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Effects of stay-at-home orders on skill requirements in vacancy postings[☆]

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The COVID-19 pandemic and containment policies have had profound economic impacts on the labor market. Stay-at-home orders (SAHOs) implemented across most of the United States changed the way of people worked. In this paper, we quantify the effect of SAHO durations on skill demands to study how firms adjust labor demand within occupation. We use skill requirement information from the 2018 to 2021 online job vacancy posting data from Burning Glass Technologies, exploit the spatial variations in the SAHO duration, and use instrumental variables to correct for the endogeneity in the policy duration related to local social and economic factors. We find that policy durations have persistent impacts on the labor demand after restrictions are lifted. Longer SAHOs motivate management style transformation from people-oriented to operation-oriented by requiring more of operational and administrative skills and less of personality and people management skills to carry out standard workflows. SAHOs also change the focus of interpersonal skill demands from specific customer services to general communication such as social and writing skills. SAHOs more thoroughly affect occupations with partial work-from-home capacity. The evidence suggests SAHOs change management structure and communication in firms.

1. Introduction

Most states in the United States implemented Stay-at-Home orders (SAHOs) in the spring of 2020. These policies had a profound impact on the work environment almost overnight, causing half the U.S. workforce to switch to home-working by the first weeks of April 2020 (Brynjolfsson et al., 2020). The pandemic and the experience of living under the SAHOs made many firms believe they have to constantly be prepared for “everyone who can must suddenly work from home” (Kirby, 2020). The scope and suitability of workplace transformation following the COVID-19 recovery is a widespread trend among firms accompanied by vigorous debates in the media.[1] Does the labor demand go back to the pre-COVID scenario or does it change in the long run? How do firms manage employees amid a turbulent situation? Answering these questions gives us important and up-to-date perceptions of the labor market and insights on how firms manage labor. In this paper, we contribute to the discussion by studying the effect of SAHO duration variation on firms’ demand for skills within occupation after the orders are lifted.

In the spring of 2020, 40 states and the District of Columbia issued SAHOs. State-level SAHO duration ranged between 28 and 97 days with a raw average of 44 days. A firm’s location determines how long it is affected by the SAHO and affects the magnitude of its labor demand change. While firms exposed to short SAHOs may choose to pause their pre-COVID functioning and go back to the old routine after orders are lifted, those affected by longer SAHOs may be more willing to seek alternative work arrangements to keep the firms running amid COVID restrictions. After the SAHOs are lifted, these firms could stick to the new way of working and demand a different set of skills when hiring, making the impact of SAHO persistent. The variation allows us to quantify the marginal effect of SAHO duration on the demand for skills and separate the effect of SAHOs from the homogeneous impact of COVID.

Studying the effect of SAHOs on labor demand through online job ads is important for understanding employment amid the pandemic and

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[1] For example, see Boland et al. (2020) and Lau et al. (2021).

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has attracted researchers' interest. A growing empirical literature argued that SAHOs were likely to have substantial and potentially long-run negative disruption to labor markets in the United States. The orders accounted for about one-quarter of new unemployment insurance claims between March 14th and April 4th, 2020 (Baek et al., 2021). A study on the SAHO and employment in California showed the tradeoff between policy duration and labor market disruption (Friedson et al., 2021). Ali et al. (2021) show that the impact of SAHOs on job postings in early care and education is 16 times larger than their impact on education hiring broadly. In addition, households living in regions with an earlier enactment of SAHOs hold more pessimistic views of the future path of the economy (Coibion et al., 2020b). However, there is still relatively little direct evidence on how firms modify employment in the face of the pandemic and the subsequent SAHOs.

In this paper, we investigate how SAHOs have changed the demand for skills. This is not a straightforward question to answer since the changes in advertised job skill requirements could plausibly be attributed to a multitude of factors other than SAHOs that occurred at the same time. For example, the pandemic worsening may cause economic uncertainty or growing demands for medical personnel. We disentangle the local effects of SAHOs from the broader economic disruption brought on by the COVID-19 pandemic and other factors affecting all states equally by taking advantage of the cross-sectional variation in the duration of SAHOs across geographical areas. The correlation between SAHO duration and the difference between pre-COVID and post-SAHO skill requirements helps us pin down the effects of SAHOs. Moreover, considering the COVID containment policies may be endogenous to local social and economic factors, we employ two instrumental variables, i.e., the number of ICU beds and the population density, for SAHO duration to identify the causal impact of SAHOs on skill demands. To the best of our knowledge, we are the first to document that SAHO duration has heterogeneous effects on the labor skill demand after the orders have been lifted.

We use a micro-level dataset collected by Burning Glass Technologies (BGT), a labor market data company, that contains the near-universe of electronically posted job vacancies in the United States from January 2018 to April 2021. The BGT data records the skill requirements in job postings. To study the change in demand for skills, we classify 98.84% of all skill requirements in job postings into 19 representative categories. Identifying skills describing personal characteristics and self-management ability allows us to capture the demand for employee characteristics. Separately defining people management, project management, and operational management skills enables a discussion on the change in management styles. We construct a panel data of statistics on skill requirements in job postings, SAHO duration, and local medical and demographic statistics for each occupation and metropolitan statistical area (MSA). We compare the demand for skills from the pre-COVID period, i.e., up to December 2019, and from the post-SAHO period, i.e., after the SAHOs are lifted, because neither period is constrained by the SAHO order.[2] Exploiting the spatial variation in SAHO duration and using two-stage-least-square (2SLS) regressions to handle endogeneity, we establish the following new facts:

We find that the effect of SAHO duration on skill requirements is more about the way of working than the content of work. First, firms that experienced longer SAHOs change their management orientation from people to the operation. To achieve this change, firms demand more skills in operational management, administration and languages, and less on people management, personality and self-management. Second, SAHOs motivate firms to shift the focus of interpersonal skills from specific communication, such as customer services, to general communication, such as social skills.

We find heterogeneous effects by the varying capability to work from home (WFH) of the occupation. Skill demands in occupations with very low capacity to WFH are hardly affected by the SAHO duration. For occupations with high WFH capacity, SAHO duration promotes specialization in these occupations by lowering the extensive margin demands and raising the intensive margin demands. The most dynamic effects are observed in occupations with partial WFH capacity. The large effects on management and work process-related skills suggest that longer SAHOs incentivize firms to explore the WFH potentials of these occupations by diminishing the necessity of in-person supervision.

This paper is related to a number of important literatures. Our paper contributes to the large literature on the consequences of the COVID-19 pandemic on the labor markets. Empirical research using household surveys (e.g., Adams-Prassl et al., 2020b; Carrillo-Tudela et al., 2022), the Nielsen Homescan data (Coibion et al., 2020a), the administrative payroll data (Cajner et al., 2020), the Homebase and Earnings data in the private sector (Chetty et al., 2020), and vacancy data (e.g., Costa Dias et al., 2021; Forsythe et al., 2020) all document substantial impacts of the unprecedented pandemic. Researchers have provided evidence that workers in low-work-from-home jobs are more vulnerable to COVID-induced job losses (e.g., Adams-Prassl et al., 2020b; Mongey et al., 2021). COVID-19 caused a reallocation of job opportunities across occupations (Barrero et al., 2021; Carrillo-Tudela et al., 2022). As a result, there have been changes in where individuals search: workers target their job search direction in favor of occupations that are more resilient to the pandemic (e.g., Carrillo-Tudela et al., 2022; Hensvik et al., 2021). In complementarity with the evidence on shifts across occupations, we study the intra-occupational margin to enrich the story about the heterogeneous impacts of COVID on occupations and document the diversified impacts of COVID on skill requirements across occupations.

Another strand of research studied the labor market impacts of the COVID-19 related policies. For example, Adams-Prassl et al. (2020a) construct a representative survey in the U.K. to investigate the characteristics and behavior of workers during the Coronavirus Job Retention Scheme, which allows employers to reduce employees' hours rather than firing them. Bartik et al. (2020) and Finamor and Scott (2021) analyze the effect of the Coronavirus Aid, Relief, and Economic Stimulus Act, a temporary unemployment insurance expansion scheme in the U.S., on employment. Mongey et al. (2021) estimate the heterogeneous impact of COVID on workers by demographics and show that economically and educationally disadvantaged workers are affected to a greater extent. Most studies on this topic have analyzed the changes in labor supply or employment. We add to this research topic by providing the effect of SAHOs from the labor demand perspective.

Third, we contribute to a growing literature exploiting the BGT data to measure skill requirements. Deming and Kahn (2018) study the link among firm performance, the pay of jobs, and skill requirements using keywords-based skill categories. Hershbein and Kahn (2018) show the magnitude of changes in skill requirements during the recovery following the Great Recession across the MSAs depends on the intensity of the recession on the local economy. Our paper is the first to study the quantitative change in skill requirements caused by the recent pandemic containment policies.

Lastly, literature has shown that firms use recessions as opportunities to adjust management structures. Hall (1991) argues that firms may restructure employment in a recession because of a decline in the opportunity cost. The model developed by Koenders and Rogerson (2005) shows that firms postpone organizational restructuring until the end of an expansion and shift managerial attention from growth to efficiency during recessions. Our paper adds to this literature by showing that COVID, as an incident similar but more complex than an economic recession, also induces changes in the restructuring of employee composition and management styles.

The paper proceeds as follows. Section 2 describes the data, the definition of skills, and the key variables. In Section 3, we present our re-

[2] Forsythe et al. (2020) use the BGT data up to the end of April 2020 and show the number of job postings falls significantly from late March.

gression specification. Section 4 presents the results, and we conclude in Section 5.

2. Data and key variables

2.1. Data sources

2.1.1. Burning glass job postings data

The Burning Glass Technologies (BGT) data has been used in many recent economic research (e.g., Deming and Kahn, 2018; Hershbein and Kahn, 2018). It is an ongoing data of all online job postings in the U.S. from January 2010 with detailed information on the job posting date, job location, industry, occupation, salary, and requirements in terms of skills, education, certification and work experience. In the data file we have, the most recent job posting was in April 2021. To study the impact of the COVID pandemic, we use all job postings in the 50 states from January 2018 to April 2021. The BGT data records all skill requirements in the job posting. To study the change in demand for skills, we classify 7481 skills into 19 categories.[3] The classified skills account for 98.84% of all skill requirements in job postings. At the job level, we fully classify all skills required in 90.92% of the postings. In Online Appendix Table A1, we list the skill categories and up to five most common skill cluster families in it.[4] For three skill skills among the 19 categories, namely personality, self-management and language skills, we list all skill names in the categories in descending order of their frequencies in the job posting data.[5]

The skill classification highlights the distinction among management skills related to people, operations, and projects. This allows us to track the changes in management structure and the allocation of management duties across occupations. We also highlight that we categorize personality and self-management as two skills. Personality includes 18 skill keywords among the 7481 we classified, but it appears in 28.68% of all job postings and accounts for 12.73% of the skills once required. Self-management skill only includes three keywords: goal setting, scheduling, and self-motivation. This skill is required in 14.24% of the jobs and accounts for 10.90% of skill requirements.

The analysis is conducted at the MSA-occupation level and focuses on skill requirements. So we restrict the analysis sample to the job posting with skill requirement information and job location in one of the 392 MSAs.[6]

2.1.2. Work-from-home capability and physical proximity

Dingel and Neiman (2020) use the Occupational Information Network (O*NET) data to classify the feasibility of working from home for all occupations within the United States. We use their WFH measure to classify 2-digit SOC occupation codes. Figure 1 shows the monthly average number of job postings for each occupational category for three different periods, namely the pre-COVID, in-SAHO and post-SAHO period. The figure suggests no clear pattern in the number of job postings over time by the WFH capacity index.

Mongey et al. (2021) also use O*NET to construct another measure of an occupation' s potential exposure to social distancing – its required degree of physical proximity to others in the workplace. We use their classification of occupations to provide additional estimates on the effects of SAHO on skill demand in jobs with different requirements on physical distance when performing the job tasks. The occupation classification and the regression estimates are reported in Online Appendix Section A.1.

2.1.3. Stay-at-home orders, hospital beds, and local economic and demographics

We use a county-level SAHO starting and end date table from the Centers for Disease Control and Prevention (2021) and a county-MSA crosswalk from Hershbein and Kahn (2018) to calculate the MSA-level SAHO duration as the unweighted average of county-level duration among all counties in the MSA. The distribution of the MSA-level SAHO duration is presented in Fig. 2.

We obtain data on ICU beds by hospital and their location from Fenton et al. (2020), extracted from the most recently filed cost reports of U.S. Centers for Medicare & Medicaid Services (CMS) received in 2017–2019. This database allows us to calculate the total number of ICU beds by MSA. At the MSA level, we use the population density from the 2010 U.S. Census, calculate the demographic composition from the 2018 and 2019 American Community Survey (ACS) data and the annual unemployment rate using data from the U.S. Bureau of Labor Statistics Local Area Unemployment Statistics program.

2.2. Skill requirement statistics

To quantify the impact of SAHOs on skill requirements in job postings, we define measures of the labor market demand for skills. We denote a skill by i, job by j, occupation by o, region by r, and time by t. In this paper, regions are specified to be MSAs. The number of skills required by job j is denoted by S_j. The number of job postings in occupation o in MSA r at time t is denoted by N_{ort}. The number of job postings that require skill i in occupation o in MSA r at time t is denoted by M_{iort}. We define two statistics to separately measure the intensive and extensive margin of skill demand.

Eq. (1) shows the formula of the intensive margin of the labor market demand for skill i, denoted by $skill^{int}_{iort}$. It is the average share of skill i in all skill requirements for a job requiring skill i. This equation accommodates the fact that the total number of skills required varies across jobs. The indicator $1\left\{ skill_s = i | j, o, r, t \right\}$ is 1 if the s-th skill of a given index of j, o, r, t is skill i, and is 0 if it is any other skill.

$$skill^{int}_{iort} = \frac{1}{M_{iort}} \sum_{j=1}^{M_{iort}} \left(\frac{1}{S_j} \sum_{s=1}^{S_j} 1\left\{ skill_s = i | j, o, r, t \right\} \right) \tag{1}$$

Eq. (2) gives the formula of the extensive margin of the labor market demand for skill i, $skill^{ext}_{irt}$. It equals to the fraction of job postings that require skill i in occupation o in MSA r at time t.

$$skill^{ext}_{iort} = \frac{M_{iort}}{N_{ort}} \tag{2}$$

We aggregate the job posting data by the skill category, month, MSA, and occupation at the 3-digit SOC code level to construct a regression dataset. Hence, the regression dataset contains 19 distinct values for i, 94 for o, 392 for r, and 40 for t. We use the number of postings with each o, r combination in the post-SAHO period as sample weight for the corresponding data point in the regression sample. To conduct the analysis by the level of educational requirement or by sector, we aggregate the raw data by, in addition to all existing strata, 3 education requirement groups, namely middle school or high school, college and advanced degree holders, or by 21 sectors. The sample weights are adjusted accordingly.

2.3. Summary statistics

Table 1 summarizes skill requirement statistics for the regression sample, in which column 1 reports the value of $skill^{int}_{irt}$ and column 2 reports $skill^{ext}_{irt}$. The skills are sorted by the values in column 1.

[3] The BGT data classified 6836 skills into 658 skill clusters. We first exclude 70 skills related to public safety and national security or religion. We further identify an additional 645 previously unclassified high-frequency skills. We then classify these 7481 skills into 19 categories to cover the majority of skill requirements that appeared in the data, after consulting but not completely following the pre-existing classifications.

[4] The most popular skills in administrative skills are data entry, typing, telephone, appointment setting, and record keeping.

[5] For language skills, 56% of the requirements are English, 20% are bilingual, and 18% are Spanish.

[6] We exclude military-related occupations with Standard Occupational Classification (SOC) code beginning with 55.

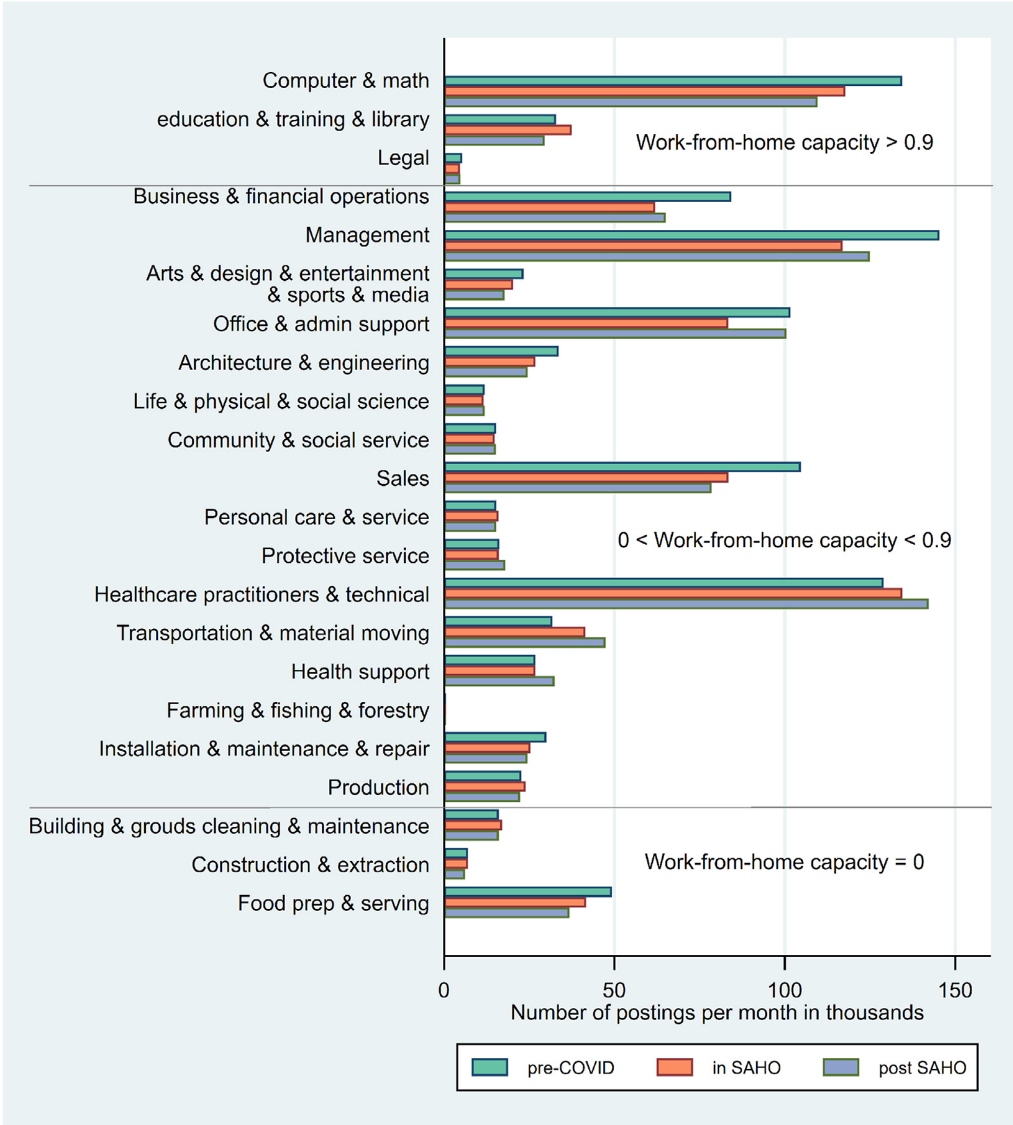

Fig. 1. Monthly average of number of job postings by occupation and periods. *Note:* The figure shows the average number of job postings per month by occupation and periods. The occupations are sorted in descending order by their work-from-home capacity. The two horizontal lines indicate the cutoffs. The turquoise bars show the monthly average number of postings from January 2018 to December 2019. The orange bars show the monthly average from March 2020 to June 2020. The grey bars show the monthly average from July 2020 to April 2021. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Comparing the two columns shows us that not only does the demand for skills differ, but also how much the job ads emphasize each skill when mentioning it. For example, STEM skills are required in 36.99% of the job vacancies, and when the skills are mentioned, they account for 30.92% of the skill requirements for the positions. General computer skills are required in 44.10% of the postings, but only account for 23.49% when they are mentioned. Columns 3-4 and 5-6 provide the statistics for the pre-COVID period (January 2018 to December 2019), and after SAHOs are lifted.[7] The demand for STEM, manual, administrative, language and self-management skills increased after SAHOs both extensively and intensively. The demand for skills in general computer use, business and finances, operation management, industry knowledge, project management, and writing decreased through both channels. Personalities are also mentioned less often in job ads.

3. Econometric approach

We employ a 2-stage Lease Square approach to estimate how the duration of SAHOs affected the demand for skills. To exploit cross-sectional geographic variation in the duration of the SAHOs that only relates to Covid containment considerations, we use the number of ICU beds and population density by MSA as instrumental variables. Moreover, we include a few demographic variables at the MSA level to account for other local factors that may correlate with the SAHO duration.

Firms in MSAs with longer SAHOs are more likely to seek alternative work arrangements and more actively adjust the skill requirements of their employees. Our approach compares the changes in skill requirements of firms in MSAs with longer SAHOs to those in MSAs with shorter SAHOs. Hence, the dependent variables are the MSA-occupation-specific

[7] The SAHO duration varies across areas. We make use of the specific SAHO end date of each area, and count job ads posted at least 15 days after the end of the SAHO of the job location as post-SAHO jobs.

Table 1
Summary statistics of the measures for the demand for skill .

	Full sample Jan 2018 to April 2021		Pre-COVID		Post-SAHO	
	$skill^{int}$ (1)	$skill^{ext}$ (2)	$skill^{int}$ (3)	$skill^{ext}$ (4)	$skill^{int}$ (5)	$skill^{ext}$ (6)
STEM	30.92	36.99	30.11	35.83	31.99	39.30
	[4.37]	[6.84]	[4.09]	[6.25]	[4.32]	[7.47]
Manual	29.42	35.07	29.09	34.25	29.77	36.43
	[3.45]	[7.46]	[3.04]	[7.09]	[4.28]	[8.10]
Customer services	25.04	48.19	25.10	48.34	24.97	47.99
	[2.85]	[6.04]	[2.69]	[5.54]	[3.21]	[7.02]
Computer: general use	23.49	44.10	23.72	45.07	22.74	42.73
	[3.31]	[8.62]	[3.34]	[8.19]	[3.05]	[9.12]
Business and finance	19.70	36.42	19.82	37.76	19.43	34.36
	[1.54]	[7.23]	[1.45]	[6.70]	[1.66]	[7.93]
Education	19.57	10.85	19.50	10.90	19.49	10.43
	[4.49]	[2.91]	[4.00]	[2.74]	[5.17]	[3.10]
Administration	17.97	36.67	17.60	36.55	18.87	37.32
	[2.48]	[3.95]	[1.49]	[3.65]	[4.09]	[4.55]
Computer: specialized software	16.41	17.33	16.31	17.75	16.31	16.55
	[2.41]	[7.58]	[2.31]	[7.33]	[2.45]	[8.02]
Languages	15.95	10.26	15.04	9.73	17.98	11.45
	[3.84]	[3.79]	[2.45]	[3.25]	[5.44]	[4.69]
Social	15.48	54.14	15.37	54.98	15.71	53.00
	[1.08]	[6.60]	[0.98]	[6.15]	[1.23]	[7.53]
Operational management	14.47	34.07	14.58	35.27	14.25	31.94
	[1.33]	[4.29]	[1.30]	[3.60]	[1.44]	[4.93]
Cognitive	14.45	44.46	14.37	45.36	14.63	43.19
	[1.02]	[7.14]	[1.00]	[6.45]	[1.08]	[8.46]
Personality	12.73	28.68	12.67	29.45	12.69	27.44
	[1.38]	[5.36]	[1.21]	[5.34]	[1.69]	[5.32]
Industry knowledge	12.65	19.45	12.90	19.94	12.04	18.00
	[1.52]	[3.07]	[1.52]	[2.78]	[1.47]	[2.96]
People management	11.90	30.05	11.89	30.59	11.81	29.12
	[1.18]	[3.32]	[1.12]	[3.03]	[1.32]	[3.87]
Arts and humanities	11.85	6.16	11.97	6.54	11.50	5.51
	[2.24]	[2.10]	[1.93]	[2.02]	[2.87]	[2.13]
Self-management	10.90	14.24	10.16	14.02	12.42	14.92
	[2.65]	[2.36]	[1.18]	[1.77]	[4.03]	[3.41]
Project management	10.42	15.51	10.56	16.14	10.09	14.55
	[1.06]	[5.07]	[1.09]	[4.74]	[0.97]	[5.73]
Writing	9.18	14.54	9.26	15.13	8.93	13.48
	[1.03]	[3.67]	[1.00]	[3.48]	[1.05]	[3.81]

Summary statistics of the skill requirement variables. Averages of the intensive margin ($skill^{int}$) and the extensive margin ($skill^{ext}$) of the labor market demand for each skill are presented. The definition of the variables are provided in Eqs. (1) and (2). Columns 1 and 2 present the averages on all job postings from January 2018 to April 2021. Columns 3 and 4 are the averages on pre-COVID postings from January 2018 to December 2019. Columns 5 and 6 are the averages on post-stay-at-home-order (post-SAHO) postings. Considering that the SAHO duration varies across areas, we make use of the specific SAHO end date of each area, and count job ads posted at least 15 days after the end of the SAHO of the job location as post-SAHO jobs. The sample is restricted to job postings with skill requirements in the 392 Metropolitan Statistical Areas. We exclude military-related occupation with SOC starting with 55.

extensive and intensive margin differences in the demand for each skill before Covid and after SAHOs are lifted.

The first-stage regression is:

$$\text{SAHO}_r = \delta_1 + \delta_2 beds_r + \delta_3 PopDensity_r + \delta_4 X_r + v_r \tag{3}$$

in which SAHO_r is the duration of the SAHO in MSA r. The instruments are $beds_r$, the number of ICU beds in thousands prior to the pandemic, and $PopDensity_r$, the MSA level population density from the Census. The MSA-level economic and demographic controls, denoted by X_r, include the average unemployment rate in 2018 and 2019, the fractions of people without a high school diploma, the elderly (people above 60 years old), black people and the married population, respectively. As expected, the coefficient for ICU beds is negative with an estimate of −0.0322 (0.0136), and the coefficient for population density is positive with an estimate of 0.600 (0.161). We perform the hypothesis test for weak instruments as suggested by Staiger and Stock (1997) and obtain an F-statistic of 10.28 for the first-stage regression which rejects the null and shows the eligibility of the instruments. With two instruments for one potentially endogenous variable, we also need to test whether they satisfy the overidentifying restrictions to further validate the choice of the instruments. Among the 38 second-stage regressions (19 skills × 2 margins), 35 passed the Hansen J-statistic test with p-values above 0.05, meaning that the instruments are jointly exogenous.[8]

The second-stage regressions are MSA-level, cross-sectional equations:

$$skill^{int}_{ior,post} - skill^{int}_{ior,pre} = \alpha^i_1 + \alpha^i_2 S\hat{AHO}_r + \alpha^i_3 X_r + \epsilon^{int}_{ior} \tag{4}$$

$$skill^{ext}_{ior,post} - skill^{ext}_{ior,pre} = \beta^i_1 + \beta^i_2 S\hat{AHO}_r + \beta^i_3 X_r + \epsilon^{ext}_{ior} \tag{5}$$

[8] The null hypothesis is that the overidentifying restrictions are valid (i.e., instruments and the error term are uncorrelated). The dependent variables of the three regressions that reject the null are the intensive margin demands for art and humanities skills ($p = 0.024$), industry knowledge ($p = 0.042$) and education ($p = 0.040$). To focus on the regression results of skills that pass both tests for instrument validity, we do not discuss the estimates of the above three skill demands, regardless of the significance of their coefficients.

where $skill_{ior,pre}$ is the monthly average of the demand for skill i in occupation o in MSA r before January 2020, and $skill_{ior,post}$ is the monthly average after the SAHO is lifted. The control variables, X_r, are the same as in the first stage. The MSA, occupation, skill-specific error term is denoted by ϵ_{ior}. The coefficients of interest are α_2^i and β_2^i. They capture the average impacts of SAHO on the change in skill requirements on the two margins after the SAHO was lifted for all MSA-occupation combinations. The difference in skill demands between pre- and post-COVID in MSAs without SAHOs are α_1^i and β_1^i. To address possible serial correlation within an MSA, we cluster the standard errors at the MSA level. The MSA-occupation level observations are weighted by the number of job postings in the post-SAHO period.

4. The effect of stay-at-home orders on skill requirements

In this section, we provide empirical evidence about the impact of the COVID-19 pandemic and the resulting SAHOs on changes in demand for each skill in detail. For each of the 19 skills, we first present the magnitude of the shift in skill demands that relates to the duration of the SAHO. Second, we estimate the effects on separate subsamples by the work-from-home capacity of the occupations. In the Online Appendix, we provide additional estimates and discussion on subsamples by the physical proximity required by the occupation, by the education requirements in the job postings, and by quarter of the job posting dates. We also present two case studies on the retail trade industry and on manager occupations for interested readers to gain a more figurative understanding of the effects of SAHOs on skill demands.

4.1. Main results

Table 2 presents the effect of the duration of the SAHOs and the COVID pandemic on changes in skill requirements. Columns 1 and 2 show the estimates of α_2 and β_2 in Eqs. (4) and (5), respectively. Columns 3 and 4 show the estimates of α_1 and β_1. MSAs with longer SAHO show

Table 2
Effects of SAHO and COVID on the demand for skills .

	SAHOs		COVID pandemic	
	Intensive (α_2) (1)	Extensive (β_2) (2)	Intensive (α_1) (3)	Extensive (β_1) (4)
STEM	2.478**	1.085	3.047	9.975*
	(1.171)	(0.963)	(4.853)	(5.648)
Manual	0.870	−1.552	5.173	0.034
	(0.637)	(1.190)	(3.351)	(6.518)
Customer services	0.307	−3.477**	−1.360	−0.140
	(0.449)	(1.671)	(2.295)	(8.253)
Computer: general use	−0.272	−1.604**	0.175	9.363
	(0.359)	(0.786)	(2.382)	(6.036)
Business and finance	0.001	−1.232	−2.956	−13.768**
	(0.273)	(0.926)	(2.388)	(6.312)
Education	−0.419	0.112	5.533	−7.882***
	(0.486)	(0.351)	(3.985)	(2.655)
Administration	2.623**	−1.091	0.182	−4.764
	(1.084)	(1.192)	(6.036)	(6.219)
Computer: specialized software	−0.518	−0.339	−4.609	−5.244
	(0.652)	(0.620)	(5.172)	(3.569)
Foreign languages	2.422*	3.020**	3.445	−10.886
	(1.425)	(1.391)	(6.965)	(8.317)
Social	1.191***	−0.428	−0.703	9.488
	(0.374)	(1.421)	(2.813)	(8.545)
Operational management	0.309*	−1.456	1.562	−3.388
	(0.167)	(1.143)	(1.570)	(6.193)
Cognitive	0.336	−0.395	2.558	3.531
	(0.215)	(0.746)	(1.583)	(5.940)
Personality	−0.549**	−3.279***	0.027	2.675
	(0.235)	(1.188)	(1.765)	(7.849)
Industry knowledge	0.478	−0.281	−0.746	4.168
	(0.369)	(0.767)	(2.679)	(5.980)
People management	0.067	−2.695**	1.055	5.926
	(0.206)	(1.118)	(1.218)	(7.558)
Arts and humanities	2.026**	−0.339	−2.835	−2.430
	(0.854)	(0.288)	(5.637)	(1.597)
Self-management	−0.596	−1.930*	−2.345	−11.804*
	(0.705)	(1.063)	(4.155)	(6.118)
Project management	−0.599**	0.350	−1.039	0.209
	(0.279)	(0.396)	(2.232)	(3.004)
Writing	1.173*	−1.004*	1.122	−4.904
	(0.633)	(0.541)	(2.429)	(3.557)

The table reports estimates of the effect of SAHO duration and COVID on labor market demand for skills based on regression specifications in Eqs. (4) and (5). Sample weights are used. The weight for each data point equals to the number of postings based on which the data point is calculated. Standard errors are clustered by MSA are reported in parentheses. The regressions include monthly dummies and MSA-occupation fixed effects. Column 1 reports the estimates of α_2 in Eq. (4) for each skill. Column 2 reports the estimates of β_2 in Eq. (5). Column 3 reports the estimates of α_1 in Eq. (4). Column 4 reports the estimates of β_1 in Eq. (5). The sample excludes job vacancies posted when the SAHO at the job location is in execution or has ended in less than 15 days. The mean [standard deviation] of the number of postings in each data point is 2642.9 [6683.8]. The total number of postings behind the regression analysis is about 34.5 million observations.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

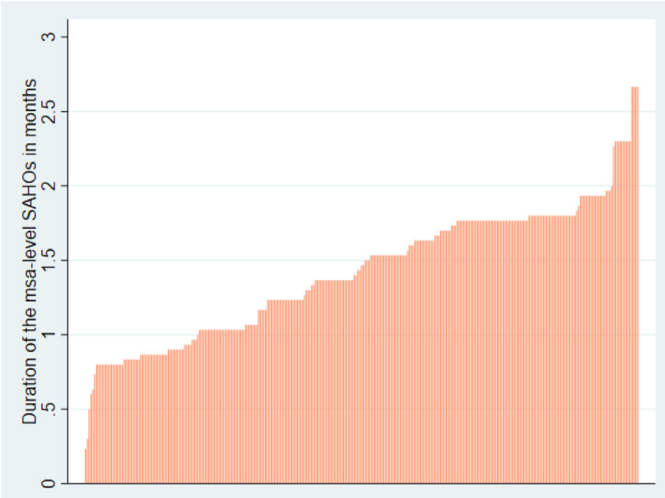

Fig. 2. Distribution of estimated SAHO duration by MSA. *Note:* The figure shows the distribution of SAHO durations in 301 MSAs. Each orange bar is an MSA. The data for analysis includes 381 MSAs with non-missing measures of SAHO durations, among which 79 MSAs are excluded from this figure for they never had a SAHO in effect, i.e., duration = 0. We also exclude the Urban Honolulu, HI MSA, for its outlying SAHO duration of 183 days. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

increases in the demand for STEM, administrative, languages, social, operation management, arts and humanity skills, and writing, and decreases in the skill demand for customer services, computer (general use), people management, self-management, project management, and specific personality requirements.

The results reflect two changes in the labor skill demand. First, the focus on management shifts from people to operations and work processes. Second, the demand for interpersonal skills deviates from specific communication to general communication. In the rest of this subsection, we discuss how the empirical results support these statements in detail.

MSAs experienced an additional month of exposure to SAHOs have −2.695 (1.118) percentage points (ppts) lower demand for people management skills on the extensive margin. The demand for personality drops on the intensive margin by −0.549 (0.235) ppts and the extensive margin by −3.279 (1.188) ppts. The decrease in self-management skill is −1.930 (1.063) ppts, in addition to the drop of −11.804 (6.118) ppt after COVID. The changes in all three skills have larger magnitudes in the extensive margin than the intensive margin. It is worth noting that the estimate of β_2 is relatively small for self-management, indicating that longer SAHOs motivate firms to rely more on employee incentives than monitoring by managers. This is likely to be the firms' solution to the challenge of managing remote workers (Deligiannis, 2021a).

One-month longer SAHOs also cause firms to require 0.309 (0.167) ppts more on operational management skills and 2.623 (1.084) ppts on administrative skills on the intensive margins after the orders were lifted. The demand for foreign language skills increased on both margins with $\alpha_2^{\text{language}} = 2.422(1.425)$ and $\beta_2^{\text{language}} = 3.020(1.391)$. The estimates suggest that experiencing business uncertainty during long SAHOs may have motivated firms to enhance operational controls and smoothen communication within firms, overcoming the additional challenges of organizing employees remotely. This is consistent with Koenders and Rogerson (2005), who argue that firms shift managerial attention from growth to efficiency during recessions. The increased demand is also in line with the concerns about more frequent job turnovers and unstable teams (Boland et al., 2020).

To recap, we find that operational management became popular on the intensive margin, while people management fades out on the extensive margin. Each aspect consists of one skill from the supervisors' perspective and two from the point of view of those being supervised. The duration of SAHOs changed the management style. The standardized workflows, relying less on particular personnel, are more resistant to risks such as sick leaves amid the pandemic. Our estimates provide quantitative evidence for the discussion by Willicombe (2022) that a working pattern and arrangement with workers' consensus is more efficient than micromanagement. The finding that the operational approach became more important after COVID is consistent with Olckers and Koekemoer (2022) and Schivardi et al. (2021). Moreover, we find that the magnitude of the operational managerial shift depends on the duration of SAHOs complements the survey outcome that operational management and administration are keys to an effective remote work environment (Consultancy.uk, 2021).[9]

The SAHO duration has significant effects on the demand for all skills related to communication. The demand for jobs with customer service skill requirement is lowered by 3.477 (1.671) ppts in MSAs with one-month longer SAHOs. The demand for jobs with writing skill requirement also dropped by 1.004 (0.541) ppts. Both decreases are on the extensive margin. Meanwhile, the demands for administrative, social skills, and writing skills increased on the intensive margin by 2.623 (1.084), 1.191 (0.374), and 1.173 (0.633) ppts, respectively. The estimates imply that firms' preference for employees' interpersonal skills shifted from employing a few specialists in specific positions for external communication to a new culture where many workers are well capable of efficient work communication internally and externally. As many papers and articles pointed out, communication efficiency is of crucial importance to a firm's productivity (e.g., Willicombe, 2022). Our finding of the increased demand for flexible communication skills is in line with Olckers and Koekemoer (2022) who find that social interactions among managers and employees are essential for maintaining the employees' morale and well-being. In addition, the increased demand for social skills makes sense as previous research has found that it is essential for team production and complements cognitive skills (Deming, 2017; Deming and Kahn, 2018), and that it has played an important role for knowledge workers and especially managers during the pandemic (Josten and Lordan, 2021).

SAHOs affect a few other skills. On the intensive margin, the demand increased for STEM by 2.478 (1.171) ppts and decreased for project management by 0.599 (0.279) ppts. On the extensive margin, the demand for jobs with general computer skills drops by 1.604 (0.786) ppts.

4.2. The work-from-home capacity of occupations

The soaring uncertainty about COVID and the resultant work arrangements pushes firms to evaluate to what extent their workforce can work remotely and keep looking for ways to expand this boundary (Deligiannis, 2021b). In this section, we explore how firms achieve such goals by separately examining the changes in skill demands of occupations with different capacities of working from home.

Among all job postings between January 2018 and April 2021, 6.9% were from occupations with a WFH capacity index equal to 0 (non-WFH capable). This group includes three 2-digit SOC occupations: construction and extraction occupations, food preparation and serving occupations, and transportation and material moving occupations. Another 16.3% of the postings had a WFH capacity index higher than 0.9. This group includes legal, education and training, and computer and mathematical occupations. Aside from the two extremes, the WFH capacity index values for 76.8% of the job postings from 16 SOC codes are between 0.01 and 0.9. Examples of occupations in this group are management, office and administrative support, salesperson, and business and financial specialists.

[9] In Online Appendix Section A.2, we show that the main undertaker of the change in demand for administrative and language skills are workers without a college degree.

Table 3
The effect of SAHO on demands for skills by the work-from-home capacity of the occupation .

	WFH capacity = 0		0 < WFH capacity ≤ 0.9		WFH capacity > 0.9	
	Intensive (1)	Extensive (2)	Intensive (3)	Extensive (4)	Intensive (5)	Extensive (6)
STEM	0.251*	0.031	0.086**	0.031	0.039	0.011
	(0.131)	(0.079)	(0.040)	(0.042)	(0.027)	(0.026)
Manual	0.020	−0.033	0.035	−0.062	0.036	−0.025
	(0.054)	(0.068)	(0.024)	(0.047)	(0.026)	(0.023)
Customer services	−0.016	−0.078	0.010	−0.164**	0.024**	0.044
	(0.030)	(0.069)	(0.020)	(0.064)	(0.011)	(0.049)
Computer: general use	0.044	0.024	−0.005	−0.063**	−0.012	−0.045**
	(0.112)	(0.043)	(0.014)	(0.031)	(0.012)	(0.021)
Business and finance	0.012	0.060	−0.002	−0.062*	0.011	−0.001
	(0.046)	(0.069)	(0.012)	(0.034)	(0.009)	(0.032)
Education	0.016	0.015	−0.019	0.005	0.004	−0.010
	(0.065)	(0.073)	(0.020)	(0.016)	(0.018)	(0.014)
Administration	−0.011	−0.007	0.119**	−0.045	0.001	−0.041
	(0.032)	(0.128)	(0.047)	(0.045)	(0.009)	(0.025)
Computer: specialized software	0.184	0.027	−0.024	−0.015	0.007	−0.035*
	(0.232)	(0.029)	(0.024)	(0.023)	(0.013)	(0.020)
Foreign languages	0.055	0.045	0.109*	0.133**	0.005	0.005
	(0.046)	(0.060)	(0.057)	(0.060)	(0.027)	(0.015)
Social	−0.041	0.086	0.053***	−0.035	0.007	−0.016
	(0.032)	(0.064)	(0.015)	(0.054)	(0.005)	(0.036)
Operational management	0.010	0.042	0.010*	−0.075*	0.022***	−0.000
	(0.030)	(0.038)	(0.006)	(0.045)	(0.008)	(0.027)
Cognitive	0.032	0.049	0.008	−0.026	0.021**	−0.019
	(0.035)	(0.062)	(0.007)	(0.029)	(0.008)	(0.029)
Personality	−0.121**	−0.063	−0.015*	−0.133***	−0.009	−0.038
	(0.051)	(0.095)	(0.008)	(0.042)	(0.007)	(0.042)
Industry knowledge	0.044	0.164**	0.014	−0.019	0.014	−0.006
	(0.049)	(0.073)	(0.016)	(0.027)	(0.010)	(0.031)
People management	−0.038	−0.057	0.002	−0.122***	0.013**	0.003
	(0.037)	(0.084)	(0.007)	(0.045)	(0.006)	(0.028)
Arts and humanities	0.358	−0.004	0.076**	−0.014	0.021	−0.008
	(0.274)	(0.016)	(0.031)	(0.010)	(0.014)	(0.014)
Self-management	−0.099	−0.129**	−0.020	−0.074*	0.006	−0.014
	(0.076)	(0.050)	(0.028)	(0.045)	(0.006)	(0.014)
Project management	−0.085*	0.027	−0.026**	0.015	0.015*	−0.009
	(0.049)	(0.018)	(0.013)	(0.015)	(0.008)	(0.019)
Writing	−0.009	−0.024	0.049*	−0.032	0.013**	−0.054**
	(0.025)	(0.031)	(0.027)	(0.021)	(0.005)	(0.025)

The table reports estimates of the effect of SAHO duration on labor market demand for skills by the work-at-home capacity of the occupation. Columns 1 and 2 report the results for occupations incapable of working from home, i.e., those with WFH capacity index = 0. Columns 3 and 4 report the results for occupations that are somewhat capable of working from home, i.e., those with WFH capacity index values between 0 and 0.9. Columns 5 and 6 report the results for occupations mostly capable of working from home, i.e., those with WFH capacity index values > 0.9. Fig. 1 lists these occupations and their WFH capacity index values. See the notes for Table 2.
$p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 3 presents the estimates of α_2 and β_2 for these three subsamples of different levels of WFH capacity. The effects of SAHO duration on skill requirements are very different across the groups. Columns 1 and 2 show that for occupations that cannot work from home, SAHO duration hardly affects the demand for skills. The demand increases in STEM intensively and in industry knowledge extensively. The demand for management-related skills, including personality, self-management, and project management, decreases. The skill demands shifting from managerial skills to essential technical skills to the industries is consistent with Maurin and Thesmar (2004), who show the trend that French manufacturing firms hire more high-skilled workers to design new products instead of administration and management. It is worth noting that the demand for personality decreases by −0.121 (0.051) ppts despite the fact that these occupations are incapable of WFH. This is likely because physical distancing requirements at the workplace are usually in place after SAHOs are lifted, making the work environment for occupations with low WFH capacity different from their pre-COVID situation.[10]

Columns 5 and 6 of Table 3 present the regression results for occupations with high WFH capacity. Contrary to the estimates from the full sample, these occupations have increased demand for customer service, people management and project management on the intensive margin. This group accounts for the changes in demand for basic computers, operational management and writing skills that we observed in the full sample. The dynamic changes in all three management skills, once considering that managers are not in this group, imply that remote working in computer science and math, education-related and legal occupations creates substantial management challenges. The fact that most of the significant changes are on the intensive margin tells us that firms aim at altering the skill sets of people in these occupations, instead of adjusting their roles in the firm production. All changes in the intensive margin are positive while those on the extensive margin are negative, indicating that these occupations move towards further specialization without demanding diversification within the skill set of each worker.

We take a closer look at the 2-digit occupation in this group.[11] Computer-based and mathematical occupations, accounting for 77% of

[10] World Health Organization, April 7, 2020. “COVID-19 and food safety: guidance for food businesses”.

[11] The occupation-specific estimates are not reported in the tables.

job postings in occupations with high WFH capacity, promote specialization by emphasizing cognitive and STEM-related skills while relaxing writing skill requirements, and pursuing a self-sustaining work system by requiring more operational management and self-management skills while emphasizing less on personal characteristics. Education occupations, accounting for another 20% of the high WFH capable postings, increase their requirements on customer service, social and writing skills, as online education promotes personalized teaching, which strengthens the personal service nature of the education industry (Lockee, 2021).

Columns 3 and 4 show that SAHO makes the most dynamic changes to the labor market demand for skills in occupations that are partially capable of working from home. We observe the most significant changes in the demands for people management skills, personalities, administrative, social, customer service, and arts and humanity skills. These results suggest SAHO incentivizes firms to improve functioning in future WFH scenarios by relying more on professional administration protocols than on managers' hands-on supervision and organization. The decreased demand for customer service skills ($\beta_2^{\text{customer}} = -0.164$ (0.064)) mirrors the intensive margin increase of 0.024 (0.011) ppts in high WFH-capable occupations, implying the reallocation of customer service tasks across occupations.

Another related impact of the SAHO orders on work capacity is the physical distance among coworkers. Working from home may not matter much for jobs that do not require close physical proximity, but the restriction could shut down most work capacity of other jobs. In Online Appendix Section A.1, we group the occupations by physical proximity measure constructed by Mongey et al. (2021) and provide estimates for the effect of SAHO durations on each group. The results tell the same story as this section.

5. Conclusion

In this paper, we studied the effect of SAHO duration on the skill demand using online job postings in the United States from 2018 to 2021 and spatially varying SAHO policies. We used instrumental variables to handle the endogeneity issue of SAHO duration related to local social and economic factors, and identified the impact of variation in the SAHO policies due to pandemic containment considerations. We classified over 98% of the skill requirements into 19 skill categories, such as administration, personality, self-management, and people management and showed that the labor skill demand changed from pre-COVID to post-SAHO period within occupations.

Longer SAHOs yield higher demands for operational management, administration, and languages, and lower demands for people management, self-management and specific personal characteristics. This suggests that SAHO motivates firms to adjust their management from people-oriented supervision of employees to operation-oriented monitoring of the work process, and that remote working shifts managerial attention away from the employee relationship. The increased demand for social skills and the decreased demand for customer service skills, along with other changes in interpersonal skills, show that firms experienced long SAHOs tend to require professional work communication as a general skill.

We estimated the effect of SAHO duration on skill demands by the WFH-capability of occupations. We found that occupations that are partially capable of working from home are the focus of skill restructure. The SAHO duration had significant effects on management-related skills for supervisors and supervisees. This suggests that firms that suffered from long SAHOs are more actively exploiting these occupations' potential to work from home by promoting standard work protocols.

This paper documented the impact of SAHO duration on the change in skill requirements within occupations. Just as technologically-driven changes in the skill demand focus on skills related to job content, this SAHO-driven change happens mostly on skills that shape the way of working and management. Our evidence shows that temporary workplace closure can have a long-term impact on the labor skill demand throughout the post-COVID recovery.

Data availability

The authors do not have permission to share data.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.labeco.2023.102342.

References

Adams-Prassl, A., Boneva, T., Golin, M., Rauh, C., 2020. Furloughing. Fisc. Stud. 41 (3), 591–622. doi:10.1111/1475-5890.12242.

Adams-Prassl, A., Boneva, T., Golin, M., Rauh, C., 2020. Inequality in the impact of the coronavirus shock: evidence from real time surveys. J. Public Econ. 189, 104245. doi:10.1016/j.jpubeco.2020.104245.

Ali, U., Herbst, C.M., Makridis, C.A., 2021. The impact of COVID-19 on the U.S. child care market: evidence from stay-at-home orders. Econ. Educ. Rev. 82 (February), 102094. doi:10.1016/j.econedurev.2021.102094.

Baek, C., McCrory, P.B., Messer, T., Mui, P., 2021. Unemployment effects of stay-at-home orders: evidence from high-frequency claims data. Rev. Econ. Stat. 103 (5), 979–993. doi:10.1162/rest_a_00996.

Barrero, J.M., Bloom, N., Davis, S.J., 2021. COVID-19 is also a reallocation shock. In: AEA Papers and Proceedings 2021, vol. 111, pp. 287–291. doi:10.1353/eca.2020.0012.

Bartik, A.W., Bertrand, M., Cullen, Z., Glaeser, E.L., Luca, M., Stanton, C., 2020. The impact of COVID-19 on small business outcomes and expectations. Proc. Natl. Acad. Sci. USA 117 (30), 17656–17666. doi:10.1073/pnas.2006991117.

Boland, B., Smet, A.D., Palter, R., Sanghvi, A., 2020. Reimagining the Office and Work Life After COVID-19. McKinsey. June 8, 2020, https://www.mckinsey.com/capabilities/people-and-organizational-performance/our-insights/reimagining-the-office-and-work-life-after-covid-19

Brynjolfsson, E., Horton, J.J., Ozimek, A., Rock, D., Sharma, G., TuYe, H.-Y., 2020. COVID-19 and Remote Work: An Early Look at US Data. NBER Working Paper.

Cajner, T., Crane, L.D., Decker, R.A., Grigsby, J., Hamins-Puertolas, A., Hurst, E., Kurz, C., Yildirmaz, A., 2020. The US labor market during the beginning of the pandemic recession. Brook. Pap. Econ. Act. 2020 (Special Edition), 3–33. doi:10.1353/eca.2020.0005.

Carrillo-Tudela, C., Comunello, C., Clymo, A., Jäckle, A., Visschers, L., Zentler-Munro, D., 2022. Search and Reallocation in the COVID-19 Pandemic: Evidence from the UK. Working Paper. 10.2139/ssrn.3896794

Centers for Disease Control and Prevention, 2021. U.S. state and territorial stay-at-home orders: March 15, 2020–August 15, 2021 by county by day. https://data.cdc.gov/Policy-Surveillance/U-S-State-and-Territorial-Stay-At-Home-Orders-Marc/y2iy-8irm.

Chetty, R., Friedman, J. N., Hendren, N., Stepner, M., T. O. I. Team, 2020. The Economic Impacts of COVID-19: Evidence from a New Public Database Built Using Private Sector Data. Working Paper.

Coibion, O., Gorodnichenko, Y., Weber, M., 2020a. Labor markets during the COVID-19 crisis: apreliminary view. Working Paper.

Coibion, O., Gorodnichenko, Y., Weber, M., 2020b. The Cost of the COVID-19 Crisis: Lockdowns, Macroeconomic Expectations, and Consumer Spending. Working Paper.

Consultancy.uk, 2021. Lockdown makes people management more time consuming. https://www.consultancy.uk/news/27676/lockdown-makes-people-management-more-time-consuming.

Costa Dias, M., Johnson-Watts, E., Robert, J., Postel-Vinay, F., Spittal, P., Xiaowei, X., 2021. Worker mobility and labour market opportunities. Working Paperhttps://ifs.org.uk/uploads/WP202129-Worker-mobility-and-labour-market-opportunities.pdf.

Deligiannis, N., 2021. How to Manage a Remote Team. Hays. https://www.linkedin.com/pulse/how-manage-remote-team-nick-deligiannis/

Deligiannis, N., 2021. Remote Work After COVID-19: 6 Considerations for Managers. Hays. https://www.hays.com.au/blog/insights/remote-work-after-covid-19-6-considerations-for-managers

Deming, D.J., 2017. The growing importance of social skills in the labor market. Q. J. Econ. 132 (4), 1593–1640. doi:10.1093/qje/qjx022.

Deming, D.J., Kahn, L.B., 2018. Skill requirements across firms and labor markets: evidence from job postings for professionals. J. Labor Econ. 36 (S1), S337–S369. doi:10.1086/694106.

Dingel, J.I., Neiman, B., 2020. How many jobs can be done at home? J. Public Econ. 189, 104235. doi:10.1016/j.jpubeco.2020.104235.

Fenton, J., Petenko, E., Mayo, J., 2020. Covid Hospitals Demographics.

Finamor, L., Scott, D., 2021. Labor market trends and unemployment insurance generosity during the pandemic. Econ. Lett. 199, 109722. doi:10.1016/j.econlet.2020.109722.

Forsythe, E., Kahn, L.B., Lange, F., Wiczer, D., 2020. Labor demand in the time of COVID-19: evidence from vacancy postings and UI claims. J. Public Econ. 189, 104238. doi:10.1016/j.jpubeco.2020.104238.

Friedson, A.I., McNichols, D., Sabia, J.J., Dave, D., 2021. Shelter-in-place orders and public health: evidence from california during the COVID-19 pandemic. J. Policy Anal. Manag. 40 (1), 258–283. doi:10.1002/pam.22267.

Hall, R.E., 1991. Labor demand, labor supply and employment volatility. In: Blanchard, O., Fischer, S. (Eds.), NBER Macroeconomics Annual. MIT Press, Cambridge, MA, pp. 17–61. doi:10.2307/3585047.

Hensvik, L., Le Barbanchon, T., Rathelot, R., 2021. Job search during the COVID-19 crisis. J. Public Econ. 194 (March 2020), 104349. doi:10.1016/j.jpubeco.2020.104349.

Hershbein, B., Kahn, L.B., 2018. Do recessions accelerate routine-biased technological change? Evidence from vacancy postings. Am. Econ. Rev. 108 (7), 1737–1772. doi:10.1257/aer.20161570.

Josten, C., Lordan, G., 2021. The accelerated value of social skills in knowledge work and the COVID-19 pandemic. LSE Public Policy Rev. 1 (4), 1–10. doi:10.31389/lseppr.31.

Kirby, S., 2020. 5 Ways COVID-19 has Changed Workforce Management. World Economic Forum. June 6, https://www.weforum.org/agenda/2020/06/covid-homeworking-symptom-of-changing-face-of-workforce-management/

Koenders, K., Rogerson, R., 2005. Organizational dynamics over the business cycle: aview on jobless recoveries. Federal Reserve Bank St. Louis Rev. 87 (4), 555–579. doi:10.20955/r.87.555-580.

Lau, V., Bragg, B., Stevenson, B., Wolfers, J., Brown, T., Kanter, R.M., 2021. The Big Question: Is the World of Work Forever Changed?. The New York Times. December 8, https://www.nytimes.com/2021/12/08/special-series/pandemic-future-work-lifestyle.html

Lockee, B.B., 2021. Online education in the post-covid era. Nat. Electron. 4 (1), 5–6.

Maurin, E., Thesmar, D., 2004. Changes in the functional structure of firms and the demand for skill. J. Labor Econ. 22 (3), 639–664.

Mongey, S., Pilossoph, L., Weinberg, A., 2021. Which workers bear the burden of social distancing? J. Econ. Inequal. 19 (3), 509–526. doi:10.1007/s10888-021-09487-6.

Olckers, C., Koekemoer, E., 2022. The COVID-19 pandemic: managing unplanned change as the new normal in the workplace. Manag. Hum. Resour. 31–52.

Schivardi, F., Patnaik, M., Linarello, A., Lamorgese, A., 2021. Management Practices and Resilience to Shocks: Evidence from COVID-19. CEPR Discussion Paper No. DP15987. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3816875

Staiger, D., Stock, J.H., 1997. Instrumental variables regression with weak instruments. Econometrica 65 (3), 557–586.

Willicombe, S., 2022. How has COVID-19 affected management and leadership?https://www.itecskills.ac.uk/blog/2022/02/09/how-has-covid-19-affected-management-and-leadership/.