Effects of Stay-at-home Orders on Skill Requirements in Vacancy Postings*

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Abstract

The COVID-19 pandemic and containment policies have profound economic impacts on the labor market. Most states issued stay-at-home orders (SAHOs) that change the location and the way of working. We categorize the skill requirements of online job postings from 2018 to 2021. Exploiting spatial variations in the SAHO duration, we find that the time span of this temporary policy has persistent impacts on the skill requirement in labor demand after restrictions are lifted. Longer SAHOs motivate management style transformation to adapt to remote working schemes by requiring more self-management skills and less on personality to reduce reliance on people management skills of managers. SAHOs increase the demand for administration and language skills. We also find that SAHOs have larger and more thorough impacts for occupations with partial work-from-home capacity, and jobs that do not require a postsecondary degree. The evidence suggests SAHOs change management structure and job task assignments in firms.

JEL Classification: E24, J24, J63, L22, M51

Keywords: Skill demand, Stay-at-Home orders, COVID-19

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1 Introduction

Most U.S. states issued Stay-at-Home orders (SAHOs) throughout the spring of 2020 to slow the spread of COVID-19 and alleviate hospital capacity constraints experienced. These policies restricting people from leaving their homes for non-essential activities had a profound impact almost overnight. In response to the SAHOs, hundreds of millions of people made the abrupt shift to working from home, turning once-bustling offices into rows of empty desks. Brynjolfsson et al. (2020) find that half the U.S workforce had already switched to home-working during the first weeks of April 2020. Transferring workplaces is undoubtedly a trend following the COVID-19 recovery, but the scope and suitability of the transformation remain the focus of vigorous debates in the media.[1] Some firms consider it a good chance to save on rent for office space and business travels, while some others may be reluctant in facing the adjustment cost of restructuring employment in view of the temporariness of the lockdowns.

The nation's first SAHO was enacted in California on March 19, 2020; about three weeks later, 40 states and the District of Columbia had also issued one. Figure 1 presents the SAHO duration by state and shows the substantial variation in the SAHO duration, with a mean and median of 51 days and a standard deviation of 19 days. The fluctuating situation of the pandemic and the experience of living under the SAHOs make many firms believe they have to be constantly prepared for "everyone who can must suddenly work from home" (Kirby, 2020). This kind of perception may depend on how long the SAHOs were. 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.

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)). The SAHO in California caused roughly 14-16 jobs lost per case saved over the month following the order enactment (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 restructured employment in the face of the pandemic and the subsequent SAHOs.

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

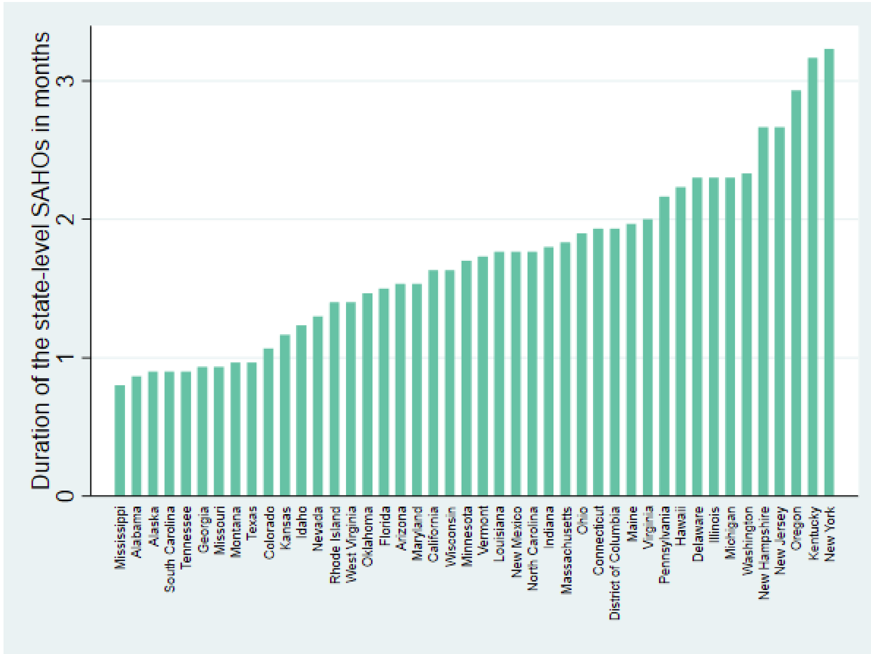

Figure 1: Distribution of SAHO duration by state

Note: The figure shows the duration of the state-level SAHOs. States that did not issue any SAHO are excluded.

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. 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 dataset collected by Burning Glass Technologies (BGT) that contains the near-universe of electronically posted job vacancies over the period January 2018 to April 2021. The BGT data records all 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 enable an analysis of the change in management styles. We construct an MSA-by-occupation panel of statistics on skill requirements in job postings and SAHO duration.

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, 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. Firms that experienced longer SAHOs change their management style by relying less on people management skills of supervisors and more on self-management skills of supervisees. The lack of in-person communication makes firm demand less on specific personalities in skill requirements. SAHOs also motivate firms to enhance workplace regulation and communication by broadly requiring administration and language skills. The economic recession after COVID drives upskilling in computer skills, reflected in the increased demand for specialized software skills and slightly decreased demand for general computer skills within occupation.

Occupations vary in their capability to work from home (WFH). Estimating the effect of SAHO duration by the WFH capacity of the occupation shows substantial differences across the groups. Computer and mathematics-related occupations, as well as education occupations, are highly capable of WFH, and their skill requirements are hardly affected by the SAHO duration. For management, administration, sales, and business and financial occupations, their job tasks are partially capable of WFH and are much more dynamically affected by the SAHO duration. The large effects on self-management, administration, and people-management suggest that longer SAHOs incentivize firms to explore the WFH potentials of these occupations by diminishing the necessity of in-person supervision.

Estimates of the effect of SAHO duration by education requirement of the job suggest a reassignment of job tasks by education background. Long SAHOs turn job opportunities for people without a college degree into positions that do not require highly technical, professional, or management skills. Job postings that require college diploma shifts emphases to technical skills, operational management, and project management. SAHO duration only mildly affects the demand for customer service skills and personality on the extensive margin for jobs that require advanced degrees.

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 Earnin data in the private sector (Chetty et al., 2020), and vacancy data (e.g., Forsythe et al., 2020; Costa Dias et al., 2021) 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

[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.

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 within occupation.

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 UK to investigate the characteristics and behavior of workers on 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 CARES Act, a temporary unemployment insurance expansion scheme in the US, on employment. Most studies in this topic have analyzed the changes in labor supply or employment. We add to this research topic by exploring the effect of SAHO on the labor demand.

Third, we contribute to a growing literature exploiting the Burning Glass Technologies data to measure skill requirements. Deming and Kahn (2018) study the link among firm performance, the pay of jobs, and skill requirements using key-words based skill categories. Hershbein and Kahn (2018) show the magnitude of changes in skill requirements during the recovery following the Great Recession across MSAs depends on the intensity of the recession on the local economy. Our paper is the first to study the effect of the SAHO duration on the size of the change in skill requirements.

Lastly, literature have shown that firms use recessions as opportunities to adjust management structure. Hall (1991) argue that firms may restructure employment in a recession because of a decline in the opportunity cost. Koenders and Rogerson (2005)'s model 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 regression 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 Overview

The Burning Glass Technologies (BGT) data has been used in many recent economic research (e.g., Hershbein and Kahn, 2018; Deming 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 on the skill, education, certificate, 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 7,481 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 table A1, we list the skill categories and up to five most common skill cluster families in it.[4] For personality, self-management, and language skills, we list all detail-level 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 detail-level skills among the 7,481 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 3 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 change in the two skills on personal characteristics change in very different directions after the COVID.

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 Metropolitan Statistical Areas. We exclude military-related occupations with SOC code beginning with 55.

2.1.2 Work-from-home capability and education requirement

Dingel and Neiman (2020) use O*NET to classify occupations where telework is very likely not possible and estimate that only 37% of US jobs can plausibly be performed at home. We use their WFH measure to classify 2-digit SOC occupation codes. Figure 2 shows the monthly average number of job postings for each occupational category for three different periods, pre-COVID, in-SAHO, and the post-SAHO period. The figure suggests no clear pattern in the number of job postings over time and the WFH capacity index.

2.1.3 Stay-at-home orders, hospital beds, and the population density

The variables we need related to the COVID pandemic include the state-level SAHO starting date, end date, and the total number of ICU beds by state and by MSA. We obtain information on state-level SAHOs from Raifman et al. (2020). The distribution of the state SAHO duration is presented in Figure 1. We obtain data on ICU beds by hospital and location of hospitals from

[3]The BGT data classified 6,836 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 7,481 skills into the 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 administration 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.

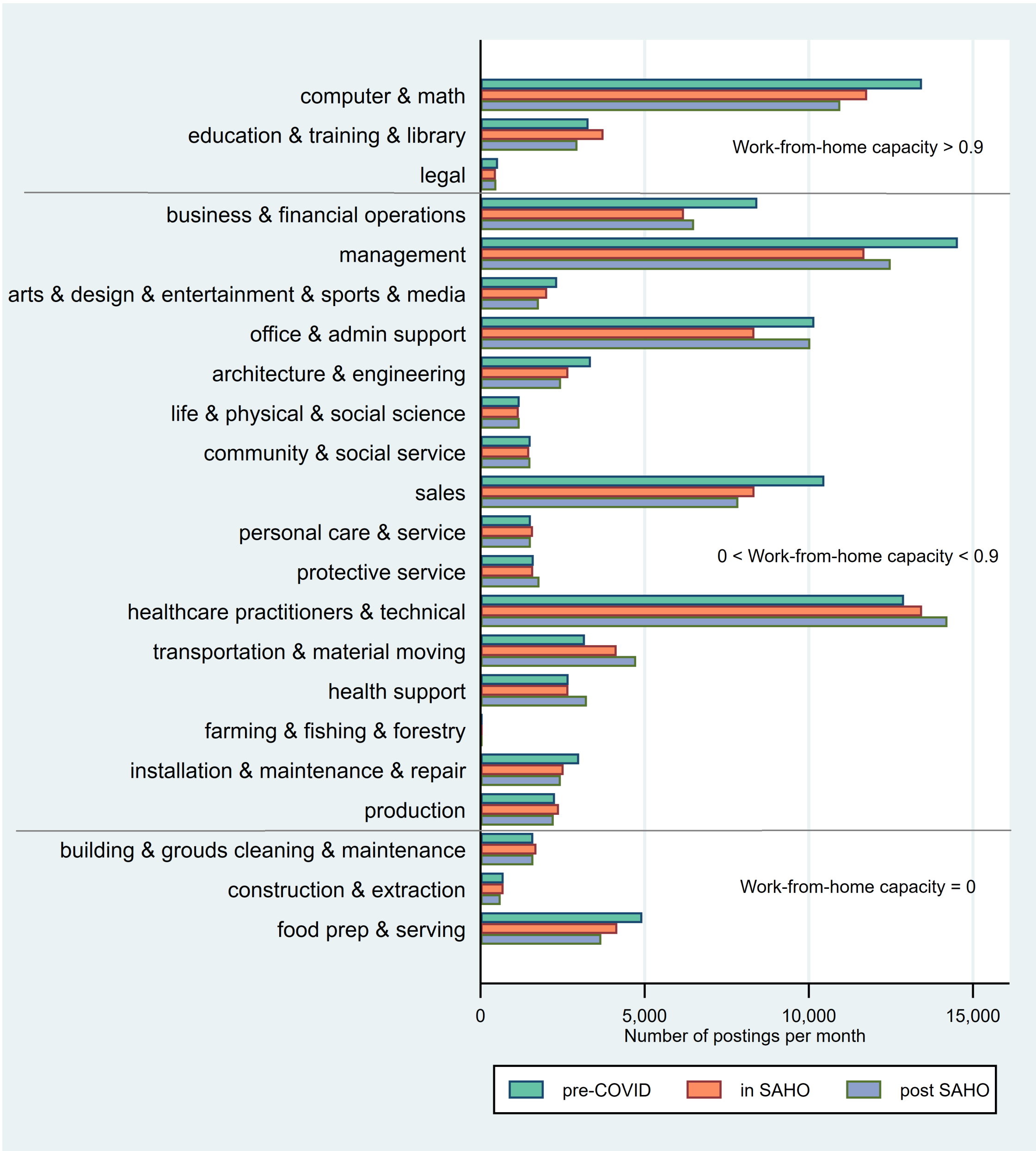

Figure 2: Monthly average of number of job postings by occupation and periods

Note: The figure shows the average number of job postings per month by occupation and periods. The occupations are sorted descendingly 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.

Fenton et al. (2020), extracted from the most recently filed cost reports of U.S. Centers for Medicare & Medicaid Services (CMS) received in 2017 or later. This database allows us to calculate the total number of ICU beds by state or MSA.

We also need to calculate population density by state and by MSA. The information on the population count by state is from Tauberer (2020). The area of the land and data on MSA level population density is from the 2010 US Census.

2.2 Skill requirement statistics

In order to use regression analysis to quantify the impact of SAHOs on skill requirements in job postings, we need to 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. The number of skills required by job j is denoted by S_j. The number of job postings in occupation o in region r at time t is denoted by N_{ort}. The number of job postings that require skill i in occupation o in region r at time t is denoted by M_{iort}. We define two statistics to separately measure the intensive and extensive margin of skill demand.

Equation 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.

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

Equation 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 region 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 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 education level 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.

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

	Jan 2018 to April 2021		Pre-COVID		Post-SAHO	
	$skill^{int}$	$skill^{ext}$	$skill^{int}$	$skill^{ext}$	$skill^{int}$	$skill^{ext}$
	(1)	(2)	(3)	(4)	(5)	(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]

Note: 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 equations 1 - 2. Columns 1-2 present the averages on all job postings from January 2018 to April 2021. Columns 3-4 are averages on pre-COVID postings from January 2018 to December 2019. Column 5-6 are 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.

Comparing the two columns shows us that not only does the demand for skills differ, but also how much do the job ads emphasize each skill when mentioning it. For example, STEM skills are required in 36.99% of the jobs 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 for after SAHOs are lifted.[6] The demand for STEM, manual, administration, 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

Our goal is to understand how the duration of SAHOs affected the demand for skill. We exploit cross-sectional geographic variation in the duration of the SAHOs. 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 general approach is to compare the changes in skill requirements of firms in MSAs with longer SAHOs to those in MSAs with shorter SAHOs.

Our main research design is a region-level, cross-sectional regression:

$$skill^{int}_{ior,post} - skill^{int}_{ior,pre} = \alpha^i_1 + \alpha^i_2 SAHO_r + \epsilon^{int}_{ior} \tag{3}$$

$$skill^{ext}_{ior,post} - skill^{ext}_{ior,pre} = \beta^i_1 + \beta^i_2 SAHO_r + \epsilon^{ext}_{ior} \tag{4}$$

where $skill_{ior,pre}$ is monthly average of the demand for skill i in occupation o in region r before January 2020, and $skill_{ior,post}$ is the monthly average after the the SAHO is lifted. $SAHO_r$ is the duration of the SAHO in region r. The region, occupation, skill-specific error term is denoted by ϵ_{ior}. α^i_2 and β^i_2 are the coefficients of interest. 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. α^i_1 and β^i_1 are the difference in skill demands between pre- and post-COVID in MSAs without SAHOs. To address possible serial correlation within a region, we cluster our standard errors at the MSA level.

3.1 Local level SAH policy

Ideally, we would like to use the duration of SAHOs at the MSA level. However, that data is only available at the state level.[7] One way to address this issue is to use state-level SAHO duration to

[6]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.

[7]The New York Times once published the start date for county-level SAHOs at https://www.nytimes.com/interactive/2020/us/coronavirus-SAH-order.html. However, when a state-wide SAHO was

predict the MSA-level duration. Because we are concerned about the endogeneity between economic performance and the duration of the SAHOs, we use data on pre-pandemic ICU beds (per 1000 people per square meter) to capture the quantitative relationship between policy duration and medical constraints. The idea is that regions with higher densities of ICU beds are easier to deal with the pandemic, which could allow for earlier lifting of SAHOs. Specifically, we run

$$SAHO_{state} = \theta_0 + \theta_1 bed_{state} + \epsilon_{state} \tag{5}$$

where $SAHO_{state}$ is the duration of the state-level SAHO, and bed_{state} is the pre-pandemic density of ICU beds in that state. Then we use the estimated coefficients and residuals to predict the MSA-level SAH policy

$$SAHO_{MSA} = \hat{\theta}_0 + \hat{\theta}_1 bed_{MSA} + \hat{e}_{state} \tag{6}$$

where we add the error term from the state-level regression to capture the heterogeneity in other factors across states. We assume the state-level error terms are orthogonal to other MSA level factors that may affect the duration of the local policy. The absence of other MSA level factors in this design helps us avoid endogeneity caused by the local economic factors, such as labor market composition, on the local level policy duration. Our estimates for $\hat{\theta}_0$ is 64.168 (4.636) and $\hat{\theta}_1$ is -0.066 (0.021). The correlation coefficient between $SAHO_{MSA}$ and $SAHO_{state}$ is 0.906. Figure 3 presents the distribution of the estimated MSA-level SAHO duration. The distribution is in general consistent with the state-level SAHO duration, while this measure eliminates the effect of local labor market on the local policy duration.

Another way to proceed is to use state-level SAHOs directly. This approach introduces substantial endogeneity concerns and neglects the variation across local policies within states.[8] Therefore, we use the estimated $SAHO_{MSA}$ in the main analysis and present estimates of the second approach in table A2.

issued, the New York Times stopped separately reporting sub-state orders. We did not find data on the duration of county-level SAHOs.

[8]For example, Philadelphia had a longer SAHO than the state of Pennsylvania.

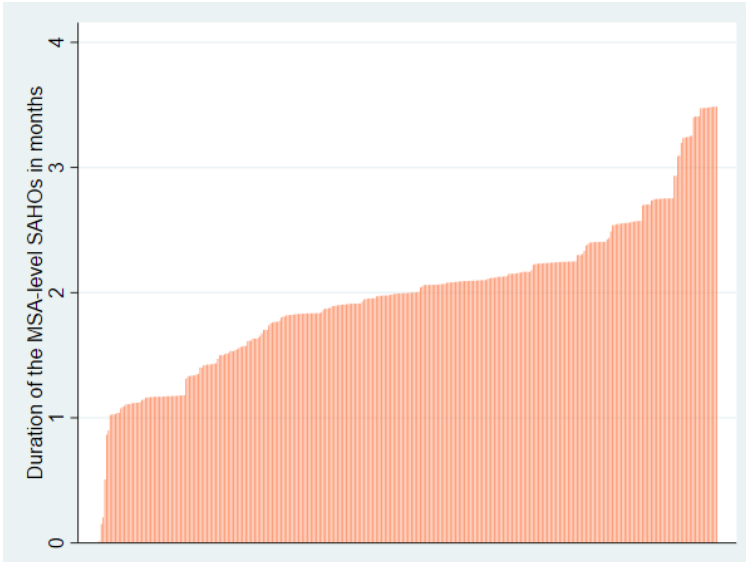

Figure 3: Distribution of estimated SAHO duration by MSA
Note: The figure shows the distribution of the estimated MSA-level SAHO duration. The estimation process is discussed in section 3.1.

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, and by education requirements of the job. Third, to gain a concrete understanding of the effects of SAHOs on skill requirements, we present a case study on the retail trade industry, and a second case study on manager occupations.

4.1 Results using the full sample of job postings

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 equations (3) and (4), respectively. Columns 3 and 4 show the estimates of α_1 and β_1. MSAs with longer SAHO show increases in the demand for administration skills, language skills, and self-management skills, and decreases in the demand for people management skills, computer skills, and specific personality requirements.

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

	SAHOs		COVID pandemic	
	Intensive (α_2)	Extensive (β_2)	Intensive (α_1)	Extensive (β_1)
	(1)	(2)	(3)	(4)
STEM	0.074	-0.045	0.233	0.816*
	(0.123)	(0.252)	(0.197)	(0.449)
Manual	0.131	-0.030	0.132	0.876*
	(0.121)	(0.193)	(0.203)	(0.457)
Customer services	0.027	-0.278	-0.290	-0.542
	(0.111)	(0.279)	(0.205)	(0.457)
Computer: general use	-0.116*	-0.381	-0.093	0.645
	(0.062)	(0.236)	(0.143)	(0.408)
Business and Finance	0.145	0.142	-0.421***	-1.125***
	(0.094)	(0.225)	(0.151)	(0.369)
Education	-0.230***	-0.064	0.256	-0.446**
	(0.085)	(0.098)	(0.203)	(0.204)
Administration	0.438**	0.564**	0.081	-0.024
	(0.173)	(0.220)	(0.337)	(0.460)
Computer: specialized software	0.013	0.020	0.799***	0.567***
	(0.168)	(0.084)	(0.303)	(0.179)
Languages	0.412**	0.681***	0.496	0.234
	(0.200)	(0.184)	(0.357)	(0.362)
Social	0.075	-0.294	0.109	0.187
	(0.055)	(0.351)	(0.088)	(0.660)
Operational Management	-0.011	-0.316	-0.284***	-1.700***
	(0.036)	(0.244)	(0.072)	(0.441)
Cognitive	-0.053	-0.137	0.231**	-0.108
	(0.047)	(0.169)	(0.101)	(0.314)
Personality	-0.180***	-0.617***	0.351***	0.574
	(0.058)	(0.202)	(0.124)	(0.395)
Industry Knowledge	0.122	-0.152	-0.920***	-0.585*
	(0.090)	(0.142)	(0.196)	(0.324)
People Management	-0.077	-0.551**	0.039	0.371
	(0.049)	(0.242)	(0.092)	(0.409)
Arts and Humanities	0.449**	-0.087	-0.560	-0.117
	(0.205)	(0.067)	(0.407)	(0.132)
Self-management	0.164*	0.456**	0.601***	0.196
	(0.090)	(0.194)	(0.196)	(0.357)
Project Management	-0.045	0.099	-0.246*	-0.404**
	(0.058)	(0.099)	(0.128)	(0.182)
Writing	0.112**	-0.035	-0.374***	-0.841***
	(0.048)	(0.115)	(0.080)	(0.235)

Note: The table reports estimates of the effect of SAHO duration and the effect of COVID on labor market demand for skills based on regression specifications in equations 3 and 4. 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 equation 3 for each skill. Column 2 reports the estimates of β_2 in equation 4. Column 3 reports the estimates of α_1 in equation 3. Column 4 reports the estimates of β_1 in equation 4. 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

MSAs experienced an additional month of exposure to SAHOs have -0.551 (0.242) percentage points (ppts) lower demand for people management skills on the extensive margin. The demand for personality drops on the intensive margin by 0.180 (0.058) ppt and the extensive margin by 0.617 (0.202). The demand for self-management skills increases on the intensive margin by 0.164 (0.090) ppt and the extensive margin by 0.456 (0.194) ppt. The changes in all three skills have larger magnitudes in the extensive margin than the intensive margin. Why do firms in areas that experienced longer SAHOs need fewer positions with people management skills or some specific personality and more positions with self-management skills than pre-COVID? The results make us believe that SAHOs have changed the way firms manage people. Remote working is hard to monitor, leaving managers with not many choices but to trust the employees (Deligiannis, 2021a). One solution to this dilemma is to substitute the supervision of people managers with the self-management of employees. The longer the SAHOs, the more active the firms are in adopting these new work arrangements. Fewer face-to-face interaction makes communication more mechanical, firms also require less on the personalities. These changes in employee characteristics allow managers to spend less time on the interpersonal relationships with and among the employees, and switch gears towards job content. The restructure of skill requirements is related to management style and the firm's feasibility to function amid temporary workplace closures in the future.

MSAs with 1-month longer SAHOs have 0.438 (0.173) ppts higher demand for administration skills and 0.412 (0.200) ppts higher demand for language skills on the intensive margins after the orders were lifted. Longer SAHOs have also increased the demand for jobs with administration and language skill requirements (β_2^{admin}=0.564 (0.220) and $\beta_2^{language}$=0.681 (0.184)). The coefficients on the two margins are both positive and significant and have comparable magnitudes. The estimates suggest that experiencing business uncertainty during long SAHOs may have motivated firms to enhance regulation within firms and smoothen communication, overcoming the additional challenges in organizing employees remotely. This is consistent with Koenders and Rogerson (2005), which argue that firms shift managerial attention from growth to efficiency during recessions. The increased extensive margin demand is also in line with the concerns about more frequent job turnovers and unstable teams (Boland et al., 2020). The workflows, less relying on language professionalists or key administration staff, are more resistant to risks such as sick leaves amid the pandemic.[9]

On computer-related skills, the demand for specialized software skills increases on both margins after COVID ($\alpha_1^{cs-specialized}$=0.799 (0.303) and $\beta_1^{cs-specialized}$=0.567 (0.179)), while the demand for general computer skills slightly decreases on the intensive margin ($\alpha_2^{cs-general}$=-0.116 (0.062)). These trends are consistent with the evidence from Modestino et al. (2020) that employers require higher skills for the same job title in recessions.

SAHOs also have effects on the intensive margin demand for a few other skills. Job postings in areas experienced longer SAHOs mention less of education skill (α_2^{edu}=-0.230 (0.085)), and more of arts and humanities skill (α_2^{arts}=0.449 (0.205)) and writing skill (α_2^{write}=0.112 (0.048)).

[9] In section 4.3, we show that the main undertaker of the change in demand for administration and language skills are workers without a college degree.

4.2 By the work-from-home capacity of occupations

The soaring uncertainty about the COVID and work arrangements pushes firms to evaluate to what extent can their workforce 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 3 2-digit SOC occupations, including construction and extraction occupations, food preparation and serving occupations, 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 include management, office and administrative support, salesperson, and business and financial specialists.

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 1-2 show that for occupations that cannot work from home, the demand increases in STEM and manual skills and decreases in personality, people management, and project management skills on the intensive margin. 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-skill workers to design new products instead of administration and management. The demands for personality increase with substantial magnitudes after COVID and extending SAHOs counteracts the change ($\alpha_1^{personal}$= 2.538 (0.989) and $\alpha_2^{personal}$= -1.271 (0.463)). 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 remains different from the pre-COVID condition.[10]

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

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	Extensive	Intensive	Extensive	Intensive	Extensive
	(1)	(2)	(3)	(4)	(5)	(6)
STEM	0.721**	-0.280	0.011	-0.091	0.117	0.213
	(0.314)	(0.296)	(0.131)	(0.292)	(0.091)	(0.204)
Manual	0.558*	0.629	0.105	-0.096	0.190	-0.013
	(0.290)	(0.399)	(0.140)	(0.217)	(0.148)	(0.210)
Customer services	0.120	-0.023	-0.016	-0.519	0.255***	0.893***
	(0.190)	(0.530)	(0.133)	(0.324)	(0.083)	(0.298)
Computer: general use	0.506	0.006	-0.164***	-0.393	-0.001	-0.423***
	(0.358)	(0.265)	(0.061)	(0.284)	(0.109)	(0.155)
Business and Finance	0.168	-0.346*	0.141	0.165	0.163*	0.204
	(0.251)	(0.199)	(0.117)	(0.256)	(0.085)	(0.238)
Education	-0.536	-0.333**	-0.283***	-0.006	0.178	-0.267***
	(0.439)	(0.162)	(0.084)	(0.123)	(0.123)	(0.090)
Administration	0.184	0.211	0.520**	0.658***	0.085	0.009
	(0.181)	(0.598)	(0.208)	(0.240)	(0.095)	(0.189)
Computer: specialized software	0.350	0.008	0.065	0.099	-0.281**	-0.469*
	(0.555)	(0.073)	(0.194)	(0.079)	(0.128)	(0.242)
Languages	-0.116	-0.175	0.474**	0.872***	0.311	-0.026
	(0.233)	(0.250)	(0.231)	(0.229)	(0.195)	(0.121)
Social	-0.244	-0.809*	0.114*	-0.335	-0.003	0.013
	(0.186)	(0.424)	(0.067)	(0.401)	(0.046)	(0.306)
Operational Management	0.127	0.242	-0.033	-0.426	0.091	0.000
	(0.173)	(0.197)	(0.046)	(0.289)	(0.064)	(0.212)
Cognitive	0.213	0.351	-0.078*	-0.159	0.002	-0.285
	(0.181)	(0.248)	(0.045)	(0.196)	(0.073)	(0.252)
Personality	-1.271***	-1.277**	-0.127**	-0.705***	-0.023	0.114
	(0.463)	(0.510)	(0.051)	(0.221)	(0.061)	(0.284)
Industry Knowledge	-0.235	0.273	0.149	-0.206	0.076	0.039
	(0.241)	(0.407)	(0.103)	(0.167)	(0.105)	(0.215)
People Management	-0.529**	-0.351	-0.058	-0.674**	-0.010	-0.023
	(0.234)	(0.301)	(0.052)	(0.282)	(0.060)	(0.207)
Arts and Humanities	0.822	0.095	0.480**	-0.050	0.189	-0.376**
	(0.773)	(0.071)	(0.244)	(0.065)	(0.137)	(0.158)
Self-management	0.105	0.117	0.197*	0.595**	0.002	-0.174
	(0.346)	(0.262)	(0.108)	(0.234)	(0.061)	(0.117)
Project Management	-0.679**	-0.001	-0.018	0.115	0.009	0.049
	(0.308)	(0.099)	(0.066)	(0.107)	(0.067)	(0.157)
Writing	0.309	0.308*	0.109*	0.022	0.039	-0.477**
	(0.206)	(0.174)	(0.058)	(0.129)	(0.044)	(0.196)

Note: 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 1-2 report the results for occupations incapable of working from home, i.e. with WFH capacity index = 0. Columns 3-4 report the results for occupations that are somewhat capable of working from home, i.e. with WFH capacity index between 0 and 0.9. Columns 5-6 report the results for occupations mostly capable of working from home, i.e. with WFH capacity index > 0.9. Figure 2 lists these occupations and their WFH capacity index values. See the notes for table 2.
* p<0.1, ** p<0.05, *** p<0.01

Columns 5-6 of Table 3 present the regression results for occupations with high WFH capacity. The duration of SAHO does not affect the demand for skills related to employee management, i.e. people management, personality, self-management, administration, and languages. The ways of working and interaction in highly-WFH-capable occupations do not depend much on work location, so it is not surprising that SAHOs did not further change the demand for these management-related skills. On the other hand, skills that are much more closely related to the job content, including customer service and computer skills are significantly dependent on the SAHO duration. Customer service skills are more important both extensively and intensively ($\alpha_2^{customer}$=0.255 (0.083) and $\beta_2^{customer}$=0.893 (0.298)). A closer look at each 2-digit occupation shows that computer and mathematical occupations, accounting for 77% of highly teleworkable job postings, require customer service skills in more jobs ($\beta_2^{customer}$=1.254 (0.262)), and education occupations, accounting for another 20% of the postings, emphasize the skill in their postings ($\alpha_2^{customer}$=0.755 (0.242)).

The interpretation on the change in demands for computer skills has to take into account both the effect of COVID in general, i.e. α_1 and β_1 reported in Table A3, and the effect of the duration of SAHO, i.e. α_2 and β_2 reported in Table 3. The COVID pandemic promotes the importance of computer skills significantly. The MSA-occupation level average fraction of job postings requiring some general computer skills increased by 1.352 (0.324) ppts, holding the SAHO duration constant at zero. The demand for specialized software skills increase by 3.377 (0.524) ppts on the extensive margin and 0.357 (0.211) ppts on the intensive margin. However, the duration of SAHOs has negative effects on the demand for these skills. Our interpretation for the opposite signs of the coefficient is that firms desperately need people with computer skills after COVID starts, then longer experience amid SAHO makes firms more informed about the new hires' skill composition in teleworkable occupations, hence no longer emphasizing so much on skills that are generally equipped by most job candidates in those positions.

Columns 3-4 shows SAHO makes the most dynamic changes to the labor market demand for skills in occupations that are partially capable of working from home. In these occupations, the demands for people management, self-management, administration, and language skills change in the same direction as in occupations incapable of working from home. The detail, however, is different for people management, with a substantial, negative extensive margin ($\beta_2^{ppl-manage}$=-0.824 (0.302)) and a small, positive intensive margin ($\alpha_2^{ppl-manage}$=0.062 (0.042)). These results suggest SAHO incentivizes firms to prepare for functioning in future WFH scenarios by relying more on self-management and professional administration protocol than on managers' hands-on supervision and organization. Similar to the pattern on computer skills in teleworkable occupations, the extensive margin demand for general computer skills in partially teleworkable occupations has increased by 1.654 (0.428) ppt because of the COVID pandemic, while longer SAHO offsets the effect ($\alpha_2^{cs-general}$=-0.771 (0.290)). The decreased demand for customer service skills ($\alpha_2^{customer}$=-0.761 (0.366)) mirrors the increase in teleworkable occupations, implying the reallocation of customer service tasks across occupations.

4.3 By education requirements

Among all job posts included in the BGT database from January 2018 to April 2021, 64.6% of them provide specific education requirements, which were recorded as minimal years of education taking values on 12, 14, 16, 18, and 21.[11] Table (4) presents the estimates for the effect of the SAHO duration on the demand for skills, i.e. the coefficients and standard errors of α_2 and β_2 on subsamples by education requirement. Table (A4) presents the corresponding estimates for the remaining effect of COVID, i.e. α_1 and β_1. By counting the number of skill categories with significant extensive margin changes in response to COVID and/or SAHO, we observe a clear pattern that jobs with higher education requirements are less affected. Specifically, among the 19 skill categories, 15 of them statistically significantly depend on the duration of SAHO for middle school or high school graduates, 6 for college graduates, and 2 for people with graduate degrees.

Skill requirements in job postings without a college degree requirement respond to both the pandemic and the policy. Column 1 of table 4 shows that in areas with longer SAHO, the demands for language and self-management skills increase on both margins, and administration increases on the intensive margin. However, the demands for 9 technical, professional, and management skills decrease on the extensive margin, meaning that most of the negative effects of SAHO take place through suppressing the fraction of job postings requiring advanced technical ability or management potentials without requiring a college diploma.[12] In addition, the extensive margin is negative and the intensive margin is positive for customer service and social skills, suggesting that longer SAHO condenses the labor market demand for skills on oral and written communication on workers without a college degree. Columns 1 and 2 of table A4 show increased demand for general and specialized computer skills after COVID, in opposite direction as the effect of SAHO. This is consistent with the pattern we discussed concerning the demand for computer skills in partially teleworkable occupations in section 4.2.

[11] We have to assume that the set of job postings in the data with each specific education requirement is a representative sample of all online job postings with this education requirement. We also want to remind the readers that the subsample of all job postings with education requirements is not a representative sample of the full data.

[12] The skills are industry knowledge, STEM, customer services, general computer, business and finance, specialized computer, and cognitive skills, and operation, project, and people management skills

Table 4: The effect of SAHO on demands for skills by education requirement

	Middle or high school		College		Graduate degree	
	Intensive	Extensive	Intensive	Extensive	Intensive	Extensive
	(1)	(2)	(3)	(4)	(5)	(6)
STEM	-0.018	-0.780**	0.067	0.458***	0.276*	0.342
	(0.132)	(0.364)	(0.082)	(0.158)	(0.162)	(0.247)
Manual	0.387*	-0.788**	-0.059	0.025	-0.403***	-0.155
	(0.216)	(0.327)	(0.047)	(0.238)	(0.109)	(0.335)
Customer services	0.504**	-1.256**	-0.046	-0.006	0.116	0.742*
	(0.211)	(0.519)	(0.081)	(0.146)	(0.109)	(0.398)
Computer: general use	0.005	-1.444***	-0.097	-0.269	-0.296**	-0.132
	(0.087)	(0.514)	(0.074)	(0.173)	(0.137)	(0.265)
Business and Finance	0.500**	-0.735***	0.045	0.118	0.288**	-0.038
	(0.196)	(0.259)	(0.051)	(0.188)	(0.129)	(0.297)
Education	-0.037	-0.123	-0.018	-0.178	-0.062	-0.127
	(0.141)	(0.138)	(0.071)	(0.117)	(0.157)	(0.239)
Administration	1.378***	0.039	-0.016	-0.146	-0.077	0.225
	(0.352)	(0.461)	(0.062)	(0.239)	(0.084)	(0.240)
Computer: specialized software	-0.124	-0.281***	-0.029	-0.005	-0.229	0.235
	(0.181)	(0.080)	(0.069)	(0.144)	(0.197)	(0.155)
Languages	0.902***	2.114***	0.179**	-0.253**	-0.300	-0.272
	(0.336)	(0.561)	(0.071)	(0.126)	(0.233)	(0.196)
Social	0.575***	-1.449**	-0.008	-0.070	-0.017	-0.459
	(0.157)	(0.574)	(0.037)	(0.310)	(0.075)	(0.294)
Operational Management	0.021	-1.698***	0.024	0.345**	0.029	-0.247
	(0.056)	(0.492)	(0.050)	(0.142)	(0.114)	(0.306)
Cognitive	-0.060	-1.295***	-0.010	0.116	0.072	0.424
	(0.097)	(0.320)	(0.046)	(0.172)	(0.088)	(0.298)
Personality	-0.071	-1.392***	-0.034	-0.283	-0.001	-0.370**
	(0.079)	(0.388)	(0.034)	(0.239)	(0.128)	(0.187)
Industry Knowledge	0.192*	-0.942***	0.062	0.072	-0.060	-0.152
	(0.101)	(0.290)	(0.082)	(0.218)	(0.138)	(0.200)
People Management	-0.014	-1.638***	-0.004	0.008	-0.316***	0.094
	(0.074)	(0.373)	(0.039)	(0.213)	(0.084)	(0.257)
Arts and Humanities	1.295**	-0.002	-0.020	-0.333***	-0.417	0.081
	(0.503)	(0.115)	(0.068)	(0.088)	(0.360)	(0.153)
Self-management	0.792***	1.163**	-0.019	-0.295**	-0.217	-0.018
	(0.191)	(0.516)	(0.047)	(0.140)	(0.166)	(0.212)
Project Management	-0.114	-0.225***	0.008	0.322**	-0.040	-0.020
	(0.136)	(0.071)	(0.043)	(0.142)	(0.095)	(0.183)
Writing	0.317**	-0.223	-0.012	-0.177	-0.080	-0.223
	(0.124)	(0.211)	(0.026)	(0.132)	(0.110)	(0.180)

Note: The table reports estimates of the effect of SAHO duration on labor market demand for skills by education requirement in the job postings. Columns 1-2 report the results for job postings that require a middle school or high school diploma. Columns 3-4 report the results for job postings that require a four-year college degree. Columns 5-6 report the results for job postings that require an advanced degree, including doctorates. See the notes for table 2.
* $p<0.1$, ** $p<0.05$, *** $p<0.01$

In job postings targeting college graduates, column 4 of table 4 shows that firms being exposed to longer SAHO become slightly less demanding on languages ($\beta_2^{language}$=-0.253 (0.126)), while requiring more STEM skill (β_2^{STEM}=0.458 (0.158)), operational management skill ($\alpha_2^{op-manage}$=0.345 (0.142)), and project management skill ($\beta_2^{prj-manage}$=0.322 (0.142)). To our surprise, the demand for self-management skill decreases with SAHO duration ($\beta_2^{self-manage}$=-0.295 (0.140)) after a significant increase after COVID ($\beta_1^{self-manage}$=0.790 (0.281)). Our interpretation for this result is similar to the one for computer skills in teleworkable occupations – SAHOs make firms believe self-management is very important in ensuring efforts while experiencing SAHOs helps firms gain information that college graduates can self-manage, hence no longer list this skill requirement often. Moreover, the statistically significant effects of COVID on demand for skills are all positive on the extensive margin and negative on the intensive margin, implying firms prefer college graduates with composite backgrounds over those with clear specialties.

Job opportunities for people with graduate degrees are very mildly affected by SAHO. On the intensive margin, the demand for STEM increases on the extensive margin after COVID and on the intensive margin with SAHO (α_2^{STEM}=0.276 (0.161), β_1^{STEM}=1.684 (0.449)). The demand for business and finance also increase with SAHO, but far from enough to offset the significant decrease after COVID. On the other hand, although the demand for people management and personality decrease with SAHO ($\alpha_2^{ppl-manage}$=-0.316 (0.084), $\alpha_2^{personal}$=-0.370 (0.187)), COVID makes employers care more about highly-educated people's ability to interact with people by increasing their demand by much larger magnitudes ($\alpha_1^{ppl-manage}$=0.930 (0.182), $\alpha_1^{personal}$=1.578 (0.410)).

This set of results suggests a new assignment scheme of job tasks by education background: people without college education provide workplace support such as administration, and basic technical support such as general computer-related or manual work. College graduates conduct scientific and technical tasks, have professional communication, and are in charge of operational and project management. People with graduate degrees become technical experts or people managers.

4.4 Case studies of the effects of SAHO and COVID on skill requirements

The regression estimates of the effects of SAHO duration provide an overview of the change in labor demand and employment structure after the pandemic. In this section, we zoom in to look at two cases: one sector and one occupation.

4.4.1 Skill requirements in the retail trade industry

Since COVID begin, the retail trade industry made a remarkable transformation towards online sales.[13] Throughout this transition, firms have to rapidly change their working methods, including granting to employees to use company computers outside the workplace, and to adjust the rotation system for online or hybrid sales. As COVID shakes the supply chains that the retail trade industry has to rely on, firms need new strategies in dealing with the unstable supply of goods. Moreover,

[13]Vodafone Business, April 30, 2021. "How Covid-19 has changed the retail industry".

remote work and digitization are replacing labor-intensive operations at an accelerated speed. As the pandemic prolongs, firms' primary objective turns to business continuity, making them focus more on market analysis, supply chain, and maintaining business partnerships.[14]

The BGT data includes 4.79 million job postings from the industry from 2018. The five most common occupations in this industry are sales (39% with WFH capacity = 0.14), office and administrative support (16%, WFH=0.33), transportation (9%, WFH = 0), management (6%, WFH = 0.89), and computer and math (4%, WFH = 1). The number of postings does not vary much from before COVID, March to June 2020 when most states have ongoing SAH orders, to after the SAHOs have been lifted (numbers not reported). Table 5 presents the estimates to equations (3) and (4) on this subsample, in which we group the skills into four groups: management related skills, essential skills for the retail trade industry, STEM supportive skills, and other supportive skills.

On people management and employee characteristics, personality is mentioned in fewer jobs after prolonged SAHOs. Self-management skills occupy a larger share of the skill requirements since COVID starts, and more job postings mention them as the duration extends. The changes are reasonable since staff for online sales can work from home. People management skills are less important after COVID, while SAHO duration has a positive effect on the intensive margin and a negative effect on the extensive margin, signaling that firms promote more concentrated people management power. The COVID-driven adaptation of digitized operations reduces the demand for operational management skills and shifts managerial attention to the projects.

For jobs in the retail trade industry, we consider customer service, business and finance, and industry knowledge as essential skills. The demand for all three skills decreases after COVID starts. Longer SAHOs make skill requirements on industry knowledge more condensed on fewer jobs, implying specialization in jobs related to these essential skills. The extensive margin demand for customer service skills reduces and the intensive margin demand for business and finance rises. The results suggest that retail trade firms, hoping to survive the pandemic, change their preference on skills from practical skills of retail trade to professional skills that help with understanding the business environment.

[14] ABeam Consulting, September, 2020. "The impact of COVID-19 on the retail industry and the next actions to be taken".

Table 5: Changes in skill requirements in the retail trade industry

	SAHOs		COVID pandemic	
	Intensive	Extensive	Intensive	Extensive
	(1)	(2)	(3)	(4)
	Management			
Personality	-0.159	-2.322***	0.183	0.514
	(0.110)	(0.657)	(0.232)	(1.452)
Self-management	-0.261	2.462**	3.638**	0.724
	(0.788)	(1.005)	(1.407)	(1.999)
People Management	0.885***	-3.485***	-1.834***	1.081
	(0.322)	(0.918)	(0.649)	(1.490)
Project Management	1.225**	-0.227	-1.778**	1.385***
	(0.610)	(0.206)	(0.795)	(0.416)
Operational Management	-0.063	-2.175**	-0.535*	-4.866***
	(0.148)	(0.954)	(0.315)	(1.733)
	Essential skills for the industry			
Industry Knowledge	0.465***	-2.362***	-3.122***	-1.725
	(0.121)	(0.797)	(0.236)	(1.585)
Customer services	-0.013	-4.531***	-1.796**	-3.351
	(0.480)	(1.622)	(0.776)	(2.961)
Business and Finance	1.282**	1.446	-0.694	-2.759*
	(0.616)	(1.278)	(1.024)	(1.531)
	STEM supportive skills			
STEM	-0.239	-1.905***	0.804*	0.805
	(0.214)	(0.614)	(0.415)	(1.146)
Computer: general use	0.206	-1.468***	-0.782**	2.898***
	(0.150)	(0.528)	(0.330)	(1.052)
Computer: specialized software	0.752	-0.149	3.548**	1.195***
	(0.826)	(0.208)	(1.621)	(0.431)
	Other supportive skills			
Languages	2.077**	4.024***	3.227	5.844***
	(0.945)	(1.124)	(2.287)	(1.959)
Administration	2.099**	2.159*	2.977	4.528*
	(0.850)	(1.219)	(2.002)	(2.366)
Social	1.217**	-3.265**	-1.025	0.535
	(0.490)	(1.356)	(0.734)	(2.519)
Writing	1.015***	-0.018	-1.291***	-1.447*
	(0.292)	(0.361)	(0.396)	(0.805)

Note: The table reports regression estimates from equations 3 and 3 on the sample of job postings in the retail trade sector. Columns 1-2 report the effect of SAHO duration, i.e. the estimates of α_2 and β_2. Columns 3-4 report the effect of the COVID pandemic, i.e. the estimates of α_1 and β_1. We only report skills with statistical significant coefficients. See the notes for table 2.

* p<0.1, ** p<0.05, *** p<0.01

The demand for STEM supportive skills, including STEM and computer skills, unsurprisingly increased significantly after COVID, with the prevalence of online sales. Longer SAHOs correlate with the decrease in demand for STEM and general computer skills, which is consistent with the results we presented in section 4.2 on the subsample with WFH capacity close to 1. The demand for specialized software skills is unaffected by SAHOs as a result of online sales. Among other supportive skills, administration and language skills are more important, in line with the observed transition in work protocol amid online business. The COVID pandemic suppresses the demand for social and writing skills, but SAHO brings the intensive margin demands back to their pre-COVID levels.

4.4.2 Manager occupations

We often mention the change in management style throughout this section. In addition to interpreting the change in skill requirements on extensive and intensive margin for the full sample, it would be useful to take a closer look at manager occupations. According to guides for CEOs and managers from consulting groups and articles on global media, the priorities of the firm leaders are the agility of operation and management, the adaptation to technology, and the proper regulation to ensure compliance with government policies.[15]

In the BGT data, the 3-digit SOC occupation classification gives four types of managers: 9.23% are top-level executives, 19.15% are professional managers, including advertising, marketing, promotions, public relations, and sales managers, 17.12% are operations specialties managers, and 54.50% are other managers, such as managers in the education, healthcare, and construction industries. We estimate equations (3) and (4) for each 3-digit SOC manager occupation, and report the coefficients with significance levels in table 6.

[15] Victoria Masterson, February 15, 2021. "The post-pandemic future of work - according to 3,000 CEOs from around the world", World Economic Forum.

Table 6: Changes in skill requirements in manager occupations

Manager occupation name	Skill name	SAHOs Intensive (1)	SAHOs Extensive (2)	COVID pandemic Intensive (3)	COVID pandemic Extensive (4)	Skill name	SAHOs Intensive (5)	SAHOs Extensive (6)	COVID pandemic Intensive (7)	COVID pandemic Extensive (8)
		Technical Knowledge and Skills					Business and Industry Knowledge			
Top	STEM	0.199	0.009	0.635	0.902	Business & Finance	0.077	0.667**	-0.982***	-1.184
	CS-general	-0.382**	-0.798*	-0.059	3.207***					
	CS-specialized	-0.099	-0.249	-0.003	2.843***	Industry Knowledge	0.123	0.563	-1.051***	-2.916***
	Cognitive	0.049	-0.157	0.573	2.004**					
Professional	STEM	-0.018	0.787***	0.574	1.295***	Business & Finance	-0.152	0.292	-0.661**	-1.426**
	CS-general	-0.186*	-0.581	0.428*	3.148***					
	CS-specialized	-0.063	0.234	-0.120	3.455***	Industry Knowledge	-0.109	0.277	-0.297**	-1.349*
	Cognitive	0.058	-0.219	0.502***	5.651***					
Operational	STEM	0.141	0.331	-0.395	1.980***	Business & Finance	0.032	-0.347	-0.806**	0.124
	CS-general	-0.165	-0.275	-0.054	2.094***					
	CS-specialized	-0.035	-0.191	0.290*	2.187***	Industry Knowledge	0.095	0.105	-0.474**	0.553
	Cognitive	-0.024	0.842***	0.222**	-0.293					
Other	STEM	-0.061	0.706***	1.448***	2.778***	Business & Finance	-0.009	0.319	-0.467***	-1.540***
	CS-general	-0.112	0.353	-0.004	-0.281					
	CS-specialized	0.002	0.420**	0.192	-0.166	Industry Knowledge	0.073	0.337*	-0.721***	-1.092***
	Cognitive	-0.023	0.669**	0.201*	-0.650					
		Management skills					Personality and communication skills			
Top	People	-0.074	0.472	-0.056	-2.345***	Personality	-0.135**	-0.417	0.028	2.685***
	Operational	0.240**	0.429	-1.099***	-0.644	Writing	-0.027	-0.352	-0.102	1.530***
	Project	0.098	-0.453	-0.104	3.815***					
Professional	People	0.085*	0.729***	-0.334***	-1.883***	Personality	-0.153***	-0.435	0.219*	3.183***
	Operational	-0.102**	-0.949**	0.099	3.689***	Writing	-0.006	-0.736**	-0.273**	1.428**
	Project	0.092*	-0.261	-0.433***	4.580***					
Operational	People	-0.026	-0.403	-0.424***	0.415	Personality	0.004	-0.551	0.201	4.281***
	Operational	0.131	0.012	-0.838***	-0.308	Writing	-0.037	-0.295	-0.233	0.733*
	Project	-0.044	-0.236	-0.241*	1.501***					
Other	People	-0.221***	0.236	0.491***	-0.042	Personality	-0.020	-0.205	-0.129	0.863**
	Operational	0.001	0.399*	-0.399**	-2.746***	Writing	-0.028	0.036	-0.255**	-0.728**
	Project	-0.120*	0.507	-0.585***	-2.614***					

Note: The table reports regression estimates from equations 3 and 3 on the sample of job postings in the manager occupation (2 digit SOC code = 11). Coefficient values with statistical significance are reported, and clustered standard errors are suppressed. Columns 1-2 and 5-6 report the effect of SAHO duration, i.e. the estimates of α_2 and β_2. Columns 3-4 and 7-8 report the effect of the COVID pandemic, i.e. the estimates of α_1 and β_1. The regressions are separately run on job postings from the four 3-digit SOC occupations in the manager occupation. Top-level managers (called "Top Executives" in the SOC occupation dictionary) regression sample contains 438,215 job ads. The professional managers ("Advertising, Marketing, Promotions, Public Relations, and Sales Managers" in the dictionary) sample has 919,012 job ads. The operational managers ("Operations Specialties Managers") sample has 815,751 job ads. And other managers ("Other Management Occupations") sample includes 2,582,819 job ads. We only report skills with statistically significant coefficients. See the notes for table 2.

* p<0.1, ** p<0.05, *** p<0.01

Technical knowledge and skills, including STEM, computer, and cognitive skills, are required in many more manager jobs since COVID begins. Longer SAHOs, as we have observed in previous sections, make firms mention less of general computer skills when hiring top-level or professional managers. The change in demand for these skills is very consistent among top-level, professional, and operational managers. Recall that in section 4.3, we observed that jobs requiring college degrees demand more technical skills and less general communication skills. The two pieces of results point to a trend of specialization: workers with strong technical backgrounds specialize in their expertise, and managers should have some knowledge of specific industries and are responsible for communication with the technical experts. Moreover, as firms understand technology will have big impacts on the business world, many would prefer top-level executives with solid technical skill backgrounds.

Business and industry knowledge are less important, possibly because firms do not expect managers to have many insights for the future amid the unprecedented pandemic. As firms experience longer SAHOs, they expect the newly hired CEOs to know the big picture of the upcoming challenges but do not expect the same from other mid-level managers.

Managers, while classified as top-level, professional, and operational based on their positions in hierarchical firms, share the duties to supervise people, firm operations, and projects. The lower left panel of table 6 shows how SAHOs, as well as the COVID pandemic, change the skill requirements related to these three types of management. Longer SAHOs motivate firms to assign more people management duties to professional managers. Operational management skills become more important for top-level executives as SAHOs extend, which is consistent with the practical advice for CEOs suggesting them to pay more attention to the operations (Hatami et al., 2020). The demand for project management skills does not change with the SAHO duration, but the COVID effect generates negative coefficients on the intensive margin for all four types of managers, and positive extensive margins for top-level, professional, and operational managers. This suggests that project management duties are more distributedly allocated among more managers at each level of management.

Communication skills are required in many more manager jobs than pre-COVID. SAHOs promoting remote working makes personality and writing skills less important, especially for top-level and professional managers.

Moreover, we notice that statistically significant coefficients for the effect of SAHOs (α_2 and β_2) and the effect of COVID (α_1 and β_1) have opposite signs in almost all the cases. This interesting finding suggests that firms may seek substantial restructure in their employee skill composition in response to the pandemic shock, but longer SAHOs may help with bringing the labor demand for skills back to the pre-COVID scenario.

5 Conclusion

In this paper, we use online job postings in the United States from 2018 to 2021 and the spatial variation in the duration of the SAHOs to study their effect on the change in labor skill demand. We classify over 98% of the skill requirements into 19 skill categories, such as administration, personality, self-management, and people management. We show that the labor skill demand changed from pre-COVID to post-SAHO period within occupations. The changes are heterogeneous across geographical areas and are correlated with the duration of local SAHOs.

Longer SAHOs yield higher demand for self-management skills and lower demand for people management skills and requirements on personality. This suggests that SAHO motivates firms to adjust their management style from supervision-based to self-motivation-based, and that remote working shifts managerial attention away from interpersonal relationships. The demand for administration and language skills also increase on the intensive and extensive margin, showing firms experienced long SAHOs want to reinforce regulation and communication. The increase in the demand for advanced computer skills and a small decrease in the demand for basic skills signal a trend of upskilling as a result of the economic recession.

We estimate the effect of SAHO duration on skill demands by the WFH capability of occupations. We find that occupations that are partially capable of working from home are the focus of skill restructure. The SAHO effects on self-management, administration, and people management are larger than the average effects on the full sample, suggesting that firms that suffered from long SAHO are more actively exploiting these occupations' potential to work from home.

The effects of SAHO duration also vary by education requirement in the job postings. Skill demands in jobs that do not require a college degree heavily depend on the SAHO duration, which turns labor demands towards jobs that do not require technical, professional, or managerial skills. Skill demands for jobs that target college graduates emphasize technical skills and management of job content but not people. Job postings for candidates with advanced degrees do not vary much with SAHO duration. The findings suggest adjusted assignments of job tasks segregated by education background and are consistent with the evidence from Maurin and Thesmar (2004), who show that new technologies improve firm efficiency by motivating occupational structural changes that reduce the proportion of high-skill workers in administrative and managerial activities.

This paper documents 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.

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Appendix

Table A1: Classification of skill requirements in the Burning Glass Technology data

Skill Category (1)	Skill Cluster Family defined by BGT (2)	Percentage (3)
Administration	Administration	39.39
	Human Resources	26.63
	Business	8.04
	Customer and Client Support	6.67
	Health Care	4.80
Arts and Humanities	Media and Writing	35.73
	Engineering	31.50
	Design	20.07
	Architecture and Construction	9.64
	Education and Training	2.61
Manual	Maintenance, Repair, and Installation	22.81
	Supply Chain and Logistics	12.95
	Personal Care and Services	11.33
	Manufacturing and Production	7.84
	Architecture and Construction	6.18
Business and Finance	Finance	50.89
	Marketing and Public Relations	22.29
	Business	19.50
	Sales	5.50
	Architecture and Construction	0.58
Cognitive	Analysis	16.14
	Economics, Policy, and Social Studies	2.68
	Science and Research	1.80
	Marketing and Public Relations	0.77
	Manufacturing and Production	0.01
Computer: general use	Information Technology	72.85
	Design	1.57
	Health Care	1.46
	Engineering	0.89
	Media and Writing	0.52
Computer: specialized software	Information Technology	71.45
	Design	9.79
	Analysis	4.45
	Finance	3.04
	Engineering	1.96
Customer services	Sales	38.01
	Customer and Client Support	31.48
	Health Care	25.48
	Marketing and Public Relations	4.18
	Business	0.05
Education	Education and Training	84.67
	Personal Care and Services	10.52

...continued

Skill Category (1)	Skill Cluster Family defined by BGT (2)	Percentage (3)
Industry Knowledge	Industry Knowledge	60.93
	Legal	24.95
	Sales	11.84
	Finance	1.41
	Supply Chain and Logistics	0.04
Languages	English, Bilingual, Spanish, Chinese, English as a Second Language, French, Arabic, Business English, American Sign Language, Japanese, Portuguese, Korean, Sign Language, German, Russian, Vietnamese, Filipino, Persian, Polish	
Operational Management	Business	36.57
	Supply Chain and Logistics	33.43
	Customer and Client Support	4.68
	Manufacturing and Production	4.43
	Sales	2.75
Personality	Changeman, Creativity, Detail-Oriented, Energetic, Executive Presence, Implementor, Independent Thinking, Initiative, Intolerance, Meeting Deadlines, Multi-Tasking, Overcoming Obstacles, Persuasion, Positive Disposition, Quick Learner, Self-Starter, Smarty, Thought Leadership	
People Management	Business	27.96
	Human Resources	2.08
	Health Care	1.15
	Sales	0.70
	Supply Chain and Logistics	0.56
Project Management	Business	57.78
	Manufacturing and Production	15.87
	Education and Training	9.81
	Architecture and Construction	6.11
	Media and Writing	2.17
Self-management	Goal Setting, Scheduling, Self-Motivation	
Social	Sales	1.30
	Business	1.24
	Health Care	1.13
	Marketing and Public Relations	0.22
	Customer and Client Support	0.08
STEM	Health Care	77.83
	Science and Research	7.74
	Engineering	7.14
	Environment	3.85
	Energy and Utilities	2.00
Writing	Media and Writing	13.57
	Health Care	0.14
	Legal	0.09

Note: Column 1 presents 19 aggregated skill categories that are constructed from 7,481 detailed level skills. For languages, personality, and self-management skills, columns 2 and 3 are combined and list all skill names in the two categories. For all other skill categories, column 2 presents the five most common skill cluster families (aggregated skill groups defined by the Burning Glass Technologies and provided in the raw data). Column 3 presents the share of each skill cluster family in the aggregated skill category.

Table A2: The effect of the state-level SAHOs on demands for skills

	SAHOs		COVID pandemic	
	Intensive (α_2)	Extensive (β_2)	Intensive (α_1)	Extensive (β_1)
	(1)	(2)	(3)	(4)
STEM	0.049	0.048	0.298	0.651*
	(0.121)	(0.266)	(0.210)	(0.379)
Manual	0.067	-0.043	0.279	0.887**
	(0.132)	(0.190)	(0.202)	(0.396)
Customer services	0.034	-0.299	-0.291	-0.597
	(0.126)	(0.319)	(0.195)	(0.509)
Computer: general use	-0.217***	-0.598**	0.036	0.878**
	(0.060)	(0.279)	(0.105)	(0.444)
Business and Finance	0.191*	0.265	-0.451***	-1.281***
	(0.113)	(0.245)	(0.149)	(0.311)
Education	-0.191*	-0.041	0.118	-0.504***
	(0.107)	(0.108)	(0.221)	(0.194)
Administration	0.417**	0.548**	0.256	0.182
	(0.186)	(0.234)	(0.333)	(0.415)
Computer: specialized software	0.171	0.134	0.546*	0.387**
	(0.219)	(0.094)	(0.299)	(0.151)
Languages	0.362*	0.691***	0.710**	0.436
	(0.212)	(0.188)	(0.357)	(0.336)
Social	0.073	-0.199	0.135	-0.064
	(0.055)	(0.392)	(0.092)	(0.595)
Operational Management	-0.007	-0.292	-0.295***	-1.841***
	(0.041)	(0.280)	(0.072)	(0.422)
Cognitive	-0.078*	-0.327	0.255***	0.157
	(0.044)	(0.223)	(0.084)	(0.332)
Personality	-0.170***	-0.507**	0.277***	0.196
	(0.054)	(0.206)	(0.102)	(0.369)
Industry Knowledge	0.018	-0.144	-0.711***	-0.648**
	(0.069)	(0.152)	(0.129)	(0.275)
People Management	-0.032	-0.583**	-0.060	0.245
	(0.056)	(0.277)	(0.094)	(0.390)
Arts and Humanities	0.474**	-0.051	-0.456	-0.205*
	(0.226)	(0.071)	(0.378)	(0.112)
Self-management	0.283***	0.430*	0.460**	0.386
	(0.108)	(0.227)	(0.213)	(0.377)
Project Management	-0.083	0.174*	-0.198*	-0.494***
	(0.063)	(0.103)	(0.113)	(0.160)
Writing	0.115***	-0.069	-0.341***	-0.797***
	(0.039)	(0.136)	(0.083)	(0.264)

Note: The table serves as a robustness check for the main table. In this set of regressions, we use the actual state-level SAHO duration as the key independent variable.
* p<0.1, ** p<0.05, *** p<0.01

Table A3: The effect of COVID 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	Extensive	Intensive	Extensive	Intensive	Extensive
	(1)	(2)	(3)	(4)	(5)	(6)
STEM	-1.990***	0.870	0.541**	0.452	-0.391**	2.793***
	(0.512)	(0.613)	(0.219)	(0.526)	(0.184)	(0.419)
Manual	0.711	-1.974**	0.234	1.205**	-0.822***	0.481
	(0.504)	(0.804)	(0.232)	(0.520)	(0.267)	(0.467)
Customer services	0.020	-0.854	-0.169	-0.248	-1.128***	-2.011***
	(0.421)	(0.990)	(0.244)	(0.522)	(0.191)	(0.578)
Computer: general use	0.518	1.243**	-0.024	0.418	-0.907***	1.463***
	(0.684)	(0.491)	(0.140)	(0.493)	(0.278)	(0.316)
Business and Finance	-0.551	0.631	-0.344*	-1.602***	-0.774***	0.605
	(0.506)	(0.471)	(0.188)	(0.383)	(0.179)	(0.539)
Education	1.297	0.322	0.376*	-0.712***	-0.808**	0.632***
	(0.915)	(0.495)	(0.192)	(0.247)	(0.331)	(0.195)
Administration	-0.418	-3.291**	0.262	0.134	-0.565**	0.946**
	(0.388)	(1.386)	(0.406)	(0.496)	(0.240)	(0.419)
Computer: specialized software	2.336	0.127	0.734**	0.123	0.470	3.189***
	(1.623)	(0.172)	(0.333)	(0.148)	(0.287)	(0.552)
Languages	0.952**	0.567	0.837**	0.237	-1.421***	0.229
	(0.470)	(0.565)	(0.415)	(0.439)	(0.424)	(0.272)
Social	0.613*	0.057	0.098	-0.109	-0.027	1.953***
	(0.359)	(0.846)	(0.103)	(0.740)	(0.103)	(0.665)
Operational Management	0.141	-2.497***	-0.252***	-1.941***	-0.714***	-0.111
	(0.359)	(0.413)	(0.086)	(0.514)	(0.133)	(0.427)
Cognitive	0.299	-1.168**	0.238**	-0.523	0.102	2.575***
	(0.418)	(0.488)	(0.100)	(0.365)	(0.147)	(0.550)
Personality	2.538**	1.944*	0.251**	0.646	-0.029	-0.399
	(0.989)	(0.999)	(0.105)	(0.421)	(0.126)	(0.625)
Industry Knowledge	-1.129**	0.360	-0.891***	-0.689*	-0.889***	-0.623
	(0.516)	(0.725)	(0.225)	(0.366)	(0.215)	(0.533)
People Management	0.674	-0.413	0.029	0.428	-0.139	0.433
	(0.433)	(0.680)	(0.098)	(0.476)	(0.130)	(0.435)
Arts and Humanities	-1.776	-0.523***	-0.343	-0.274**	-1.232***	0.905***
	(1.609)	(0.122)	(0.467)	(0.124)	(0.287)	(0.335)
Self-management	-0.013	-0.210	0.793***	0.207	-0.098	0.430*
	(0.734)	(0.475)	(0.231)	(0.438)	(0.134)	(0.241)
Project Management	0.874	-0.045	-0.290*	-0.550***	-0.364**	0.209
	(0.679)	(0.212)	(0.151)	(0.195)	(0.148)	(0.313)
Writing	-1.216***	-0.983***	-0.300***	-1.203***	-0.391***	1.101**
	(0.407)	(0.369)	(0.091)	(0.265)	(0.094)	(0.432)

Note: The table reports estimates of the difference in labor market demand for each skill between the pre-COVID and post-SAHO periods by WFH capacity groups. Column 1, 3, 5 report the estimates of α_1 in equation 3. Column 2, 4, 6 report the estimates of β_1 in equation 4. See the notes for table 3.
* p<0.1, ** p<0.05, *** p<0.01

Table A4: The effect of COVID on demands for skills by education requirement

	Middle or high school		College		Graduate degree	
	Intensive	Extensive	Intensive	Extensive	Intensive	Extensive
	(1)	(2)	(3)	(4)	(5)	(6)
STEM	0.312	0.855	-0.134	1.768***	0.127	1.684***
	(0.265)	(0.682)	(0.162)	(0.320)	(0.358)	(0.449)
Manual	0.372	2.021***	-0.317***	0.175	0.545**	0.725
	(0.362)	(0.645)	(0.102)	(0.536)	(0.226)	(0.772)
Customer services	-0.719**	-1.245	-0.621***	0.683**	-0.623***	-2.129***
	(0.326)	(0.927)	(0.203)	(0.302)	(0.232)	(0.734)
Computer: general use	0.019	1.510*	-0.508***	1.042***	0.456	-0.152
	(0.179)	(0.848)	(0.181)	(0.341)	(0.323)	(0.592)
Business and Finance	-0.502*	-0.773*	-0.562***	0.345	-1.802***	-0.567
	(0.300)	(0.426)	(0.111)	(0.424)	(0.286)	(0.674)
Education	-0.410	-0.655**	-0.497***	0.537**	0.080	-0.474
	(0.256)	(0.317)	(0.157)	(0.252)	(0.316)	(0.487)
Administration	-0.626	0.405	-0.448***	1.305**	-0.248	-0.648
	(0.652)	(0.816)	(0.117)	(0.538)	(0.187)	(0.561)
Computer: specialized software	0.787**	0.386***	0.196	1.522***	0.157	0.018
	(0.339)	(0.144)	(0.146)	(0.320)	(0.451)	(0.330)
Languages	1.153*	-0.434	-0.594***	0.792***	0.310	0.286
	(0.648)	(0.914)	(0.176)	(0.250)	(0.506)	(0.421)
Social	-0.312	-0.622	-0.109	2.327***	-0.094	2.221***
	(0.206)	(1.083)	(0.085)	(0.702)	(0.168)	(0.595)
Operational Management	-0.265**	-1.255	-0.371***	-0.241	-0.508**	0.850
	(0.122)	(0.838)	(0.096)	(0.320)	(0.227)	(0.714)
Cognitive	0.215	0.182	0.171*	2.285***	-0.134	-1.104*
	(0.200)	(0.577)	(0.099)	(0.374)	(0.171)	(0.638)
Personality	0.121	-0.437	-0.052	1.748***	-0.214	1.578***
	(0.159)	(0.713)	(0.069)	(0.508)	(0.245)	(0.410)
Industry Knowledge	-0.269	-0.632	-0.570***	0.483	-0.494	0.931*
	(0.199)	(0.550)	(0.177)	(0.470)	(0.318)	(0.474)
People Management	0.097	0.801	-0.219***	1.128**	0.930***	0.131
	(0.153)	(0.661)	(0.079)	(0.445)	(0.182)	(0.585)
Arts and Humanities	-0.851	-0.228	-0.546***	0.471**	0.650	-0.828***
	(0.975)	(0.188)	(0.153)	(0.191)	(0.798)	(0.316)
Self-management	0.223	0.497	-0.157	0.790***	0.776**	-0.106
	(0.382)	(0.847)	(0.104)	(0.281)	(0.312)	(0.423)
Project Management	0.405	-0.015	-0.333***	-0.070	-0.143	-0.885**
	(0.269)	(0.143)	(0.097)	(0.295)	(0.208)	(0.370)
Writing	-0.548***	-1.694***	-0.247***	0.436	-0.084	-0.233
	(0.176)	(0.442)	(0.055)	(0.292)	(0.196)	(0.444)

Note: The table reports estimates of the difference in labor market demand for each skill between the pre-COVID and post-SAHO periods by education requirement. Column 1, 3, 5 report the estimates of α_1 in equation 3. Column 2, 4, 6 report the estimates of β_1 in equation 4. See the notes for table 4.
* $p<0.1$, ** $p<0.05$, *** $p<0.01$