postsecondary
Medical Scientists, Except Epidemiologists	Anthropology and Archeology Teachers, Postsecondary
Astronomers	Area, Ethnic, and Cultural Studies Teachers, Postsecondary
Physicists	Economics Teachers, Postsecondary
Materials Scientists	Geography Teachers, Postsecondary
Climate Change Analysts	Political Science Teachers, Postsecondary
Environmental Restoration Planners	Psychology Teachers, Postsecondary
Industrial Ecologists	Sociology Teachers, Postsecondary
Hydrologists	Health Specialties Teachers, Postsecondary
Remote Sensing Scientists and Technologists	Nursing Instructors and Teachers, Postsecondary
Economists	Education Teachers, Postsecondary
Environmental Economists	Library Science Teachers, Postsecondary
Survey Researchers	Criminal Justice and Law Enforcement Teachers, Postsecondary
School Psychologists	Law Teachers, Postsecondary
Clinical Psychologists	Social Work Teachers, Postsecondary
Counseling Psychologists	Art, Drama, and Music Teachers, Postsecondary
Industrial-Organizational Psychologists	Communications Teachers, Postsecondary
Neuropsychologists and Clinical Neuropsychologists	English Language and Literature Teachers, Postsecondary

High Skill Jobs	
History Teachers, Postsecondary	Veterinarians
Philosophy and Religion Teachers, Postsecondary	Advanced Practice Psychiatric Nurses
Graduate Teaching Assistants	Clinical Nurse Specialists
Home Economics Teachers, Postsecondary	Nurse Anesthetists
Recreation and Fitness Studies Teachers, Postsecondary	Nurse Midwives
Special Education Teachers, Preschool	Nurse Practitioners
Archivists	Audiologists
Curators	Acupuncturists
Librarians	Naturopathic Physicians
Farm and Home Management Advisors	Orthoptists
Instructional Coordinators	Cytotechnologists
Instructional Designers and Technologists	Orthotists and Prosthetists
Set and Exhibit Designers	Athletic Trainers
Chiropractors	Genetic Counselors
Dentists, General	Foreign Language and Literature Teachers, Postsecondary
Oral and Maxillofacial Surgeons	
Orthodontists	
Prosthodontists	
Dietitians and Nutritionists	
Optometrists	
Pharmacists	
Anesthesiologists	
Family and General Practitioners	
Internists, General	
Obstetricians and Gynecologists	
Pediatricians, General	
Psychiatrists	
Surgeons	
Allergists and Immunologists	
Dermatologists	
Hospitalists	
Neurologists	
Nuclear Medicine Physicians	
Ophthalmologists	
Pathologists	
Physical Medicine and Rehabilitation Physicians	
Preventive Medicine Physicians	
Radiologists	
Sports Medicine Physicians	
Urologists	
Physician Assistants	
Anesthesiologist Assistants	
Podiatrists	
Occupational Therapists	
Low Vision Therapists, Orientation and Mobility Specialists, and Vision Rehabilitation Therapists	
Physical Therapists	
Art Therapists	
Speech-Language Pathologists	
Exercise Physiologists	

Appendix B NAICS Industry Classification

Table B.1. List of 3-Digit NAICS Industries

This table reports the list of 3-digit NAICS codes belonging to each industry.

Industry Category	3-Digit NAICS Codes
Agriculture	111,112,115
Mining, Oil & Gas	211,212,213
Utilities	221
Construction	236,237,238
Food	311,722
Beverage & Tobacco Manufacturing	312
Textile Manufacturing	313,314,315,316
Wood Product Manufacturing	321
Printing & Paper	322,323
Chemicals	324,325,326
Metals & Machinery	327,331,332,333
Computer & Electronic Manufacturing	334
Electrical Equipment Manufacturing	335
Transportation Equipment Manufacturing	336
Furniture Product Manufacturing	337
Wholesalers	423,424,425
Retail Trade	441,442,443,444,445,446,447,448,451,452,453,454
Transportation & Warehousing	481,482,483,484,485,486,487,488,492,493
Publishing Industries	511
Telecom & Information Services	512,515,517,518,519
Financial Services	522,523,524,525
Real Estate	531,532,533
Professional, Scientific & Technical Services	541
Management Services	551
Administrative & Support Services	561
Waste Management & Remediation	562
Educational Services	611
Ambulatory Health Care Services	621
Hospitals	622
Nursing & Residential Care Facilities	623
Social Assistance	624
Amusement, Gambling & Recreation	713
Accommodation	721
Repair & Maintenance	811
Personal & Laundry Service	812

Table C.1. The Impact of COVID-19 on Job Postings: Worker Skills Robustness

This table reports output from Eq. (1). The dependent variables are *High (4-5)-to-Low (1-2)-Skills Postings Ratio*, *High (5)-to-Low (1-2)-Skills Postings Ratio*, and *High (4-5)-to-Low (1)-Skills Postings Ratio*. The unit of observation is a firm–ZIP–week, where ZIP is the three-digit ZIP-code of a job posting. *High (4-5)-to-Low (1-2)-Skills Postings Ratio* is the total number of job postings created for occupations with O*NET occupation codes corresponding to Job Zones 4 and 5 divided by the total number of job postings created for occupations with O*NET occupation codes corresponding to Job Zones 1 and 2. *High (5)-to-Low (1-2)-Skills Postings Ratio* is the total number of job postings created for occupations with O*NET occupation codes corresponding to Job Zone 5 divided by the total number of job postings created for occupations with O*NET occupation codes corresponding to Job Zones 1 and 2. *High (4-5)-to-Low (1)-Skills Postings Ratio* is the total number of job postings created for occupations with O*NET occupation codes corresponding to Job Zones 4 and 5 divided by the total number of job postings created for occupations with O*NET occupation codes corresponding to Job Zone 1. *Post COVID* is an indicator variable that takes the value of 1 for each week after February 29^{th}, 2020 and zero otherwise. *High COVID Exposure* is an indicator variable that takes the value of 1 for each county-week belonging to the highest tercile of the number of confirmed COVID cases per capita and 0 for each county-week belonging to the lowest tercile of the number of confirmed COVID cases per capita. State and firm controls are as defined in Table 2. Firm×quarter–, ZIP–, and week–fixed effects are included as indicated. All regressions are estimated over a sample of private and public firms over the January 1^{st}, 2017 to May 5^{th}, 2020 period. Robust standard errors, reported in parentheses, are triple–clustered by firm, ZIP, and week.

	High (4-5)-to-Low (1-2)-Skills Postings Ratio		*High (5)-to-Low (1-2)-Skills Postings Ratio*		*High (4-5)-to-Low (1)-Skills Postings Ratio*	
	(1)	(2)	(3)	(4)	(5)	(6)
Post COVID	–0.015***		–0.036***		–0.082**	
	(0.005)		(0.003)		(0.038)	
Post COVID × *High COVID Exposure*		–0.034***		–0.051***		–0.092***
		(0.09)		(0.005)		(0.016)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects						
Firm × Quarter	Yes	Yes	Yes	Yes	Yes	Yes
ZIP	Yes	Yes	Yes	Yes	Yes	Yes
Week	Yes	Yes	Yes	Yes	Yes	Yes
Observations	544,138	397,951	544,138	397,951	544,138	397,951
R-squared	0.202	0.202	0.204	0.209	0.541	0.539

Statistical significance is indicated as follows: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table C.2. The Impact of COVID-19 on Job Postings: COVID-19 Exposure Robustness

This table reports output from Eq. (1). The dependent variables are *New Job Postings* and *High-to-Low-Skills Postings Ratio*. The unit of observation is a firm–ZIP–week, where ZIP is the three-digit ZIP-code of a job posting. *New Job Postings* is the logarithm of one plus the total number of job postings created. *High-to-Low-Skills Postings Ratio* is the total number of job postings created for occupations with O*NET occupation codes corresponding to Job Zone 5 divided by the total number of job postings created for occupations with O*NET occupation codes corresponding to Job Zone 1. *Post COVID* is an indicator variable that takes the value of 1 for each week after February 29th, 2020 and zero otherwise. *High COVID Exposure* (*Quartiles*) is an indicator variable that takes the value of 1 for each county-week belonging to the highest quartile of the number of confirmed COVID cases per capita and 0 for each county-week belonging to the lowest quartile of the number of confirmed COVID cases per capita. *High COVID Exposure* (*Quintiles*) and *High COVID Exposure* (*Deciles*) are analogously defined. State and firm controls are as defined in Table 2. Firm×quarter–, ZIP–, and week–fixed effects are included as indicated. All regressions are estimated over a sample of private and public firms over the January 1st, 2017 to May 5th, 2020 period. Robust standard errors, reported in parentheses, are triple–clustered by firm, ZIP, and week.

	New Job Postings			*High-to-Low-Skills Postings Ratio*		
	(1)	(2)	(3)	(4)	(5)	(6)
Post COVID × *High COVID Exposure* (*Quartiles*)	–0.042***			–0.066**		
	(0.013)			(0.028)		
Post COVID × *High COVID Exposure* (*Quintiles*)		–0.047***			–0.092**	
		(0.013)			(0.041)	
Post COVID × *High COVID Exposure* (*Deciles*)			–0.051***			–0.098**
			(0.015)			(0.044)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects						
Firm × Quarter	Yes	Yes	Yes	Yes	Yes	Yes
ZIP	Yes	Yes	Yes	Yes	Yes	Yes
Week	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,030,895	4,804,020	1,941,381	224,017	175,644	69,949
R-squared	0.387	0.394	0.414	0.600	0.604	0.580

Statistical significance is indicated as follows: *** p <0.01, ** p <0.05, * p <0.1.