# STEM Employment Resiliency During Recessions: Evidence from the COVID-19 Pandemic[*]

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**Abstract**

STEM occupational employment suffered smaller peak-to-trough percentage declines than non-STEM employment during both the Great Recession and COVID-19 recession, suggesting a relative resiliency of STEM employment during recessions in the digital age. We exploit the sudden peak-to-trough declines in STEM and non-STEM employment during the COVID-19 recession to measure STEM recession-resiliency during the pandemic, decomposing our difference-in-differences estimate into parts explained by various sources including differences in demographics, educational attainment, job tasks, remote work capability, industry, and STEM knowledge importance on the job. We find that STEM knowledge importance on the job explains the greatest share of STEM employment resiliency, and that workers in non-STEM occupations who nonetheless use STEM knowledge experienced higher employment rates during the pandemic. We show that R&D expenditures and employment also remained resilient, suggesting only a mild effect of the COVID-19 pandemic on innovative activity. Altogether, our findings suggest that increasing opportunities for STEM training—including outside the college-track—may help improve the employment resiliency of workers during future recessions. (*JEL* J21, I1, I26, O3)

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# 1 Introduction

STEM workers are central to the creation and diffusion of new knowledge and technology—and thus long-run economic growth—both through their direct role in R&D and their role in implementing new technologies that enhance the productivity of the firms where they work (Barth et al., 2018). Federal STEM education subsidies and immigration policies favoring STEM workers reflect their status as an important national resource.[1] The STEM workforce is growing, both in absolute numbers and relative to the non-STEM workforce, numbering 9.3 million workers, or 6.7% of US employment, as of 2020.[2] Because the demand for STEM workers is expected to remain strong and STEM salaries are comparatively high, policymakers interested in reducing economic inequality have made attracting underrepresented minorities and women to STEM a special policy focus.[3] Given the significant public investments and policies aimed at developing and attracting workers with STEM skills—and the importance of these skills to the US economy—a study of how the STEM workforce fares during the pandemic and in response to negative economy-wide shocks generally is of significant interest.

In this paper, we find that while both STEM and non-STEM workers experienced abrupt and sharp declines in employment at the onset of the pandemic, the negative impact on non-STEM employment was much greater: in the first full quarter of the COVID-19 recession (2020Q2), STEM employment dropped by 5% and non-STEM employment by 14% relative to their pre-pandemic peak values obtained in 2019Q4.[4] Similarly, STEM and non-STEM workers both experienced declines in labor force participation and weekly work hours at the onset of the pandemic, with non-STEM workers suffering greater declines. Both STEM and non-STEM employment began their recoveries in 2020Q3, and while the initial pace of recovery in non-STEM employment was more rapid, STEM employment ultimately recovered to its pre-pandemic level in two-thirds the time. A similar pattern of STEM employment resiliency held during the Great Recession, suggesting a relative recession-resiliency of STEM workers in the digital age.[5]

[1] The U.S. STEM workforce comes up in policy discussions related to American competitiveness, economic growth, national security, and immigration policy, and as such US statistical agencies (e.g., the Bureau of Labor Statistics) regularly single out STEM workers for additional data collection and analysis (e.g., in BLS's Employment Projections program; see https://www.bls.gov/emp/tables.htm). In a recent overview of federal STEM education policy efforts, Granovskiy (2018) reports that depending on how they are measured there are between 105 and 254 separate STEM education programs or activities across multiple federal agencies with the total federal expenditure on these programs and activities ranging between $2.8 billion and $3.4 billion annually. Examples of STEM-favorable immigration policies include the H-1B temporary worker visa program, and the STEM OPT extensions in April 2008 and May 2016 that allow foreign-born STEM graduates of US universities to work in the US for up to three years after graduation while in F-1 status. Non-STEM graduates are limited to an OPT period of only one year.

[2] See https://www.bls.gov/oes/additional.htm.

[3] The median salary of workers in STEM occupations is more than double that of workers in non-STEM occupations (Table 3-13 of National Science Board (2018)).

[4] In this paper, "STEM worker" refers to workers in STEM occupations using the 2012 Census Bureau definition which was formulated by a consortium of nine federal agencies that study the STEM workforce to improve data comparability (https://www.census.gov/newsroom/blogs/random-samplings/2013/09/who-is-a-stem-worker.html).

[5] During the Great Recession, STEM employment and non-STEM employment dropped by 4% and 7% relative

What accounts for the greater recession-resiliency of STEM workers in the digital age? To answer this question, we exploit the COVID-19 labor market shock to obtain a plausible measure of STEM employment resiliency utilizing a longitudinal sample of workers observed both before and during the pandemic and a difference-in-differences approach. Our measure of STEM employment resiliency reflects the recession-induced increase in the *gap* between the employment rates of US workers in STEM versus non-STEM occupations as measured at the trough of the recession. During typical recessions, output and employment reach their troughs at least several quarters after they start to decline, and so it is difficult to assess how much of any relative change in labor market outcomes between two groups is due to the recession itself or the continuation of some secular trend. In contrast, the troughs in output and employment during the COVID-19 pandemic were immediate: we show that the employment rates, labor force participation rates, and weekly work hours of a longitudinal sample of STEM and non-STEM workers were all stable before the COVID-19 pandemic, and then suddenly declined at the pandemic's onset. Given the markedly parallel trends in pre-pandemic STEM and non-STEM employment rates—and thus a relatively constant gap between the two—followed by a sudden widening of the employment rate gap at the start of the pandemic, the difference in the rates of employment loss among STEM and non-STEM workers plausibly reflects the differential impact of the COVID-19 recession on STEM vs. non-STEM workers rather than the continuation of some other secular trend.

After leveraging the COVID-19 labor market shock to estimate STEM resiliency in employment, labor force participation, and weekly work hours during the first quarter of the pandemic, we introduce measures that capture possible sources for this relative resiliency of STEM worker outcomes. Such sources include differences between STEM and non-STEM workers in terms of demographics, educational attainment, employer industry and size, geographic location, remote work feasibility, non-routine and cognitive task intensity of work, education requirements for the job, and the importance of STEM knowledge on the job. We find that these sources together explain all of the employment advantage, all of the labor force participation advantage, and two-thirds of the work hour advantage of STEM over non-STEM workers in the pandemic's initial three months. We then decompose our measure of STEM employment resiliency into the parts explained by each source, finding that while no single factor accounts for all of this resiliency, the largest factor is the importance of STEM knowledge to one's job, especially among college-educated workers.[6]

While STEM employment resiliency seemingly mirrors the better employment record of more highly-educated workers in previous recessions (Elsby, Hobijn, and Şahin, 2010; Hoynes, Miller, and Schaller, 2012), we find that the greater educational attainment of STEM workers only partially explains the STEM worker employment advantage over non-STEM workers during the pandemic

to their respective pre-recession levels during their respective troughs, and STEM employment recovered to its pre-recession level in about half the time as non-STEM employment.

[6]The decomposition method we employ may be of interest to researchers exploring possible channels of effect in difference-in-differences models. STEM knowledge importance is measured based on occupation-level measures obtained via O*NET.

and does little to explain STEM employment resiliency among college-educated workers. At the onset of the pandemic, papers appeared examining the ease with which occupations could be performed remotely to predict which jobs and workers would be most affected. This research found that jobs with less remote work feasibility tend to be lower paid and held by workers who are less-educated, less-skilled, and have less wealth (Mongey, Pilossoph, and Weinberg, 2021; Dingel and Neiman, 2020; Brynjolfsson et al., 2020; Bartik et al., 2020), with subsequent work confirming greater job losses in less remote work capable occupations (Montenovo et al., 2020). While remote work capability is important in explaining employment disparities during the COVID-19 pandemic, we find that other factors are quantitatively more important in explaining the recession-resiliency of STEM over non-STEM employment, including the importance of STEM knowledge on the job, the non-routine and cognitive task intensity of work, and industry of employment. Among college-educated workers, the portion of STEM employment resiliency explained by the greater importance of STEM knowledge on the job is over three times larger than that explained by the greater remote work capability of STEM workers.

Complementary research finds that college-educated workers with degrees in quantitatively-oriented fields tend to fare better during recessions (Altonji, Kahn, and Speer, 2016; Abel and Deitz, 2018), and that the Great Recession increased the number of college students choosing STEM majors (Shu, 2016; Liu, Sun, and Winters, 2019) and other less "recession-sensitive" fields of study (Ersoy, 2020).[7] We find that STEM knowledge itself is an important source of STEM workers' employment resiliency during recessions in the digital age, supporting the notion that STEM skills enable workers to better-adapt to changing labor markets (Black et al., 2021). Furthermore, we show that workers who utilize STEM knowledge on the job—and not just recent college graduates with STEM degrees or those working in occupations formally classified as STEM—enjoy a greater degree of employment resiliency during recessions. This finding is important given that, as we show, workers in "non-STEM" occupations where STEM knowledge is important outnumber workers employed in occupations formally classified as "STEM."[8] Our finding that STEM skills are important in occupations beyond those formally classified as STEM complements prior research showing that greater STEM training in high school increases the ability of workers to obtain jobs in high-skill non-STEM occupations (Black et al., 2021) and aligns with evidence from the UK

[7] Blom, Cadena, and Keys (2021) find that the movement of students toward STEM fields associated with a typical recession is significant and comparable in magnitude to the effects of a program studied by Denning and Turley (2017) that paid up to $8,000 in cash incentive to students to choose particular majors.

[8] National Science Board (2018) highlights the important distinction between workers with degrees in S&E fields and workers employed in the S&E occupations that make up the bulk of STEM occupations (Table 3-2; STEM occupations include workers in S&E occupations as well as S&E technicians and managers). In 2015, over half of all college-educated workers in S&E occupations conducted R&D as part of their work, with workers in S&E occupations who have non-S&E degrees being more likely to conduct R&D than S&E degree holders working outside S&E occupations (Figure 3-13). Most workers with STEM degrees work outside STEM occupations, with over three times as many workers with S&E degrees in 2015 as there were workers in S&E occupations (Table 3-3). Many occupations outside S&E require some level of S&E technical expertise at the college-level, with almost three times as many such occupations as there are S&E occupations (Table 3-3).

showing that many occupations classified as non-STEM nonetheless require STEM skills (Grinis, 2019).

Given that STEM workers are key inputs to innovation, we explore whether STEM employment resiliency coincided with a resiliency in R&D during the COVID-19 pandemic. We show that employment in R&D-intensive industries declined less than overall STEM employment during 2020Q2 and was followed by a quick recovery to above its peak pre-recession value in 2020Q3. Thereafter, the growth rate in R&D expenditures has continually exceeded the rates of employment and real output growth and has continued on its positive trajectory throughout the period of output declines in 2022Q1 and 2022Q2. This suggests only a mild effect of COVID-19 on the level of US inventive activity, which is consistent with similar patterns observed for the number of patent applications submitted to the USPTO during the pandemic as shown in earlier work by the present authors and Park et al. (2022).

At the start of the COVID-19 pandemic, a key question was whether the economy would simply snap back to its original shape or whether the recovery would entail a more permanent shift in the relative demand for skills. Previous work finds that workers in routine-intensive jobs have suffered the greatest job loss during the last three recessions (Jaimovich and Siu, 2020), including the Great Recession wherein firms restructured production toward routine-biased technologies which drove persistent labor market "upskilling" after the Great Recession (Hershbein and Kahn, 2018). Furthermore, Ross (2020) finds that within-occupation increases in routine task intensity were associated with greater outgoing transition rates to nonemployment or a different occupation during the Great Recession. Compared to non-STEM jobs, STEM jobs involve fewer routine tasks and more non-routine analytical tasks, which we show helps to explain the relative resiliency of STEM employment during the COVID-19 pandemic, especially among the non-college-educated for whom it is the primary factor. Spurred on by the pandemic, firms may continue to explore ways to increase the efficiency of remote work and automate processes currently carried out by workers in routine occupations, potentially adding to the employment rate gap between STEM and non-STEM workers that we document.

## 2 STEM Employment Resiliency: Evidence and Explanations

Figure 1 plots seasonally-adjusted quarterly employment of workers in STEM and non-STEM occupations during the Great Recession and COVID-19 recession and recovery, with pre-recession peak employment normalized to 100. STEM and non-STEM employment are constructed using quarterly data on industry employment (at the 4-digit NAICS level) from the Bureau of Labor Statistics' *Quarterly Census of Employment and Wages* (QCEW) combined with the STEM-share of employment in each industry as computed using annual data from the Bureau of Labor Statistics'

*Occupational Employment Statistics* (OES) program.[9] During the Great Recession, STEM and non-STEM employment declined by 4% and 7%, respectively, while during the COVID-19 pandemic STEM and non-STEM employment declined by 5% and 14%. During the Great Recession, the trough in STEM and non-STEM employment occurred in the 7th and 9th quarter of the recession, respectively, whereas STEM and non-STEM employment both reached their respective troughs simultaneously in the 1st full quarter of the COVID-19 recession and recovery period (2020Q2). The recovery in STEM employment back to pre-recession levels occurred more quickly than non-STEM employment during both the Great Recession and COVID-19 recession, with a recovery in about one-half and two-thirds the time as non-STEM employment during the Great Recession and COVID-19 recession, respectively.[10]

What is it about STEM workers and the jobs that they occupy which makes their employment relatively resilient during recessions in general and the COVID-19 pandemic in particular? Was it simply that STEM workers were better able to work remotely, or that they work in industries less negatively impacted by the pandemic? Is it because STEM workers are more likely to be engaged in non-routine tasks and so are less substitutable than workers who perform routine tasks, or is it that knowledge in a STEM field itself serves as a distinct form of human capital conferring employment protection during recessions beyond that attributable to the non-routine analytical task-intensity of one's job and one's level of educational attainment? To answer these questions, we construct a longitudinal sample of workers observed both before and during the pandemic, discuss how STEM and non-STEM workers in this sample differ across various factors, and then exploit the COVID-19 labor market shock to empirically assess the relative importance of each factor in explaining STEM employment resiliency.[11]

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[9]STEM employment is constructed as the sum of quarterly employment in each industry weighted by its STEM-share of employment. We use the 2012 Census Bureau definition of STEM occupations that was developed by a federal interagency committee, and combine "STEM-related" (primarily healthcare) occupations with non-STEM occupations. See Figure A.1 for a plot of the level and year-over-year changes in monthly STEM and non-STEM employment using QCEW-OES data. For Figure 1, we seasonally-adjust quarterly STEM and non-STEM employment using the US Census Bureau's X-13-ARIMA-SEATS Program (`https://www.census.gov/data/software/x13as.About_X-13.html`) via the R package `seasonal`. A key advantage of administrative-based QCEW data over household survey-based estimates of employment during the COVID-19 pandemic is that response rates have remained high. See Appendix B.2 for supplementary details on data sources used in this paper, including a comparison of STEM employment as measured by QCEW-OES data and CPS data.

[10]QCEW data is released with some lag, and so we include total employment data from the Bureau of Labor Statistics' *Current Employment Statistics* (CES) program which is released more frequently to give a more recent account of the COVID-19 employment situation. As non-STEM employment makes up over 90% of US employment, it closely tracks with total nonfarm employment and so is likely at close to a full recovery back to its pre-pandemic level.

[11]In Appendix C, we identify plausible factors driving STEM employment resiliency using previous studies of employment disparities during recessions and aggregate data on differences between STEM and non-STEM workers and occupations.

## 2.1 Analytical Sample

We use monthly person-level data from the Bureau of Labor Statistics' *Current Population Survey* (CPS) to analyze the impact of the COVID-19 pandemic on the labor market outcomes of STEM and non-STEM workers.[12] We restrict our analytical sample to the set of individuals who participated in the March 2020 CPS Annual Social and Economic Supplement (ASEC), were between the ages of 25 and 65, and were observed before and in or after the April 2020 monthly CPS survey (i.e., both before and during the pandemic).[13] We associate each worker with a single occupation and industry based on their response in the March 2020 ASEC as to the occupation and industry of the job in which they were employed the longest during 2019. We note that it is crucially important that we limit our analytical sample to individuals observed both before and during the pandemic to guard against results being driven by differences in respondents sampled before and during the pandemic, especially since the rate of survey nonresponse was particularly high among those first entering the CPS survey during the initial pandemic period. To ensure that the employment trends present in our restricted CPS analytical sample are representative of the broader employment trends in the US economy, we compare the year-over-year changes in STEM and non-STEM employment in our CPS analytical sample with those observed in QCEW data—an administrative-based data source with response rates largely unaffected by the pandemic—and find remarkably consistent patterns.[14] We also utilize CPS basic monthly weights, which are adjusted for nonresponse, in the calculation of summary statistics and for weighting regressions.

Figure 2 shows the evolution of employment rates for STEM and non-STEM workers in our

[12]We utilize harmonized IPUMS-CPS data provided by Flood et al. (2020) at https://cps.ipums.org/cps/. The CPS is a nationally-representative monthly survey of 60,000 US households; see https://www.bls.gov/cps/cps_over.htm for additional details.

[13]The monthly CPS survey is typically conducted the week of the 19th of each month, and economic questions, such as the number of hours worked, is asked for the week of the 12th of the month (see https://www.census.gov/programs-surveys/cps/technical-documentation/methodology.html). In March 2020, this corresponds to the week beginning March 8 and ending March 14. The first public school closures in the US went into effect at the end of the school day on March 13th, and business restrictions such as those on bars and restaurants were not enacted by any US states until March 15th at the earliest (see US state-level data on social distancing policy here: https://github.com/COVID19StatePolicy/SocialDistancing). We classify March 2020 CPS responses as "pre-pandemic" because the reference week for the employment questions of the March 2020 CPS was the last pre-pandemic week.

[14]See Appendix B.2 for further details on nonresponse during the COVID-19 pandemic and Figure B.3 for evidence that the labor market patterns for STEM and non-STEM workers detected using our CPS analytical sample are similar to those found using industry employment counts from QCEW data combined with the STEM-share of employment in each industry calculated using annual OES data. QCEW data is based on administrative data collected from mandatory state unemployment insurance (UI) reports—known as Quarterly Contributions Reports (QCRs)—sent from employers to their state. A significant advantage of the QCEW over survey-based estimates of employment during the COVID-19 pandemic is that response rates have remained high: in March (June) 2020, QCEW obtained reports from 90.8% (91.8%) of establishments which represented 96.8% (97.5%) of US employment (see https://www.bls.gov/cew/response-rates/cew-response-rates-establishments.htm and https://www.bls.gov/cew/response-rates/cew-response-rates-employment.htm). For comparison purposes, in March (June) 2019, QCEW obtained reports from 92.0% (92.5%) of establishments which represented 97.6% (97.9%) of US employment in those months. See https://www.bls.gov/opub/hom/cew/data.htm for additional details on QCEW data.

analytical sample before and after the start of the COVID-19 pandemic.[15] The stability in pre-pandemic STEM and non-STEM employment rates followed by a sudden drop in both rates in the first month of the pandemic demonstrates the plausible exogeneity of the COVID-19 pandemic labor market shock, with the sudden increase in the employment rate advantage of STEM over non-STEM workers showcasing the comparative recession-resiliency of STEM employment. Figure 3 shows similar dynamics in both labor force participation rates and mean weekly work hours among employed workers, with a STEM advantage in both outcomes that expanded after the onset of the pandemic.

What differences between STEM and non-STEM workers might explain the relative resiliency of STEM labor market outcomes at the onset of the pandemic? To answer this question, we utilize worker-level information available in the CPS as well as occupation-level task information available in the Department of Labor's *Occupational Information Network* (O*NET) data.[16] O*NET data is based on the survey responses of workers within different occupations, with workers answering questions pertaining to their work activities, work context, and knowledge used on the job. We use O*NET to construct three sets of variables measuring the remote work capability, task intensity, and importance of STEM knowledge associated with each occupation, respectively. Remote work capability is measured by a continuous occupation-level Remote Work Index (RWI) that takes on values between zero and one, where higher values of RWI correspond to occupations where remote work is more feasible.[17] The task intensity of each occupation is broken down into five types of tasks as defined by Acemoglu and Autor (2011): routine cognitive (RC), routine manual (RM), non-routine cognitive-analytical (NRC-A), non-routine cognitive-interpersonal (NRC-I), and non-routine manual-physical (NRM-P).[18] Each variable is standardized to have mean zero and a standard deviation of one at the occupation level. Lastly, we construct occupation-level measures of the importance of knowledge in the following STEM categories: 1) computer knowledge, 2) engineering knowledge, 3) mathematics knowledge, 4) physics knowledge, 5) chemistry knowledge, and 6) biology knowledge.[19] These measures are derived from survey questions asking O*NET

[15]Figure 2 lacks data points for July 2019 through November 2019 and July 2020 through November 2020 because individuals sampled during these months are not both present during the March 2020 ASEC and also observed during the pandemic due to the CPS 4-8-4 rotating sampling scheme. June 2021 represents the last month that a member of our sample could be observed in the CPS.

[16]We utilize data files from the O*NET 25.0 Database.

[17]RWI is based on the degrees to which jobs require performing physical activities at one's workplace ("Physical Activity") and job tasks in close proximity to other people ("Personal Proximity"). See Appendix D for details on the construction of Physical Activity, Personal Proximity, and RWI, as well as validation that RWI is closely correlated with the probability that respondents actually report teleworking due to the COVID-19 pandemic.

[18]See the data appendix to Acemoglu and Autor (2011) for the definition of each category.

[19]We use the term "STEM knowledge" to denote this set of six knowledge categories, rather than as a single type of knowledge. Aggregating across knowledge categories to produce a single index measure for the importance of STEM-types of knowledge is complicated by the fact that some occupations may utilize a single type of category intensely (e.g., pure mathematicians) while other fields may utilize multiple categories intensely (e.g., biochemists, material science engineers). While the latter occupations are more interdisciplinary, it is arguable whether they are more intensive than pure mathematicians in the use of a STEM-type of knowledge. It might also be argued that mathematics is a more fundamental type of STEM knowledge which is a prerequisite for knowledge in other fields and so should be given higher weight. Given such complications, we maintain the distinctions between the six STEM

respondents how important knowledge in each area is to the performance of one's job, regardless of whether one's job is classified as a STEM occupation, and are standardized to have mean zero and unit standard deviation across occupations.[20]

Table 1 presents summary statistics for the person-month observations in our analytical sample for both STEM and non-STEM workers during the pre-pandemic and pandemic periods.[21] Compared to non-STEM workers, STEM workers are on average more highly educated, and more likely to work in occupations with greater educational requirements. STEM workers are more likely to be male, foreign-born, and Asian, and are more likely to be employed by large firms with at least 500 employees. STEM and non-STEM workers are similar in their propensity to live in cities, and in the prevalence of COVID-19 in their state of residence, as measured by cases and deaths per 100,000 residents (both cumulative and in the week preceding the survey reference week). Workers in STEM occupations on average have greater remote work feasibility and are less likely to be an essential worker (i.e., work in occupations prevalent in essential industries). STEM workers are more likely to hold jobs with greater non-routine cognitive-analytical task intensity, and lesser routine, non-routine cognitive-interpersonal, and non-routine manual-physical task intensities. STEM knowledge on the job is more important for workers in STEM occupations, especially knowledge in Computer, Engineering, Math, and Physics domains. The smaller gap between STEM and non-STEM workers in the importance of knowledge in Chemistry and Biology is partly due to our classifying "STEM-related" occupations (primarily in healthcare) together with non-STEM occupations.[22]

## 2.2 Empirical Specification

We use our longitudinal person-month level CPS analytical sample to estimate the differential impact of the COVID-19 pandemic on STEM and non-STEM labor market outcomes. We begin

knowledge categories rather than aggregating to a single metric.

[20]To link these O*NET-based metrics with CPS data, we convert the task data in O*NET from the finer SOC occupation coding system used in O*NET to the broader Census occupation codes ("OCC") present in CPS data. We do this by calculating employment-weighted means of each metric for all SOC codes contained within each OCC code, where employment weights are based on employment numbers from the Bureau of Labor Statistics' *Occupation Employment Statistics* (OES) 2019 data. In 2019, BLS began a partial transition of OES occupation codes from SOC 2010 to SOC 2018 codes, utilizing a hybrid SOC system during the first part of the transition (see https://www.bls.gov/oes/soc_2018.htm for details). We utilize the crosswalk found at https://www.bls.gov/oes/oes_2019_hybrid_structure.xlsx to facilitate linkage of OES 2019 data and ONET 25.0 data which uses SOC 2010 occupation codes.

[21]See Table A.1 and Table A.2 for summary statistics for the college-educated and non-college-educated subsamples.

[22]For details on variable definitions, see Appendix B.1. Reassuringly, the differences between STEM and non-STEM workers in our analytical sample mirror the aggregate pre-pandemic population differences shown in Appendix C.

our analysis by estimating the following non-staggered event study specification:[23]

$$y_{ijst} = \alpha_0 + \alpha_1 STEM_j + \sum_{\tau \neq -1} \delta_\tau * (I[t = \tau] * STEM_j) + \lambda_t + \varepsilon_{ijst}, \quad (1)$$

where $y_{ijst}$ is the labor market outcome of interest (employment status, labor force participation status, and the logarithm of the number of hours worked during the previous week) associated with person $i$ in occupation $j$ in state $s$ at month-year $t$, $STEM_j$ is an indicator variable equal to one for workers employed in a STEM occupation for their longest job in 2019 (as reported in March 2020 ASEC data), $\tau = 0$ is the first full month of the pandemic (April 2020), $I[t = \tau]$ is a month-year indicator variable with $\tau = 0$ being the first full month of the pandemic (April 2020), $\lambda_t$ are month-year fixed effects, and $\varepsilon_{ijst}$ is an idiosyncratic error term. In our context, the pandemic represents a non-staggered treatment that impacted *all* workers in the U.S. economy, with our event study estimates representing changes in employment disparities between STEM and non-STEM workers that can be interpreted as the difference in the pandemic treatment effect between these two groups (Goldsmith-Pinkham et al., 2022).

Figure 4 plots the resulting event study showing the gap between STEM and non-STEM employment rates in each month relative to the employment rate gap in the last pre-pandemic month (March 2020) for our full sample, with event studies for our college-educated and non-college-educated subsamples given in Figure A.2.[24] For the full sample and college-educated sample, we find no evidence of divergent trends in STEM and non-STEM employment rates during the pre-pandemic period.[25] We also find a sizable increase in the STEM employment rate advantage in the first three months (Apr-Jun 2020) of the pandemic ("early pandemic"), with smaller effects in the "late pandemic" period (Dec-Jun 2021). Our main goal is to explain why workers in STEM and non-STEM jobs experienced different treatment effects—that is, why STEM employment rates were more resilient than non-STEM employment rates during the pandemic. Rather than decomposing treatment effects month-by-month, we simplify our analysis based on the patterns observed in Figure 4 by grouping the 20 months for which we have data into the three time periods ($q$) shown on Figure 4: the pre-pandemic period ($q = 0$), the early pandemic period ($q = 1$) and the late pandemic period ($q = 2$). The early pandemic period represents the first full quarter of the

[23] Our event study specification represents a non-staggered two-way fixed effects (TWFE) difference-in-differences (DiD) specification with dynamic treatment effects. In our context, the pandemic represents the non-staggered treatment that begins in April 2020. Baker, Larcker, and Wang (2022) note that "TWFE DiD estimates are valid in settings with a single treatment period (even with dynamic treatment effects)...," obviating concerns regarding bias that are present when dynamic treatment effects are paired with staggered treatments in a TWFE DiD design.

[24] See Figure A.3 for labor force participation and work hours event studies. The dynamics in the STEM work hours gap during the pre-pandemic period appears less stable than for the employment rate and labor force participation rate gaps.

[25] For the non-college-educated sample we find a single pre-pandemic month where the employment rate gap was significantly larger than in the month just prior to the pandemic period. Other pre-pandemic point estimates appear mostly positive (but insignificant), indicating that, if anything, the employment rate advantage of non-college-educated STEM workers shrunk just prior to the pandemic before expanding sizably at its onset.

pandemic, with a six month gap separating the last month of the early pandemic period and the first month of the late pandemic period.

Our resulting difference-in-differences specification is thus:

$$y_{ijst} = \alpha_0 + \alpha_1 STEM_j + \sum_{\tau=1}^{2} \delta_\tau * (I[q=\tau] * STEM_j) + \lambda_q + X_{ijst}\beta + \varepsilon_{ijst}, \tag{2}$$

which is an event study specification with three time periods defined by $q$. Our specification includes two pandemic indicators ($\lambda_1 \equiv I[q=1]$ and $\lambda_2 \equiv I[q=2]$), one for the initial period of the pandemic (Apr-Jun 2020) and another for the latest period available in the data (Dec 2020 - Jun 2021), and the interaction of these pandemic indicators with $STEM_j$ so that we can analyze the differential impact of the COVID-19 pandemic on STEM versus non-STEM workers in the earlier and later periods of the pandemic as given by $\delta_1$ and $\delta_2$, respectively.[26] We use robust standard errors that allow for clustering at the person-level, and use monthly CPS survey weights in all regressions.

We estimate regressions without covariates ("base regressions") for our full analytical sample, and in subsamples for college-educated and non-college-educated workers. We then estimate regressions for these samples using a full set of covariates $\boldsymbol{X_{ijst}}$ ("full regressions") which capture possible sources of STEM employment resiliency.[27] The covariates $\boldsymbol{X_{ijst}}$ include the following variables *and their interactions with the pandemic indicators*:

**Demographics** Indicator variables for the worker's sex, race, foreign-born status, marital status, and disability status; indicator variables for whether the worker has a child living at home, and whether the worker is female and has a child at home; and variables for a quartic polynomial in the worker's years of potential work experience.[28]

**Educational Attainment** Indicator variables for whether the worker's highest educational degree is a Bachelor's degree, Master's or Professional degree, or Doctoral degree.

**Employer Industry and Size** Fixed effects for the industry in which the worker was employed for their longest job tenure in 2019, and an indicator variable for whether the worker was employed by a firm with more than 500 employees (i.e., a large firm).

[26]There are no observations for July 2020 through November 2020 as analytical sample members are not observed during these months due to the CPS 4-8-4 rotating sampling scheme paired with analytical sample restrictions that members are observed both as part of the March 2020 ASEC and in at least one month during the pandemic.

[27]We note here that occupational and employer characteristics associated with sample members that we include as controls are all based on their pre-pandemic occupation of employment, and that the characteristics themselves (e.g., remote work capability, routine task intensity, etc.) are measured using pre-pandemic data. In addition to the covariates that follow, we include month, year, and state fixed effects, as well as survey group fixed effects based on the first month that each individual is surveyed in the CPS.

[28]Potential experience is constructed by subtracting years of schooling plus six from age.

**Geographic Location** Fixed effects for the US state in which the worker lives, indicator variables for whether the worker lives in 1) a metropolitan area and 2) in a city center, and continuous variables for the cumulative number of COVID-19 cases and deaths per 100,000 residents in the state as of the day prior to the survey reference week, and the number of new COVID-19 cases and deaths in the week prior to the survey reference week.

**Remote Work Feasibility** A variable for the Remote Work Index (RWI) of the worker's occupation, and a variable for the share of workers in that occupation that are employed in essential industries.

**Non-routine and Cognitive Task Intensity of Work** Standardized variables for the task intensity of work in five task categories defined by Acemoglu and Autor (2011)—routine cognitive (RC), routine manual (RM), non-routine cognitive-analytical (NRC-A), non-routine cognitive-interpersonal (NRC-I), and non-routine manual-physical (NRM-P).

**Education Requirements for the Job** Indicator variables for whether a worker's occupation typically requires a Bachelor's degree, Master's degree, or Professional or Doctoral degree as a minimum educational requirement.[29]

**STEM Knowledge on the Job** Six standardized variables for the importance of STEM knowledge on the job in the worker's occupation, in the following domains: 1) computer knowledge, 2) engineering knowledge, 3) mathematics knowledge, 4) physics knowledge, 5) chemistry knowledge, and 6) biology knowledge.

By comparing our estimate of $\delta_1$ before and after the inclusion of the full set of covariates, we determine how much of STEM recession-resiliency is explained by all of the above factors in tandem. In Section 2.4, we decompose the differential impact of the pandemic on STEM and non-STEM workers during the early period of the pandemic ($\delta_1$) into the portion explained by each subset of covariates.[30] In this way, we estimate the contribution of each subset of factors to the resiliency of STEM employment relative to non-STEM employment.

## 2.3 Regression Results

**Regression Model without Covariates** The first column of Table 2 reports base regression (i.e., excluding the covariates $\boldsymbol{X_{ijst}}$ and fixed effects) results comparing the labor market impact

[29] These variables measure the human capital intensity of the job and also control for differences in "underemployment" between workers in STEM and non-STEM occupations—see Abel and Deitz (2018) for evidence of variation in underemployment by field of study. Measures based on BLS data available at `https://www.bls.gov/oes/2019/may/education_2019.xlsx`.

[30] We follow the recommendation of Gelbach (2016) in abstaining from the potentially misleading practice of reporting coefficients from intermediate regressions that add control sets sequentially rather than all at once.

of the COVID-19 pandemic on STEM and non-STEM workers in the full CPS analytical sample. We find that the onset of the COVID-19 pandemic was associated with a 13.7 percentage-point decline in the average non-STEM worker's likelihood of employment during the initial period of the pandemic (Apr-Jun 2020), but only a 4.7 percentage-point decrease in that of the average STEM worker, giving STEM workers a 9.0 percentage-point employment advantage (or "resiliency"). Similarly, non-STEM workers fared worse than STEM workers when it came to labor force participation and weekly work hours (for those who remain employed) after the onset of the pandemic; non-STEM workers suffered a 3.9 percentage-point drop in their labor force participation rate and a 7.7% drop in their weekly work hours, whereas STEM workers experienced a 2.1 percentage-point drop in their labor force participation rate and only a 1.1% drop in weekly work hours. By the Dec 2020 - Jun 2021 period, the impact of the pandemic on non-STEM employment lessened to a 5.6 percentage-point decrease while the impact on STEM employment lessened to a 2.7 percentage-point decrease. We also see an improvement in labor force participation and work hours during the Dec 2020 - Jun 2021 period for both STEM and non-STEM workers.

Table 2 also reports results from separate base regressions for college-educated (i.e., Bachelor's degree and above) and non-college-educated workers in columns (3) and (5). For both STEM and non-STEM workers, those with a college degree fared better than those without a college degree. For college-educated STEM and non-STEM workers, the likelihood of employment fell by 3.7 percentage points and 9.3 percentage points in the initial period of the pandemic (Apr-Jun 2020), respectively, with those remaining employed experiencing a 0.7% and 6.0% decrease in weekly work hours. Meanwhile, for non-college-educated STEM and non-STEM workers, the likelihood of employment fell by 9.1 percentage points and 16.7 percentage points in the initial period of the pandemic, respectively, with weekly hours among the employed falling by 2.3% and 9.1%. Thus, regardless of education status, STEM workers fared better than their non-STEM counterparts in terms of employment and work hours during the initial period of the pandemic, and so the greater average education of STEM workers does not entirely explain the disparate impact of the pandemic on the labor market outcomes of STEM vs. non-STEM workers.

**Regression Model with Full Set of Covariates** Table 2 also reports results from regressions including the full set of covariates for possible sources of STEM employment resiliency in recessions. Comparing the point estimate for the *STEM*Pandemic (Apr-Jun 2020)* coefficient in base and full regressions on the full sample in columns (1) and (2), we find that adding covariates to the regression reduces the estimated coefficient to zero in the employment and labor force participation regressions and reduces the estimated coefficient by 70% in the work hours regression. This suggests that the employment advantage of STEM over non-STEM workers during the pandemic can be explained by the full set of covariate factors together.[31]

[31] These mechanisms also explain STEM employment resiliency observed for the college-educated and non-college-educated subsamples.

## 2.4 Decomposition Analysis

How much of the STEM worker advantage is explained by each source of STEM resiliency separately? A naïve approach to addressing this question would be to examine how the size of the coefficient on *STEM*Pandemic (Apr-Jun 2020)* varies as we add each set of covariates. This approach, however, would be misleading, as results depend on the order in which covariates are added (Gelbach, 2016). Therefore, we implement a strategy of estimating separate Oaxaca-Blinder decompositions for two time periods: pre-pandemic, and the initial period of the pandemic (Apr-Jun 2020). To decompose the effect of the COVID-19 pandemic on the difference in labor market outcomes between STEM and non-STEM workers, we subtract the pre-pandemic period decomposition from the pandemic period decomposition. Appendix E provides a detailed description of the decomposition methods used in this paper (i.e., Oaxaca-Blinder decomposition, and simple subtraction). Here, we briefly describe the methods, and then report our results.

### 2.4.1 Decomposition Approach

We consider two periods: pre-pandemic, and the initial period of the pandemic (Apr-Jun 2020). For each period $\tau$, our empirical specification is of the following form:

$$E\left[y_{ijst}(\tau)|\boldsymbol{X_{ijst}}(\tau), STEM_j\right] = \alpha_{0,\tau} + \alpha_{1,\tau} STEM_j + \boldsymbol{X_{ijst}}(\tau)\boldsymbol{\beta_{\tau}}, \tag{3}$$

where $y_{ijst}(\tau)$ is the labor market outcome of worker $i$ in occupation $j$ and state $s$ in month $t$ which is part of time period $\tau$, $STEM_j$ is an indicator variable equal to one for workers employed in a STEM occupation for their longest job in 2019 (and thus time-invariant during our sample period), and $\boldsymbol{X_{ijst}}$ is a vector of our full set of covariates and fixed effects (i.e., those included in the controlled regressions presented in Table 2).[32] Suppressing indices, the associated pooled Oaxaca-Blinder decomposition for the STEM vs. non-STEM differential in labor market outcomes during each period $\tau$ can be written as:

$$\begin{aligned} \overline{y}_{\tau}^{STEM} - \overline{y}_{\tau}^{NonSTEM} &= \left[\overline{\boldsymbol{X}}_{\boldsymbol{\tau}}^{STEM} - \overline{\boldsymbol{X}}_{\boldsymbol{\tau}}^{NonSTEM}\right]\hat{\boldsymbol{\beta}}_{\boldsymbol{\tau}} + \hat{\alpha}_{1,\tau} \\ \Leftrightarrow \qquad \Delta\overline{y}_{\tau} &= \underbrace{\Delta\overline{\boldsymbol{X}}_{\boldsymbol{\tau}}\hat{\boldsymbol{\beta}}_{\boldsymbol{\tau}}}_{Explained} + \underbrace{\hat{\alpha}_{1,\tau},}_{Unexplained} \end{aligned} \tag{4}$$

where bars indicate sample means and hats indicate OLS estimates of coefficients from the pooled regression including both STEM and non-STEM workers. Fortin, Lemieux, and Firpo (2011) refer to this as a "regression-compatible" decomposition as it relies on assumptions that are common to a typical regression analysis where a group indicator variable is deemed sufficient to control for mean differences between groups unexplained by other factors (covariates), and where the effects

[32] In Section 2.2 we implemented this specification by including pandemic period indicators and interactions of these pandemic indicators with $STEM_j$ and all other controls in a single regression as specified in equation (2), instead of estimating regressions separately for each $\tau$.

of each covariate is assumed to impact the outcomes of each group in the same way (as opposed to including interactions between these other factors and the group indicator to allow for group-specific effects).[33] The *change* in the STEM vs. non-STEM differential in labor market outcomes is given by:[34]

$$\begin{aligned}
\Delta\overline{y}_{\tau} - \Delta\overline{y}_{\tau-1} &= \left[\Delta\overline{\boldsymbol{X}}_{\boldsymbol{\tau}}\hat{\boldsymbol{\beta}}_{\boldsymbol{\tau}} + \hat{\alpha}_{1,\tau}\right] - \left[\Delta\overline{\boldsymbol{X}}_{\boldsymbol{\tau-1}}\hat{\boldsymbol{\beta}}_{\boldsymbol{\tau-1}} + \hat{\alpha}_{1,\tau-1}\right] \\
&= \underbrace{\left[\Delta\overline{\boldsymbol{X}}_{\boldsymbol{\tau}}\hat{\boldsymbol{\beta}}_{\boldsymbol{\tau}} - \Delta\overline{\boldsymbol{X}}_{\boldsymbol{\tau-1}}\hat{\boldsymbol{\beta}}_{\boldsymbol{\tau-1}}\right]}_{Explained} + \underbrace{\Delta\hat{\alpha}_1}_{Unexplained} \\
&= \sum_{k=1}^{K}\left[\Delta\overline{\boldsymbol{X}}^{\boldsymbol{k}}_{\boldsymbol{\tau}}\hat{\boldsymbol{\beta}}^{\boldsymbol{k}}_{\boldsymbol{\tau}} - \Delta\overline{\boldsymbol{X}}^{\boldsymbol{k}}_{\boldsymbol{\tau-1}}\hat{\boldsymbol{\beta}}^{\boldsymbol{k}}_{\boldsymbol{\tau-1}}\right] + \Delta\hat{\alpha}_1, \qquad (5)
\end{aligned}$$

where $\Delta\hat{\alpha}_1 \equiv [\hat{\alpha}_{1,\tau} - \hat{\alpha}_{1,\tau-1}]$ gives the change in the STEM vs non-STEM differential that is not explained by modeled covariates. Letting $t = \tau$ denote the early pandemic period and $t = \tau - 1$ denote the pre-pandemic period, it is straightforward to show that $\Delta\overline{y}_{\tau} - \Delta\overline{y}_{\tau-1}$ is precisely the difference-in-differences estimate of the coefficient on *STEM*Pandemic (Apr-Jun 2020)* in our baseline specification *without* covariates, and that the unexplained part $\Delta\hat{\alpha}_1$ is equivalent to the difference-in-differences estimate in our full specification *with* covariates.[35] Thus, the explained part of (5) is equal to the magnitude of the movement in the estimated coefficient on *STEM*Pandemic (Apr-Jun 2020)* when comparing the estimate from a baseline difference-in-differences specification without covariates to the estimate from a full specification with covariates. Intuitively, the difference between two "regression-compatible" decompositions estimated before and after a treatment results

[33] Note that the left side of (4) is equal to the coefficient on the group indicator ($STEM_j$) in a baseline version of (3) *without* covariates and the unexplained part ($\hat{\alpha}_{1,\tau}$) is equal to the coefficient on the group indicator in a full specification *with* covariates as given by (3). Thus, the explained part of (4) is equal to the magnitude of the movement in the estimated coefficient on the group indicator when comparing results from specifications without and with covariates.

[34] We note that simply estimating a decomposition for the first quarter of the pandemic is not sufficient to decompose the effect of the COVID-19 recession on labor market outcomes during this period; this is because STEM workers also had an advantage in these outcomes before the COVID-19 pandemic, and so such a decomposition will be contaminated by decomposing the already extant difference in outcomes alongside period-specific differences brought on by the pandemic.

[35] After excluding the late pandemic period, our full specification given in equation (2) can be rewritten as:

$$\begin{aligned}
y_{ijst} =& \alpha_0 + \alpha_1 STEM_j + \gamma_1 Pandemic_t + \widetilde{\delta}_1\left(STEM_j * Pandemic_t\right) + \\
&\boldsymbol{X_{ijst}}\boldsymbol{\beta_{\tau-1}} + \left(\boldsymbol{X_{ijst}} * \boldsymbol{Pandemic_t}\right)\left(\boldsymbol{\beta_{\tau}} - \boldsymbol{\beta_{\tau-1}}\right) + \epsilon_{ijst}, \qquad (6)
\end{aligned}$$

where fixed effects are now included as part of $\boldsymbol{X_{ijst}}$ for simplicity, we break out the interactions of covariates with pandemic indicators as a separate term for clarity, and where we now reserve $\delta_1$ to represent the difference-in-differences coefficient from a baseline regression which excludes the $\boldsymbol{X_{ijst}}$ terms from above. Denote the expected difference between STEM and non-STEM outcomes in period $t$ as $E\left(\Delta y_t\right)$ and the expected difference between STEM and non-STEM characteristics/covariates as $E\left(\Delta \boldsymbol{X_t}\right)$. Using (6) to calculate $E\left(\Delta y_\tau\right) - E\left(\Delta y_{\tau-1}\right)$ and noting that the baseline difference-in-differences coefficient $\delta_1 \equiv E\left(\Delta y_\tau\right) - E\left(\Delta y_{\tau-1}\right)$ yields:

$$\delta_1 = \left[E\left(\Delta\boldsymbol{X_\tau}\right)\right]\boldsymbol{\beta_\tau} - \left[E\left(\Delta\boldsymbol{X_{\tau-1}}\right)\right]\boldsymbol{\beta_{\tau-1}} + \widetilde{\delta}_1,$$

where the sample analog of this equation using pooled OLS coefficients is given by (5) after substituting $\widehat{\delta}_1 \equiv \Delta\overline{y}_{\tau} - \Delta\overline{y}_{\tau-1}$ and thus $\widehat{\widetilde{\delta}}_1 \equiv \Delta\hat{\alpha}_1$.

in a "difference-in-differences-compatible" decomposition.

The last equality in (5) shows that we can partition the covariates into $K$ sets to evaluate what portion of STEM resiliency is explained by each set of covariates. The percentage of the change in the gap in labor market outcomes between STEM and non-STEM workers explained by the full set of controls is calculated as $[(\Delta\overline{\boldsymbol{X}}_{\boldsymbol{\tau}}\hat{\boldsymbol{\beta}}_{\boldsymbol{\tau}} - \Delta\overline{\boldsymbol{X}}_{\boldsymbol{\tau-1}}\hat{\boldsymbol{\beta}}_{\boldsymbol{\tau-1}})/(\Delta\overline{y}_{\tau} - \Delta\overline{y}_{\tau-1})] * 100\%$ and the unexplained percentage is calculated as $[\Delta\hat{\alpha}_1/(\Delta\overline{y}_{\tau} - \Delta\overline{y}_{\tau-1})] * 100\%$ where the explained and unexplained percentage sum to 100%. The percentage of the change in the gap in labor market outcomes between STEM and non-STEM workers explained by controls in group $k$ is calculated as $[(\Delta\overline{\boldsymbol{X}}^{\boldsymbol{k}}_{\boldsymbol{\tau}}\hat{\boldsymbol{\beta}}^{\boldsymbol{k}}_{\boldsymbol{\tau}} - \Delta\overline{\boldsymbol{X}}^{\boldsymbol{k}}_{\boldsymbol{\tau-1}}\hat{\boldsymbol{\beta}}^{\boldsymbol{k}}_{\boldsymbol{\tau-1}})/(\Delta\overline{y}_{\tau} - \Delta\overline{y}_{\tau-1})] * 100\%$. Note that the explained percentage will exceed 100% (and the unexplained percentage will be negative) in cases where, after including all controls in a full specification, the positive coefficient point-estimate on *STEM*Pandemic (Apr-Jun 2020)* from the baseline specification disappears and is replaced with a negative point-estimate.[36] Additionally, the portion of the difference in outcomes explained by some groups of variables can be negative when adding such variables as controls causes the coefficient point-estimate on *STEM*Pandemic (Apr-Jun 2020)* to increase rather than attenuate.[37]

Table 1 shows that there is not much change in the characteristics of STEM and non-STEM workers in our analytical sample, which is because we restrict our sample to a consistent sample of individuals who are observed both during and before the pandemic. Thus, differences in the returns to characteristics before and during the pandemic are the driving force behind the explained part of (5) in our application.

#### 2.4.2 Decomposition Results

Figure 5 visualizes our STEM employment resiliency decomposition results reported in Table 3 and Table 4.[38] Table 3 Panel A shows that STEM workers held a 3.6 and 12.6 percentage point employment rate advantage over non-STEM workers during the pre-pandemic period and the early pandemic period, respectively, implying a 9.0 percentage-point increase in the STEM vs. non-STEM employment rate differential at the onset of the COVID-19 recession.[39] Table 3 Panel

[36] Such is the case when examining the differences in labor force participation between STEM and non-STEM college-educated workers that emerged during the first full quarter of the pandemic. Table 2 shows that, without controls, STEM workers fared better than non-STEM workers during April 2020 through June 2020, but that after adding our full set of controls, the coefficient on STEM*Pandemic (Apr-Jun 2020) is negative.

[37] Such is the case when controlling for the share of workers in one's occupation employed in essential industries; since non-STEM workers are more likely to be employed in essential industries, and since workers in essential industries tend to do better in terms of labor market outcomes, conditioning on this variable increases the point-estimate on *STEM*Pandemic (Apr-Jun 2020)*.

[38] For ease of exposition, we combine the "geographic location" variables, the indicator variable for whether a worker is employed by a large firm, and month, year, and survey group fixed effects into a set of variables labeled "Other." Decomposition results for STEM resiliency in terms of labor force participation and work hours are presented in Appendix F, with Figure F.1 giving an overall summary of results. Decompositions in the pre-pandemic and pandemic period are estimated by the Stata package `oaxaca` using the `pooled` option (Jann, 2008).

[39] This corresponds precisely to the coefficient estimate on *STEM*Pandemic (Apr-Jun 2020)* in the first column of Table 2 Panel A.

B shows that our full set of covariates explains 105.2% of the increase in the STEM vs. non-STEM differential and Panel C breaks down the explained part of the decomposition into the portion explained by different subsets of covariates.[40] The factors that explain the largest shares of the pandemic-driven increase in the STEM vs. non-STEM differential in our full sample are STEM knowledge on the job (26.9%), non-routine and cognitive task intensity of work (25.2%), and industry (24.8%). Educational attainment and remote work feasibility explain 16.5% and 13.8% of the change in the STEM vs. non-STEM differential, respectively, while the greater concentration of non-STEM workers in essential industries pushes in the other direction such that controlling for the essential share of workers in one's occupation *increases* (rather than explains) the magnitude of the pandemic-induced change in the employment gap by 11.1%. Education requirements for the job and demographics explain 6.2% and 3.6% of the increase in the STEM vs. non-STEM differential, respectively, and other factors such as employer size, geographic location, and state-level measures of COVID-19 prevalence do not contribute to explaining the change in the STEM vs. non-STEM differential. Table 4 shows that, among college-educated workers, STEM knowledge on the job (47.7%) and industry (34.2%) are the most important factors, while among non-college-educated workers, non-routine and cognitive task intensity of work (51.3%), demographics (25.4%), STEM knowledge on the job (25.1%), and industry (23.0%) are the leading factors.[41]

Figure A.4 provides further detail by showing the part of STEM employment resiliency explained by each covariate comprising the "Nonroutine/Cognitive" task category and the "STEM Knowledge" category to give insight into which type of tasks and which fields of STEM knowledge are driving our main decomposition results in Figure 5. In the full and non-college-educated samples, we find that the greater emphasis of STEM jobs on non-routine cognitive-analytical tasks (16.0% and 31.5%, respectively) and the lesser emphasis on routine manual (5.7% and 13.4%) and routine cognitive (3.0% and 9.0%) tasks explain the greatest shares of STEM employment resiliency among the task intensity variables. In the full sample, we see that computer knowledge (19.9%), engineering knowledge (14.0%), and math knowledge (8.1%) have the greatest explanatory power among STEM knowledge categories. For the college-educated sample, engineering knowledge appears as the singularly important explanator among the STEM knowledge variables (90.5%) whereas computer (28.2%) and math knowledge (11.6%) are more important among non-college-educated workers. For all samples, it appears that the greater importance of physics knowledge among STEM workers pushed in the opposite direction such that controlling for it increases (rather than explains) the STEM employment rate gap. However, it is important to keep in mind that these decompositions exploit the residual variation in physics knowledge that is uncorrelated with other covariates including the importance of engineering, math, and computer knowledge; in practice,

[40] Table 4 Panel B shows that the full set of covariates explains 110.5% and 112.1% of the change in the STEM vs. non-STEM differential in employment among college-educated and non-college-educated workers, respectively.

[41] In Appendix F we find that, among college-educated workers only, the degree to which a job utilizes STEM knowledge also explains the greatest portion of the STEM advantage in labor force participation and work hours at the onset of the COVID-19 recession.

many jobs where physics knowledge is important are likely jobs where knowledge in these other categories is also important, and so we caution against an interpretation that greater knowledge of physics hurts workers employment outcomes unconditionally—a finding we rule out in the following section.

### 2.5 Which STEM Fields of Knowledge Are Associated with Employment Resiliency?

Which fields of STEM knowledge are associated with a greater degree of employment resiliency during recessions? To investigate this question, we run regressions similar to those reported in Table 2 but where we replace the STEM occupation indicator and its interactions with the pandemic indicators with each of the six STEM knowledge variables and their interactions with the pandemic indicators in turn.[42] Table 5 presents the results. Among college-educated workers, each type of STEM knowledge (including physics knowledge) is associated with increased employment resiliency in the initial period of the pandemic.[43] Among non-college-educated workers, the effect of STEM knowledge is weaker, but remains.[44] These results show that utilization of certain types of STEM knowledge on the job is likely to be a source of employment resiliency in recessions for both college-educated and non-college-educated workers.

One might wonder whether STEM knowledge is only important for workers in occupations formally classified as STEM occupations, and so we break down occupations and workers by the frequency with which different types of STEM knowledge are important on the job.[45] Table 6 shows that workers in non-STEM occupations constitute 83% of all workers in occupations where

[42]We run separate regressions for each knowledge variable, where the coefficient estimates are meant to give a descriptive account of how a one standard deviation increase in the importance of the given type of STEM knowledge to one's job relates to employment outcomes. These descriptive associations do not control for the importance of the other STEM knowledge categories as coefficient estimates from regressions which simultaneously control for all categories are prone to mislead as to whether a given knowledge category is likely to help or hurt a worker's employer outcomes during recessions *overall.* Since some jobs may require interdisciplinary skills (e.g., physics and engineering) and because knowledge in one STEM category might require knowledge in another (such as mathematics) as a prerequisite, controlling for all knowledge categories can lead to misleading findings such as a negative association between physics knowledge and employment outcomes (which only holds given that knowledge in math, engineering, etc. are all held constant). We view our approach as useful for describing general associations between each STEM knowledge category and employment outcomes during recessions but note that we lack the exogenous variation required to separate the causal effect of a given knowledge category from that of another (or from general ability).

[43]We do not include regressions controlling for the task profile of the job or industry of employment as these are likely endogenous to the degree to which a worker can perform in a job emphasizing STEM knowledge — that is, a worker's level of computer programming knowledge could make them better able to perform non-routine analytical tasks and enable them to work in high-tech industries, and so computer knowledge offers employment protection through these mechanisms. We include specification (3) which controls for the remote work feasibility and essential nature of one's job as these are factors which had an effect on employment outcomes during COVID-19 but may not be important for non-pandemic-related recessions.

[44]The negative effect of chemistry knowledge importance and the positive effect of biology knowledge importance are both eliminated when including controls for demographics, the education attained by each sample member and that typically required by their occupation, location, and measures of the remote work feasibility and essential nature of a worker's occupation.

[45]For purposes of this table only, we treat non-STEM and STEM-related occupations as separate groups.

at least one of the six fields of STEM knowledge is important on the job, and that 58% of workers in non-STEM occupations work in a job where at least one of the six fields of STEM knowledge is important.[46] Mathematics and computer knowledge are the most frequently important types of STEM knowledge for workers in non-STEM occupations, whereas other fields of STEM knowledge—such as engineering—are considerably less likely to be important. Nevertheless, while only 6% of non-STEM workers are in jobs where engineering knowledge is important, 54% of workers in a job where engineering knowledge is important work in a non-STEM occupation. In Table A.3 we estimate the same regressions as in Table 5 using the subsample of workers in non-STEM occupations. For college-educated non-STEM workers, the estimated coefficients are similar to those for all college-educated workers shown in Table 5. For non-college-educated non-STEM workers, the estimated coefficients are smaller and less statistically significant. Altogether, we find that workers in jobs where STEM knowledge is important have greater employment resiliency, even if their job is not formally classified as a STEM occupation.

# 3 R&D Resiliency During the COVID-19 Pandemic

STEM workers play an important role in creating and diffusing new technologies, and while most STEM workers are not engaged in R&D, most workers engaged in R&D are in STEM occupations (Barth et al., 2018). The relative resiliency of STEM employment during the COVID-19 pandemic suggests that R&D employment may also be resilient. To gain insight on the experience of the R&D workforce during COVID-19, we examine employment trends in the five most R&D-intensive industries in the US and the evolution of aggregate US R&D expenditures during the COVID-19 pandemic. R&D expenditures serve as both a measure of general innovative activity at US firms and as an indicator of R&D employment since the largest part of R&D expenditures is used to compensate R&D workers.[47] Table 7 presents R&D expenditures and R&D employment for the five industries with the highest R&D intensity among their R&D-performing firms in 2017.[48] These five industries account for over half of all US industrial R&D expenditures and employ almost 700,000 R&D workers who make up one in every four workers employed in these industries.

Figure 6 plots quarterly seasonally-adjusted employment for these five R&D-intensive industries alongside aggregate STEM employment, real R&D expenditures, and real output for the entire US

[46] A given knowledge category is considered important if the average evaluation of O*NET respondents on the knowledge questionnaire yields a value above 3, which is the threshold value which defines the knowledge as important on the five-point scale (with a 4 and 5 for "very important" and "extremely important", respectively).

[47] According to the NSF's Business Research and Development Survey, 51% of domestic US R&D expenditures in 2017 were for "salaries, wages, and fringe benefits" (https://ncses.nsf.gov/pubs/nsf20311/table/1).

[48] The NSF defines R&D intensity as the cost of domestic R&D performed by a company divided by the domestic net sales of the company and defines R&D employees to include all employees who work on R&D or who provide direct support to R&D, such as researchers, R&D managers, technicians, clerical staff, and others assigned to R&D groups. It excludes employees who provide only indirect support to R&D, such as corporate personnel, security guards, and cafeteria workers.

economy during both the Great Recession (Panel A) and the COVID-19 recession (Panel B).[49] We find that in the first three years (12 quarters) following the start of the Great Recession, total employment in the three R&D-intensive *non-manufacturing* industries was more resilient than aggregate STEM (and thus also non-STEM) employment, whereas total employment in the two R&D-intensive *manufacturing* industries declined more (in percentage terms) than aggregate STEM and non-STEM employment and remained below pre-recession levels even seven years after the start of the recession, reflecting in part the secular decline in US manufacturing employment.[50] Aggregate R&D expenditures fell three percent below its pre-recession level in 2009Q1 but then quickly recovered, remaining relatively flat during the period of output shortfall. After output recovered to its pre-recession level three years after the start of the Great Recession, real R&D expenditures began to grow at roughly the same rate as output. The recession-resilience of R&D expenditures compared to aggregate employment and output suggests that R&D employment was likely more resilient than non-R&D employment during the Great Recession.

Similarly, employment in R&D-intensive industries was more resilient than aggregate STEM (and non-STEM) employment during the COVID-19 recession and recovery. Aggregate R&D expenditures fell only in 2020Q2 and resumed growth in subsequent quarters at a rate vastly exceeding output growth, with steady increases in R&D notwithstanding two quarters of declines in real output during 2022Q1 and 2022Q2. Together, these results suggest that R&D employment has been more resilient than non-R&D employment during the COVID-19 pandemic, and that R&D activity has remained relatively resilient during both the COVID-19 recession and the period of output decline in 2022Q1 and 2022Q2.

# 4 Conclusion

The COVID-19 pandemic and associated "lockdown" measures led to sudden and widespread labor market disruptions with uneven effects on different types of workers. We show that, as in the Great Recession, workers in STEM occupations fared better than workers in non-STEM occupations at the onset of the pandemic, with peak-to-trough drops in STEM and non-STEM employment of 5% and 14%, respectively. By June 2021, STEM employment had returned to its pre-pandemic level, while non-STEM employment remained 5% below its pre-pandemic level and took another year to fully recover. Using a longitudinal sample of workers observed both before and during the COVID-19 pandemic, we show that STEM workers also experienced smaller declines in labor force participation and weekly work hours. We find that all of the employment advantage, all of the labor force participation advantage, and about two-thirds of the work hour advantage of STEM over non-STEM workers during the pandemic's initial three months can be explained by differences

[49] Industry employment is from the Bureau of Labor Statistics' *Current Employment Statistics* and real R&D expenditures are from `https://fred.stlouisfed.org/graph/?g=CjLL`. STEM employment is identical to that plotted in Figure 1.

[50] See Figure 1 for plots of non-STEM and total employment during the Great Recession and COVID-19 recession.

between STEM and non-STEM workers' demographics, educational attainment, employer industry and size, geographic location, remote work feasibility, non-routine and cognitive task intensity of work, education requirements for the job, and STEM knowledge on the job.

While the greater share of college-educated workers and the greater remote work capability of the STEM workforce explains some share of STEM employment resiliency in our full sample, the greater utilization of STEM knowledge on the job emerges as the single most important factor in our decomposition analysis. The importance of STEM knowledge increases when we limit to college-educated workers, with the portion of STEM employment resiliency explained by the greater use of STEM knowledge on the job over three times larger than that explained by the greater remote work capability of STEM workers. STEM knowledge on the job also explains the largest portion of the *pre-pandemic* employment advantage of STEM workers over non-STEM workers, which suggests that STEM knowledge is a persistently important factor in labor market outcomes.

Previous work finds that, among college graduates, having a STEM degree offers employment protection during economic downturns (Altonji, Kahn, and Speer, 2016; Abel and Deitz, 2018). We find that non-college-educated workers in STEM occupations also enjoy better employment outcomes during recessions. Furthermore, we find that there are more workers in non-STEM occupations where STEM knowledge is important on the job than there are workers in STEM occupations, and that workers in non-STEM occupations where STEM knowledge is important—and not just workers with STEM degrees or in STEM occupations—also benefit from greater employment resiliency. These results complement prior work showing that STEM skills benefit workers in both STEM and non-STEM occupations (Black et al., 2021) and are relevant to education policymakers as well as young persons choosing educational and career paths.

Much recent literature concerning worker vulnerability during and in the aftermath of recessions emphasizes the task content of jobs. Workers in STEM occupations are more likely to work in jobs requiring the performance of non-routine cognitive-analytical tasks and less likely to be engaged in routine tasks or non-routine manual tasks. In the recoveries from recent recessions, many routine jobs did not return (Jaimovich and Siu, 2020), displaced by routine-biased technologies and labor market "upskilling" (Hershbein and Kahn, 2018). For non-college-educated workers, our decomposition of regression results indicates that the resiliency of STEM employment relative to non-STEM employment in the COVID-19 pandemic is best explained by differences in the task content of jobs, perhaps presaging a further shift from routine task-oriented jobs in the wake and aftermath of the COVID-19 recession. Our results suggest that increasing opportunities for STEM training—including outside and prior to the college-track—may help improve the adaptability of workers as technology evolves in the 21st century. However, some caution is warranted as the degree to which artificial intelligence (AI) technologies will displace vs. augment STEM and non-STEM labor remains an open question. We hope our findings of STEM recession resiliency during earlier recessions in the digital age motivate future research into STEM recession resiliency in the new age of AI.

Lastly, we find that R&D expenditures and R&D employment remained relatively resilient during the COVID-19 pandemic. This suggests that STEM employment resiliency enabled a similar resilience in the level of innovative activity during the pandemic. Further exploration of the pandemic's effect on the direction of innovation remains a fruitful avenue for future research.

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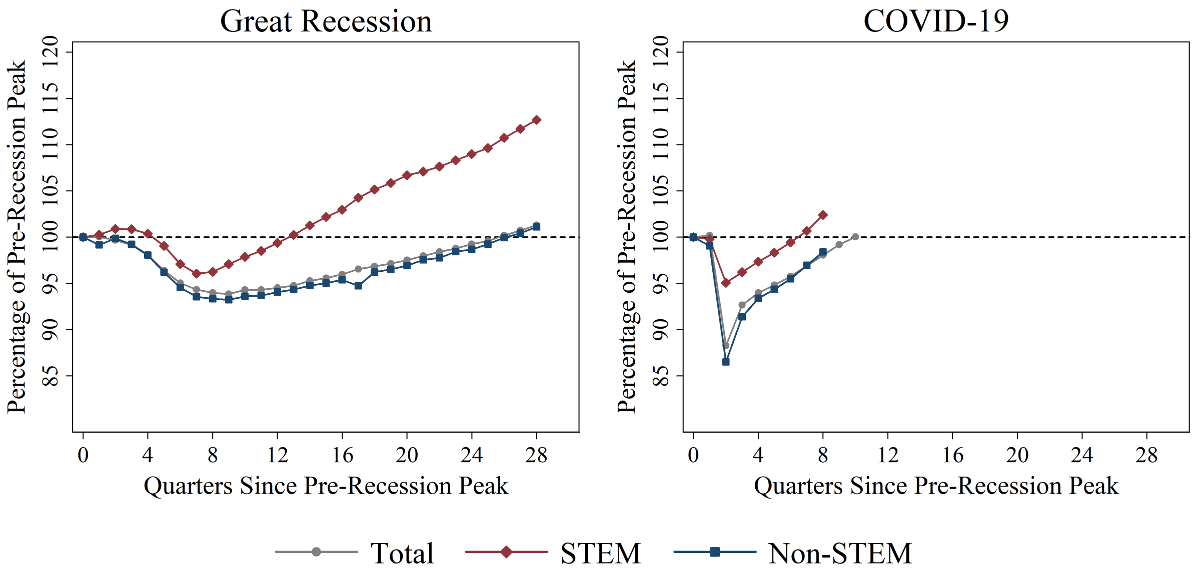
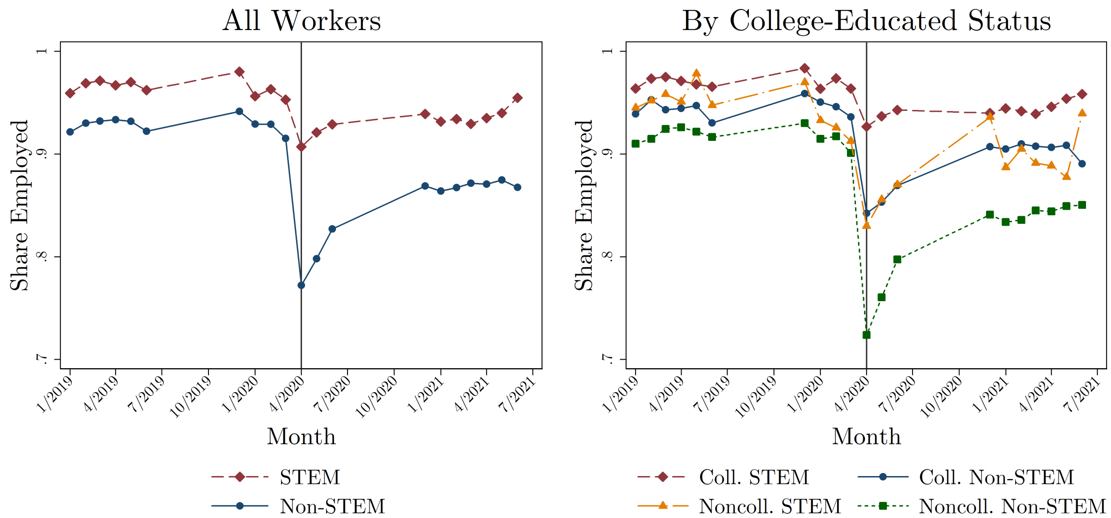
Figure 1. Employment in the Great Recession and COVID-19 Recession




*Notes*: Great Recession "pre-recession" peak defined as 2007Q4 and COVID-19 recession "pre-recession" peak defined as 2019Q4. STEM employment calculated by multiplying monthly QCEW employment for each four-digit NAICS industry by its STEM-share of employment as calculated using annual OES data and the US Census Bureau's definition of STEM occupations. The following NAICS occupations in QCEW data are excluded due to missing data in OES: "Agriculture, forestry, fishing and hunting" (110000), "Private households" (814100), "Public Administration" (920000), and 'Unclassified" (990000). OES data also exclude data from self-employed workers. STEM-related occupations are defined as non-STEM and the STEM-share of industry employment for months during 2021 is calculated using OES 2020 data. Total employment numbers are from the Bureau of Labor Statistics' *Current Employment Statistics*. We adjust monthly employment data to a quarterly basis and then seasonally-adjust quarterly employment using the US Census Bureau's X-13-ARIMA-SEATS Program via the R package `seasonal`.

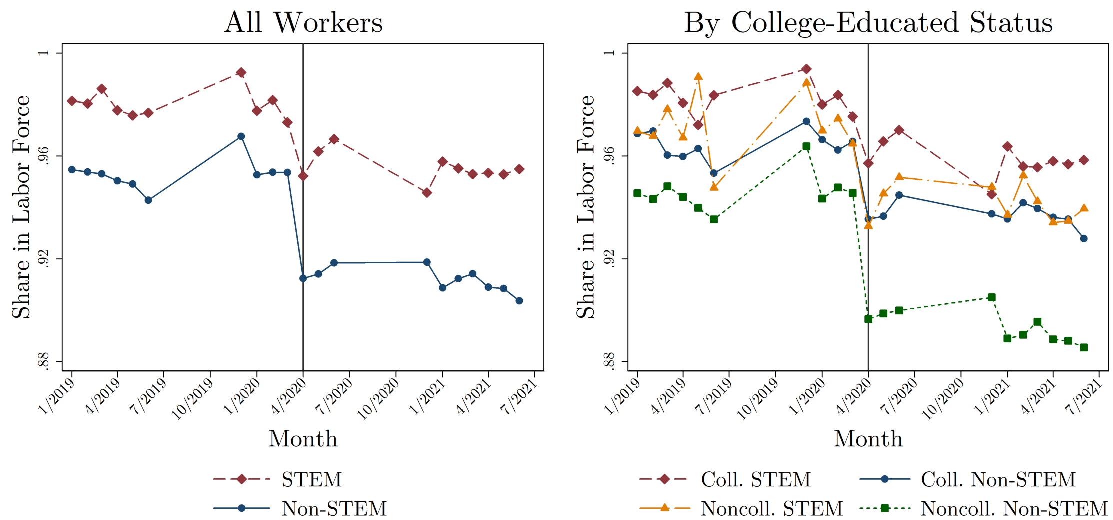
Figure 2. CPS Analytical Sample Employment Rate Before and During the COVID-19 Recession



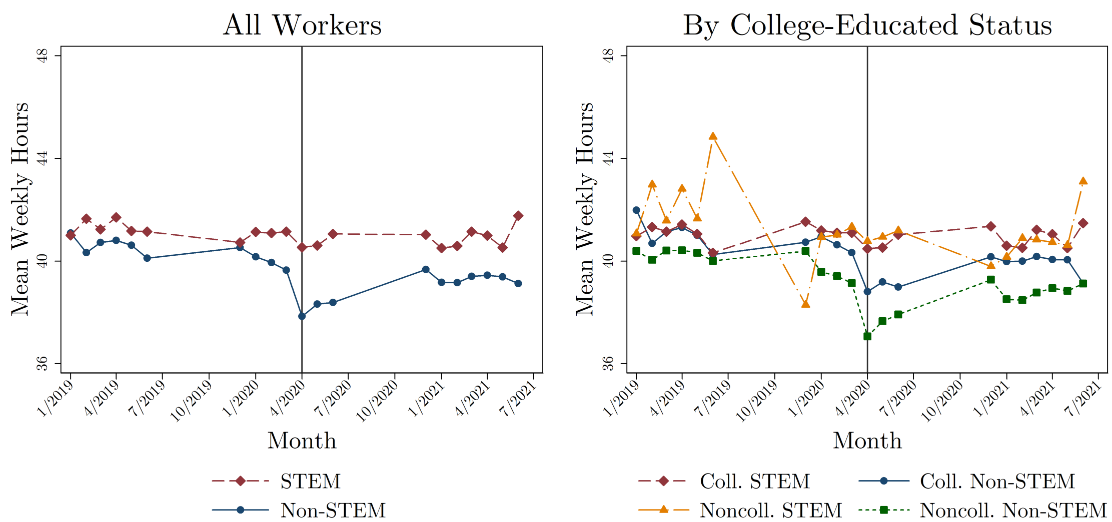

*Notes*: Sample limited to March 2020 CPS Annual Social and Economic Supplement (ASEC) respondents between the ages of 25 and 65 and who were observed both before and after March 2020 in monthly CPS data. These restrictions combined with the 4-8-4 rotating sampling scheme of the CPS mean that no members of the analytical sample are surveyed in July 2019 through November 2019, July 2020 through November 2020, or after June 2021. Each worker is classified by the occupation associated with the longest job occupied during 2019. CPS monthly basic survey weights used to compute weighted means.

Figure 3. CPS Analytical Sample Labor Force Participation Rate and Mean Weekly Work Hours Before and During the COVID-19 Recession

**A. Labor Force Participation**

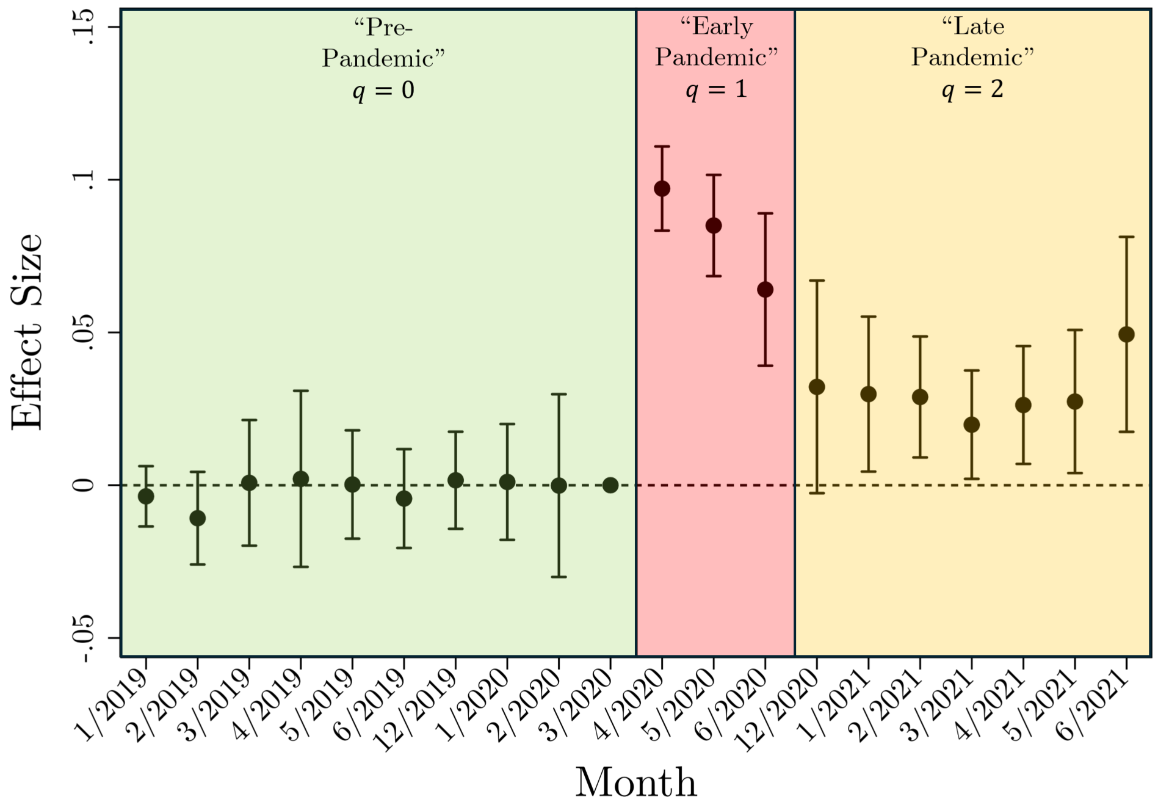



**B. Work Hours**



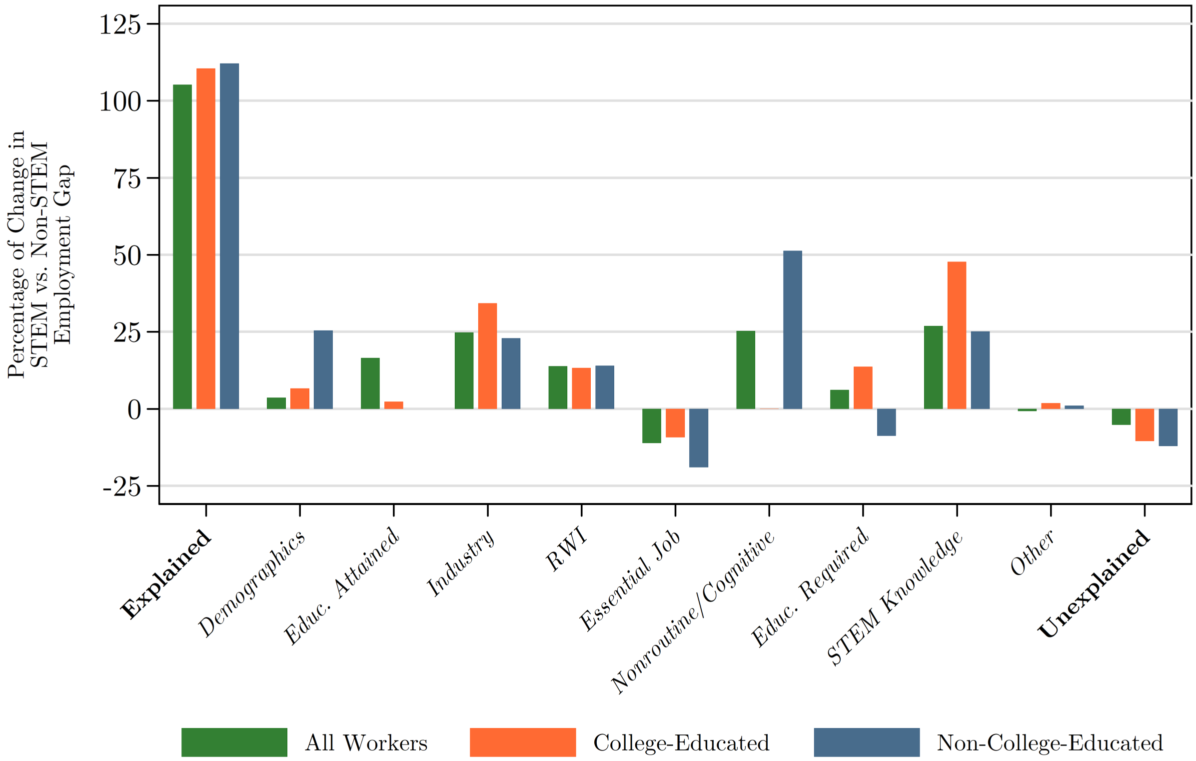

*Notes*: Sample limited to March 2020 CPS Annual Social and Economic Supplement (ASEC) respondents between the ages of 25 and 65 and who were observed both before and after March 2020 in monthly CPS data. These restrictions combined with the 4-8-4 rotating sampling scheme of the CPS mean that no members of the analytical sample are surveyed in July 2019 through November 2019, July 2020 through November 2020, or after June 2021. Each worker is classified by the occupation associated with the longest job occupied during 2019. CPS monthly basic survey weights used to compute weighted means.

Figure 4. STEM vs. Non-STEM Employment Rate Event Study




*Notes*: See notes to Figure 2. Event study shows the gap between STEM and non-STEM employment rates relative to that observed in March 2020 (last pre-pandemic month) with 95% confidence bands. Robust standard errors allow for clustering at person level. Shaded colors indicate time periods ($q$) as defined in the main analysis.

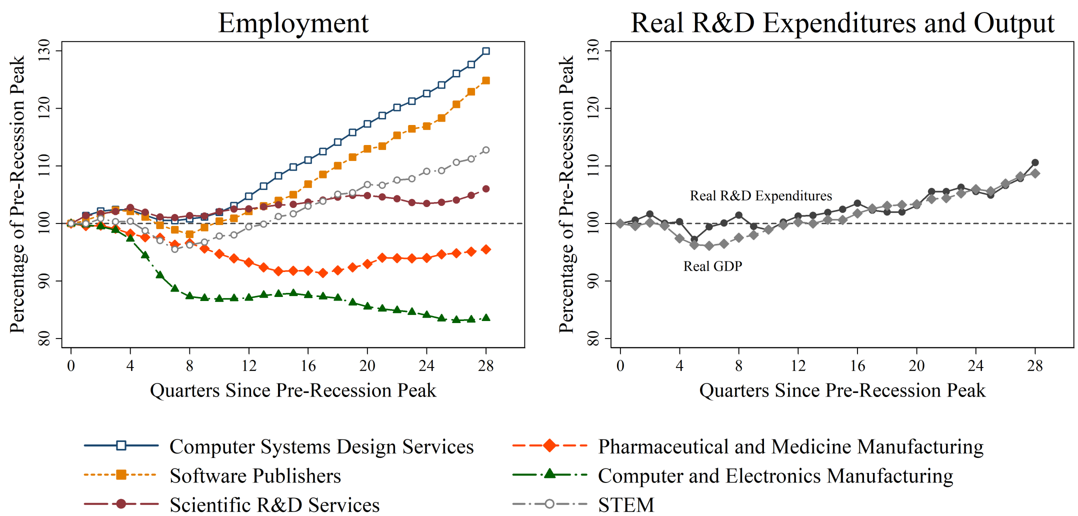
Figure 5. Decomposition of the Relative Resiliency of STEM over Non-STEM Employment at the Trough of the COVID-19 Recession into the Percentage Explained by Each Mechanism



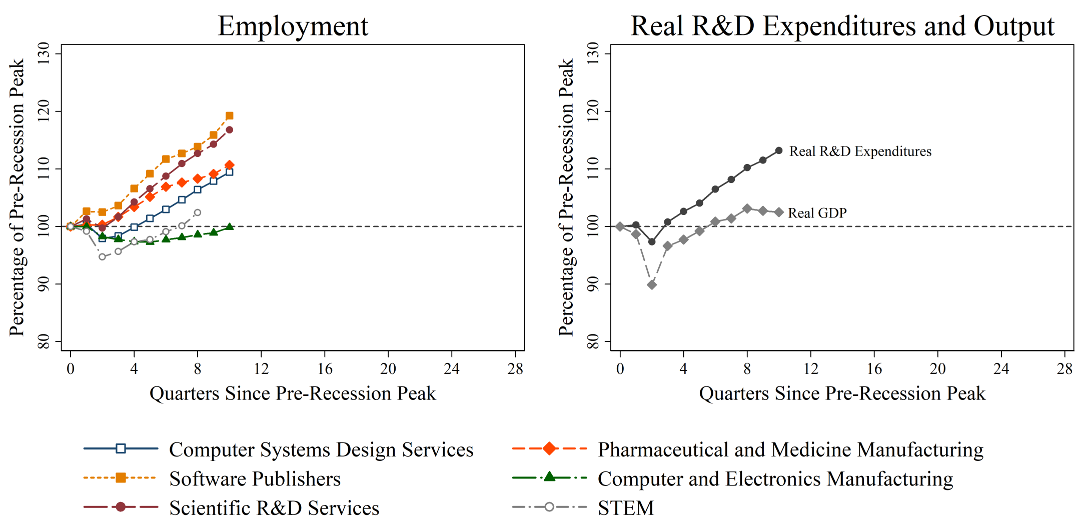

*Notes*: This figure gives the decomposition results for the impact of the pandemic on the employment gap between STEM and non-STEM workers during the first quarter of the pandemic (April 2020 through June 2020). It is the graphical representation of the Oaxaca-Blinder decomposition estimates reported in the fourth column of Table 3 and the fourth and eighth columns of Table 4 which are expressed as percentages of the change in the total difference (explained + unexplained) in the employment between STEM and non-STEM workers after the onset of the pandemic. Oaxaca-Blinder decompositions estimated using Stata package `oaxaca` using the `pooled` option (Jann, 2008). "Demographics" includes all controls listed in Table 1 between and including "Age" and "Disability Status." "Educ. Attained" includes the highest degree obtained my the worker. "Industry" includes industry fixed effects. "RWI" includes only the remote work index and "Essential Job" includes only the share of workers in one's occupation working in essential industries. "Nonroutine/Cognitive" includes standardized variables for the degree to which a worker's occupation entails routine cognitive, routine manual, non-routine cognitive-analytical, non-routine cognitive-interpersonal, and non-routine manual-physical tasks. "Educ. Required" includes indicators for the typical minimum education required for the worker's occupation. "STEM Knowledge" includes standardized variables for the degree to which the following six types of STEM knowledge is important to a worker's occupation: 1) Computer knowledge, 2) Engineering knowledge, 3) Mathematics knowledge, 4) Physics knowledge, 5) Chemistry knowledge, and 6) Biology knowledge. "Other" includes whether employer is a large firm (over 500 employees), location, the measures of COVID-19 cases and deaths included in Table 1, and month and survey group indicators.

Figure 6. Employment in R&D-Intensive Industries and Aggregate US R&D Expenditures in the Great Recession and COVID-19 Recession

**A. Great Recession**




**B. COVID-19 Recession**




*Notes*: Great Recession "pre-recession" peak defined as 2007Q4 and COVID-19 recession "pre-recession" peak defined as 2019Q4. Seasonally-adjusted monthly employment in Scientific R&D Services (NAICS 541700), Computer Systems Design and Related Services (NAICS 541500), Pharmaceutical and Medicine Manufacturing (NAICS 325400), Software Publishers (NAICS 511200), and Computer and Electronic Manufacturing (NAICS 334000) are from the the Bureau of Labor Statistics' *Current Employment Statistics* and is adjusted to a quarterly basis. Real R&D expenditures and output are from FRED: `https://fred.stlouisfed.org/graph/?g=CjLL` and `https://fred.stlouisfed.org/series/GDPC1`, respectively. STEM employment calculated by multiplying monthly QCEW employment for each four-digit NAICS industry by its STEM-share of employment as calculated using annual OES data and the US Census Bureau's definition of STEM occupations.

## Table 1. Summary Statistics

### A. Employment Regression Sample

| Period: | Pre-Pandemic | | Pandemic | |
|---|---|---|---|---|
| Group: | STEM | Non-STEM | STEM | Non-STEM |
| Employed | 0.96 | 0.93 | 0.93 | 0.83 |
| In Labor Force | 0.98 | 0.95 | 0.96 | 0.91 |
| Age | 42.79 | 44.47 | 43.41 | 45.03 |
| Female | 0.25 | 0.49 | 0.24 | 0.50 |
| White | 0.66 | 0.65 | 0.67 | 0.64 |
| Black | 0.07 | 0.12 | 0.06 | 0.12 |
| Asian | 0.18 | 0.06 | 0.19 | 0.06 |
| Hispanic | 0.08 | 0.16 | 0.08 | 0.17 |
| Other Race(s) | 0.02 | 0.03 | 0.02 | 0.03 |
| Foreign-Born | 0.25 | 0.18 | 0.25 | 0.18 |
| Married | 0.68 | 0.62 | 0.69 | 0.63 |
| Child (at home) | 0.48 | 0.50 | 0.49 | 0.51 |
| Female x Child | 0.11 | 0.26 | 0.11 | 0.26 |
| Disability Status | 0.03 | 0.04 | 0.03 | 0.04 |
| Highest Degree: BA | 0.48 | 0.25 | 0.48 | 0.26 |
| Highest Degree: MA/Prof | 0.25 | 0.13 | 0.27 | 0.14 |
| Highest Degree: PhD | 0.06 | 0.02 | 0.06 | 0.02 |
| Potential Experience | 20.69 | 24.13 | 21.23 | 24.61 |
| Large Employer | 0.67 | 0.49 | 0.68 | 0.48 |
| In Metro Area | 0.94 | 0.87 | 0.94 | 0.87 |
| In City Center | 0.32 | 0.27 | 0.32 | 0.27 |
| Cumulative Cases/100k | 0.00 | 0.00 | 4536.97 | 4468.76 |
| Cumulative Deaths/100k | 0.00 | 0.00 | 85.31 | 84.22 |
| New Cases/100k Last Week | 0.00 | 0.00 | 83.24 | 81.93 |
| New Deaths/100k Last Week | 0.00 | 0.00 | 2.32 | 2.37 |
| Physical Activity | 0.46 | 0.57 | 0.46 | 0.57 |
| Personal Proximity | 0.25 | 0.56 | 0.26 | 0.56 |
| Remote Work Index (RWI) | 0.52 | 0.31 | 0.52 | 0.32 |
| Essential Job Share | 0.29 | 0.44 | 0.30 | 0.43 |
| Routine Cognitive | -0.48 | -0.22 | -0.46 | -0.23 |
| Routine Manual | -0.76 | -0.33 | -0.76 | -0.33 |
| Non-Routine Cog.-Analytical | 1.21 | -0.03 | 1.20 | -0.02 |
| Non-Routine Cog.-Interpersonal | -0.11 | 0.32 | -0.12 | 0.33 |
| Non-Routine Man.-Physical | -0.82 | -0.25 | -0.83 | -0.27 |
| Educ Required: BA | 0.66 | 0.29 | 0.66 | 0.30 |
| Educ Required: MA | 0.19 | 0.04 | 0.18 | 0.04 |
| Educ Required: PhD/Prof | 0.03 | 0.03 | 0.04 | 0.03 |
| Computer Knowledge | 1.89 | -0.11 | 1.89 | -0.10 |
| Engineering Knowledge | 1.81 | -0.36 | 1.82 | -0.35 |
| Math Knowledge | 1.06 | -0.07 | 1.05 | -0.07 |
| Physics Knowledge | 0.94 | -0.32 | 0.94 | -0.31 |
| Chemistry Knowledge | 0.12 | -0.19 | 0.11 | -0.19 |
| Biology Knowledge | -0.04 | -0.03 | -0.05 | -0.03 |
| *N* | 9019 | 108795 | 8797 | 101694 |
| Person Count: | (2528) | (30110) | (2528) | (30110) |

### B. Work Hours Regression Sample

| Period: | Pre-Pandemic | | Pandemic | |
|---|---|---|---|---|
| Group: | STEM | Non-STEM | STEM | Non-STEM |
| Employed | 1.00 | 1.00 | 1.00 | 1.00 |
| Weekly Work Hours | 41.21 | 40.14 | 40.77 | 38.77 |
| Age | 42.72 | 44.29 | 43.27 | 44.88 |
| Female | 0.24 | 0.48 | 0.23 | 0.48 |
| White | 0.66 | 0.66 | 0.67 | 0.66 |
| Black | 0.07 | 0.11 | 0.05 | 0.11 |
| Asian | 0.18 | 0.05 | 0.19 | 0.05 |
| Hispanic | 0.08 | 0.16 | 0.08 | 0.16 |
| Other Race(s) | 0.02 | 0.03 | 0.02 | 0.03 |
| Foreign-Born | 0.25 | 0.17 | 0.25 | 0.17 |
| Married | 0.68 | 0.64 | 0.69 | 0.64 |
| Child (at home) | 0.48 | 0.51 | 0.50 | 0.51 |
| Female x Child | 0.11 | 0.25 | 0.10 | 0.26 |
| Disability Status | 0.03 | 0.03 | 0.03 | 0.03 |
| Highest Degree: BA | 0.48 | 0.26 | 0.48 | 0.27 |
| Highest Degree: MA/Prof | 0.26 | 0.14 | 0.27 | 0.15 |
| Highest Degree: PhD | 0.06 | 0.02 | 0.06 | 0.03 |
| Potential Experience | 20.56 | 23.83 | 21.02 | 24.30 |
| Large Employer | 0.67 | 0.50 | 0.69 | 0.50 |
| In Metro Area | 0.94 | 0.87 | 0.95 | 0.87 |
| In City Center | 0.32 | 0.26 | 0.32 | 0.27 |
| Cumulative Cases/100k | 0.00 | 0.00 | 4570.42 | 4660.17 |
| Cumulative Deaths/100k | 0.00 | 0.00 | 86.19 | 86.99 |
| New Cases/100k Last Week | 0.00 | 0.00 | 83.84 | 82.51 |
| New Deaths/100k Last Week | 0.00 | 0.00 | 2.31 | 2.24 |
| Physical Activity | 0.45 | 0.56 | 0.45 | 0.56 |
| Personal Proximity | 0.25 | 0.55 | 0.25 | 0.55 |
| Remote Work Index (RWI) | 0.53 | 0.32 | 0.53 | 0.33 |
| Essential Job Share | 0.29 | 0.45 | 0.30 | 0.44 |
| Routine Cognitive | -0.48 | -0.23 | -0.47 | -0.24 |
| Routine Manual | -0.77 | -0.37 | -0.77 | -0.39 |
| Non-Routine Cog.-Analytical | 1.22 | 0.04 | 1.21 | 0.06 |
| Non-Routine Cog.-Interpersonal | -0.10 | 0.38 | -0.12 | 0.39 |
| Non-Routine Man.-Physical | -0.83 | -0.29 | -0.84 | -0.31 |
| Educ Required: BA | 0.67 | 0.32 | 0.67 | 0.32 |
| Educ Required: MA | 0.19 | 0.04 | 0.18 | 0.04 |
| Educ Required: PhD/Prof | 0.03 | 0.04 | 0.04 | 0.04 |
| Computer Knowledge | 1.90 | -0.06 | 1.90 | -0.05 |
| Engineering Knowledge | 1.82 | -0.33 | 1.83 | -0.33 |
| Math Knowledge | 1.08 | -0.03 | 1.07 | -0.03 |
| Physics Knowledge | 0.94 | -0.30 | 0.94 | -0.30 |
| Chemistry Knowledge | 0.12 | -0.19 | 0.10 | -0.19 |
| Biology Knowledge | -0.04 | -0.01 | -0.06 | -0.01 |
| *N* | 8101 | 86330 | 7950 | 80855 |
| Person Count: | (2346) | (25445) | (2346) | (25445) |

*Notes*: Tables report survey-weighted means for workers in STEM and non-STEM occupations in the pre-pandemic period (before the April 2020 CPS survey) and pandemic period for the employment and work hour regression samples. STEM workers are defined as those who worked in a STEM occupation for their longest job in 2019; we classify STEM-related occupations as non-STEM. "Weekly Work Hours" are defined as each worker's hours worked at their main job in the week preceding the CPS survey. See Appendix D for the definition of the Physical Activity, Personal Proximity, and RWI of each occupation. "Essential job share" gives the share of workers in one's occupation who work in essential industries. See Appendix B.1 for more details on the definition of other variables included in the tables above. For employment sample, all differences in means between STEM and non-STEM worker characteristics significant at the 5% level except for "Educ. Required: PhD/Prof," "Biology Knowledge," and all included measures of statewide COVID-19 cases and deaths. For work hours sample, all differences in means between STEM and non-STEM worker characteristics significant at the 5% level except for "Educ. Required: PhD/Prof," "White" (pre-pandemic), "Disability Status" (pandemic), and all included measures of statewide COVID-19 cases and deaths.

Table 2. Impact of COVID-19 on Labor Market Outcomes by STEM Status

| Sample: | Full | | College-Educated | | Non-College-Educated | |
|---|---|---|---|---|---|---|
| Specification Includes Controls: | No | Yes | No | Yes | No | Yes |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| ***Panel A. Dependent Variable: Employed*** | | | | | | |
| Pandemic (Apr-Jun 2020) | -0.137*** | -0.124** | -0.0932*** | -0.159** | -0.167*** | -0.143 |
| | (0.00280) | (0.0423) | (0.00379) | (0.0531) | (0.00390) | (0.0920) |
| Pandemic (Dec-Jun 2021) | -0.0561*** | -0.0339 | -0.0365*** | -0.101$^{+}$ | -0.0719*** | 0.0806 |
| | (0.00299) | (0.0526) | (0.00400) | (0.0603) | (0.00424) | (0.119) |
| STEM x Pandemic (Apr-Jun 2020) | 0.0900*** | -0.00499 | 0.0567*** | -0.00614 | 0.0758*** | -0.00999 |
| | (0.00677) | (0.0123) | (0.00722) | (0.0145) | (0.0187) | (0.0260) |
| STEM x Pandemic (Dec-Jun 2021) | 0.0294*** | 0.00772 | 0.0119 | -0.00798 | 0.0342$^{+}$ | 0.0472 |
| | (0.00791) | (0.0142) | (0.00874) | (0.0171) | (0.0196) | (0.0289) |
| $R^2$ | 0.0307 | 0.119 | 0.0193 | 0.112 | 0.0375 | 0.141 |
| $N$ | 228305 | 228305 | 99215 | 99215 | 129090 | 129090 |
| ***Panel B. Dependent Variable: In Labor Force*** | | | | | | |
| Pandemic (Apr-Jun 2020) | -0.0392*** | -0.0481$^{+}$ | -0.0268*** | -0.105** | -0.0478*** | 0.0137 |
| | (0.00184) | (0.0279) | (0.00243) | (0.0357) | (0.00261) | (0.0632) |
| Pandemic (Dec-Jun 2021) | -0.0417*** | -0.0248 | -0.0263*** | -0.0882$^{+}$ | -0.0538*** | 0.0132 |
| | (0.00246) | (0.0437) | (0.00325) | (0.0503) | (0.00351) | (0.0991) |
| STEM x Pandemic (Apr-Jun 2020) | 0.0182*** | -0.00189 | 0.00815 | -0.0151 | 0.0164 | 0.00669 |
| | (0.00464) | (0.00825) | (0.00516) | (0.00956) | (0.0114) | (0.0165) |
| STEM x Pandemic (Dec-Jun 2021) | 0.0169** | -0.00428 | 0.00254 | -0.0243$^{+}$ | 0.0247$^{+}$ | 0.0264 |
| | (0.00654) | (0.0116) | (0.00749) | (0.0139) | (0.0142) | (0.0222) |
| $R^2$ | 0.00788 | 0.0720 | 0.00480 | 0.0844 | 0.00938 | 0.0885 |
| $N$ | 228305 | 228305 | 99215 | 99215 | 129090 | 129090 |
| ***Panel C. Dependent Variable: log(Hours)*** | | | | | | |
| Pandemic (Apr-Jun 2020) | -0.0766*** | -0.106* | -0.0596*** | -0.0790 | -0.0908*** | -0.160 |
| | (0.00363) | (0.0524) | (0.00511) | (0.0699) | (0.00510) | (0.115) |
| Pandemic (Dec-Jun 2021) | -0.0210*** | 0.0696 | -0.0124* | 0.0269 | -0.0289*** | 0.103 |
| | (0.00343) | (0.0598) | (0.00516) | (0.0798) | (0.00463) | (0.131) |
| STEM x Pandemic (Apr-Jun 2020) | 0.0661*** | 0.0197 | 0.0522*** | -0.00808 | 0.0679*** | 0.0667* |
| | (0.00759) | (0.0171) | (0.00897) | (0.0216) | (0.0169) | (0.0320) |
| STEM x Pandemic (Dec-Jun 2021) | 0.0157$^{+}$ | 0.00975 | 0.0125 | 0.0306 | 0.00168 | -0.0322 |
| | (0.00862) | (0.0164) | (0.00989) | (0.0209) | (0.0218) | (0.0317) |
| $R^2$ | 0.00701 | 0.0916 | 0.00482 | 0.0999 | 0.00813 | 0.112 |
| $N$ | 183236 | 183236 | 84829 | 84829 | 98407 | 98407 |
| ***Specification Controls*** | | | | | | |
| *Demographics-by-Pandemic* | No | Yes | No | Yes | No | Yes |
| *Educational Attainment-by-Pandemic* | No | Yes | No | Yes | No | Yes |
| *Employer Industry & Size-by-Pandemic* | No | Yes | No | Yes | No | Yes |
| *Location-by-Pandemic* | No | Yes | No | Yes | No | Yes |
| *RWI- & Essential Job-by-Pandemic* | No | Yes | No | Yes | No | Yes |
| *Nonroutine/Cognitive-by-Pandemic* | No | Yes | No | Yes | No | Yes |
| *Education Requirement-by-Pandemic* | No | Yes | No | Yes | No | Yes |
| *STEM Knowledge-by-Pandemic* | No | Yes | No | Yes | No | Yes |

*Notes:* No observations for July through November of 2019 and 2020 as analytical sample members are not observed during these months due to the CPS 4-8-4 rotating sampling scheme paired with analytical sample restrictions that members are observed both as part of the March 2020 ASEC and in at least one month during the pandemic. "Pandemic (Apr-Jun)" is equal to one in April, May, and June of 2020. "Pandemic (Dec-Jan)" is equal to one in December 2020 and January 2021. "College-educated workers" are those workers who have obtained at least a Bachelor's degree. All regressions control for "STEM", which is an indicator variable equal to one for workers whose main occupation during 2019 was a STEM occupation, and its interaction with the pandemic indicators. In addition to the listed set of controls, specification with controls also include month fixed effects, year fixed effects, and survey group fixed effects defined by each respondents' first month surveyed. See Section 2.2 for the definition of each set of controls. Robust standard errors clustered at individual-level. Regressions are weighted using CPS basic monthly weights. $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3. Decomposition of the Relative Resiliency of STEM over Non-STEM Employment at the Trough of the COVID-19 Recession

| Sample: | All Workers | | | |
|---|---|---|---|---|
| | Pre-Pandemic | Pandemic | Difference | Share |
| *Panel A. Mean Employment Rates* | | | | |
| STEM | 0.962 | 0.915 | -0.047 | |
| Non-STEM | 0.926 | 0.789 | -0.137 | |
| Difference | 0.036 | 0.126 | 0.090 | 1.000 |
| *Panel B. Overall Decomposition* | | | | |
| Explained | 0.063*** | 0.157*** | 0.095 | 1.052 |
| | (0.006) | (0.011) | | |
| Unexplained | -0.027*** | -0.032* | -0.005 | -0.052 |
| | (0.007) | (0.013) | | |
| *Panel C. Detailed Decomposition* | | | | |
| Demographics | 0.010*** | 0.013*** | 0.003 | 0.036 |
| | (0.001) | (0.003) | | |
| Educ. Attained | 0.001 | 0.016*** | 0.015 | 0.165 |
| | (0.001) | (0.003) | | |
| Industry | 0.006* | 0.028*** | 0.022 | 0.248 |
| | (0.002) | (0.005) | | |
| RWI | 0.006* | 0.019*** | 0.012 | 0.138 |
| | (0.003) | (0.005) | | |
| Essential Job | -0.002+ | -0.012*** | -0.010 | -0.111 |
| | (0.001) | (0.002) | | |
| Routine/Cognitive | 0.001 | 0.023** | 0.023 | 0.252 |
| | (0.005) | (0.009) | | |
| Educ. Required | 0.002 | 0.008 | 0.006 | 0.062 |
| | (0.003) | (0.005) | | |
| STEM Knowledge | 0.037*** | 0.061*** | 0.024 | 0.269 |
| | (0.006) | (0.011) | | |
| Other | 0.002* | 0.001 | -0.001 | -0.008 |
| | (0.001) | (0.002) | | |
| *N* | 117814 | 52460 | | |

*Notes:* "Pre-pandemic" and "Pandemic" columns give results from two-fold regression-compatible pooled Oaxaca-Blinder decompositions of the difference in employment between STEM and non-STEM workers in our analytical sample during the relevant period. Pandemic period only includes data for April 2020 through June 2020. "Difference" reports the difference between the decompositions in order to decompose the change in the gap in employment between STEM and non-STEM workers that emerged after the onset of the pandemic. "Share" represents the share of the total change in the gap (explained + unexplained) in employment between STEM and non-STEM workers. Oaxaca-Blinder decompositions estimated using Stata package `oaxaca` using the `pooled` option (Jann, 2008). Robust standard errors clustered at individual-level are in parentheses. "Demographics" includes all controls listed in Table 1 between and including "Age" and "Disability Status" (where age forms the basis of a quartic polynomial in potential experience). "RWI" includes only the remote work index, "Essential" includes only the share of workers in one's occupation working in essential industries. "Routine/Cognitive Task Intensities" includes standardized variables for the degree to which a worker's occupation entails routine cognitive, routine manual, non-routine cognitive-analytical, non-routine cognitive-interpersonal, and non-routine manual-physical tasks. "STEM Knowledge" includes standardized variables for the degree to which the following six types of STEM knowledge is important to a worker's occupation: 1) Computer knowledge, 2) Engineering knowledge, 3) Mathematics knowledge, 4) Physics knowledge, 5) Chemistry knowledge, and 6) Biology knowledge. "Industry" includes industry fixed effects. "Other" includes whether employer is a big firm (over 500 employees), location, the measures of COVID-19 cases and deaths included in Table 1, and month and survey group indicators. $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4. Decomposition of the Relative Resiliency of STEM over Non-STEM Employment at the Trough of the COVID-19 Recession, by Educational Attainment

| Sample: | College-Educated Workers | | | | Non-College-Educated Workers | | | |
|---|---|---|---|---|---|---|---|---|
| | Pre-Pandemic | Pandemic | Diff. | Share | Pre-Pandemic | Pandemic | Diff. | Share |
| *Panel A. Mean Employment Rates* | | | | | | | | |
| STEM | 0.969 | 0.932 | -0.037 | | 0.935 | 0.844 | -0.091 | |
| Non-STEM | 0.943 | 0.850 | -0.093 | | 0.914 | 0.747 | -0.167 | |
| Difference | 0.026 | 0.082 | 0.057 | 1.000 | 0.021 | 0.097 | 0.076 | 1.000 |
| *Panel B. Overall Decomposition* | | | | | | | | |
| Explained | 0.032*** | 0.095*** | 0.063 | 1.105 | 0.087*** | 0.172*** | 0.085 | 1.121 |
| | (0.007) | (0.014) | | | (0.010) | (0.021) | | |
| Unexplained | -0.006 | -0.012 | -0.006 | -0.105 | -0.066*** | -0.075** | -0.009 | -0.121 |
| | (0.008) | (0.015) | | | (0.013) | (0.025) | | |
| *Panel C. Detailed Decomposition* | | | | | | | | |
| Demographics | 0.005** | 0.009** | 0.004 | 0.067 | 0.012*** | 0.031*** | 0.019 | 0.254 |
| | (0.002) | (0.003) | | | (0.003) | (0.005) | | |
| Educ. Attained | 0.000+ | 0.002** | 0.001 | 0.023 | 0.000 | 0.000 | 0.000 | 0.000 |
| | (0.000) | (0.001) | | | | | | |
| Industry | 0.003 | 0.023*** | 0.019 | 0.342 | 0.011* | 0.029** | 0.017 | 0.230 |
| | (0.003) | (0.006) | | | (0.005) | (0.011) | | |
| RWI | 0.002 | 0.009+ | 0.008 | 0.133 | 0.013** | 0.023*** | 0.011 | 0.140 |
| | (0.003) | (0.005) | | | (0.004) | (0.007) | | |
| Essential Job | -0.003** | -0.008*** | -0.005 | -0.092 | -0.002 | -0.016*** | -0.014 | -0.190 |
| | (0.001) | (0.002) | | | (0.002) | (0.003) | | |
| Routine/Cognitive | -0.004 | -0.004 | -0.000 | -0.000 | 0.003 | 0.042** | 0.039 | 0.513 |
| | (0.005) | (0.009) | | | (0.008) | (0.015) | | |
| Educ. Required | 0.005** | 0.013*** | 0.008 | 0.137 | -0.006 | -0.013 | -0.007 | -0.088 |
| | (0.002) | (0.004) | | | (0.005) | (0.009) | | |
| STEM Knowledge | 0.022** | 0.049** | 0.027 | 0.477 | 0.053*** | 0.072*** | 0.019 | 0.251 |
| | (0.008) | (0.015) | | | (0.009) | (0.018) | | |
| Other | 0.002+ | 0.003 | 0.001 | 0.019 | 0.004* | 0.004 | 0.001 | 0.010 |
| | (0.001) | (0.002) | | | (0.002) | (0.004) | | |
| *N* | 50346 | 22822 | | | 67468 | 29638 | | |

*Notes:* "Pre-pandemic" and "Pandemic" columns give results from two-fold regression-compatible pooled Oaxaca-Blinder decompositions of the difference in employment between STEM and non-STEM workers in our analytical sample during the relevant period. Pandemic period only includes data for April 2020 through June 2020. "Difference" reports the difference between the decompositions in order to decompose the change in the gap in employment between STEM and non-STEM workers that emerged after the onset of the pandemic. "Share" represents the share of the total change in the gap (explained + unexplained) in employment between STEM and non-STEM workers. Oaxaca-Blinder decompositions estimated using Stata package `oaxaca` using the `pooled` option (Jann, 2008). Robust standard errors clustered at individual-level are in parentheses. "Demographics" includes all controls listed in Table 1 between and including "Age" and "Disability Status" (where age forms the basis of a quartic polynomial in potential experience). "RWI" includes only the remote work index, "Essential" includes only the share of workers in one's occupation working in essential industries. "Routine/Cognitive Task Intensities" includes standardized variables for the degree to which a worker's occupation entails routine cognitive, routine manual, non-routine cognitive-analytical, non-routine cognitive-interpersonal, and non-routine manual-physical tasks. "STEM Knowledge" includes standardized variables for the degree to which the following six types of STEM knowledge is important to a worker's occupation: 1) Computer knowledge, 2) Engineering knowledge, 3) Mathematics knowledge, 4) Physics knowledge, 5) Chemistry knowledge, and 6) Biology knowledge. "Industry" includes industry fixed effects. "Other" includes whether employer is a big firm (over 500 employees), location, the measures of COVID-19 cases and deaths included in Table 1, and month and survey group indicators. $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5. Impact of COVID-19 on Employment: Models by Domain of STEM Knowledge

| Sample: | College-Educated | | Non-College-Educated | |
|---|---|---|---|---|
| Dep. Var.: Employed | (1) | (2) | (1) | (2) |
| *Panel A. Key Variable: Importance of Computer Knowledge to Occupation* | | | | |
| Comp_know x Pandemic (Apr-Jun 2020) | 0.0309*** | 0.0165*** | 0.0295*** | 0.0103* |
| | (0.00368) | (0.00392) | (0.00396) | (0.00462) |
| Comp_know x Pandemic (Dec-Jun 2021) | 0.00784+ | 0.00204 | 0.00948* | 0.00231 |
| | (0.00434) | (0.00459) | (0.00447) | (0.00528) |
| *Panel B. Key Variable: Importance of Math Knowledge to Occupation* | | | | |
| Math_know x Pandemic (Apr-Jun 2020) | 0.0275*** | 0.0123** | 0.0191*** | 0.00800+ |
| | (0.00392) | (0.00434) | (0.00417) | (0.00441) |
| Math_know x Pandemic (Dec-Jun 2021) | 0.00776+ | 0.00448 | 0.00554 | -0.000891 |
| | (0.00432) | (0.00473) | (0.00465) | (0.00488) |
| *Panel C. Key Variable: Importance of Engineering Knowledge to Occupation* | | | | |
| Eng_know x Pandemic (Apr-Jun 2020) | 0.0181*** | 0.0108*** | 0.0229*** | 0.0107* |
| | (0.00267) | (0.00308) | (0.00399) | (0.00460) |
| Eng_know x Pandemic (Dec-Jun 2021) | 0.00275 | 0.0000513 | 0.00674 | 0.000439 |
| | (0.00314) | (0.00349) | (0.00423) | (0.00489) |
| *Panel D. Key Variable: Importance of Physics Knowledge to Occupation* | | | | |
| Phys_know x Pandemic (Apr-Jun 2020) | 0.0106*** | 0.00789* | 0.0177*** | 0.00966+ |
| | (0.00319) | (0.00349) | (0.00454) | (0.00516) |
| Phys_know x Pandemic (Dec-Jun 2021) | 0.00610+ | 0.00434 | 0.00790+ | 0.00278 |
| | (0.00352) | (0.00376) | (0.00468) | (0.00521) |
| *Panel E. Key Variable: Importance of Chemistry Knowledge to Occupation* | | | | |
| Chem_know x Pandemic (Apr-Jun 2020) | 0.00536+ | 0.00835* | -0.00941* | -0.00503 |
| | (0.00323) | (0.00410) | (0.00478) | (0.00518) |
| Chem_know x Pandemic (Dec-Jun 2021) | 0.00767* | 0.00788+ | -0.00276 | -0.00449 |
| | (0.00346) | (0.00454) | (0.00502) | (0.00551) |
| *Panel F. Key Variable: Importance of Biology Knowledge to Occupation* | | | | |
| Bio_know x Pandemic (Apr-Jun 2020) | 0.0107*** | 0.0111** | 0.0188*** | 0.00452 |
| | (0.00279) | (0.00406) | (0.00489) | (0.00550) |
| Bio_know x Pandemic (Dec-Jun 2021) | 0.0135*** | 0.0177*** | 0.00962+ | 0.00507 |
| | (0.00274) | (0.00442) | (0.00510) | (0.00587) |
| *N* | 99215 | 99215 | 129090 | 129090 |
| *Demographics-by-Pandemic* | No | Yes | No | Yes |
| *Educational Attainment-by-Pandemic* | No | Yes | No | Yes |
| *Location-by-Pandemic* | No | Yes | No | Yes |
| *RWI- & Essential Job-by-Pandemic* | No | Yes | No | Yes |
| *Education Requirement-by-Pandemic* | No | Yes | No | Yes |

*Notes:* All knowledge variables are standardized (zero mean and unit variance) across occupations. See Table 2 notes for additional details. Control sets not listed are excluded from all regressions. Robust standard errors clustered at individual-level are in parentheses. Regressions are weighted using CPS basic monthly weights. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6. STEM, STEM-Related, and Non-STEM Share of Occupations where Knowledge in STEM Field is Important

| Level of Observation: | Occupation | | | | Worker | | | |
|---|---|---|---|---|---|---|---|---|
| Key | Any | Non-STEM | STEM-Related | STEM | Any | Non-STEM | STEM-Related | STEM |
| Count | 531 | 433 | 36 | 62 | 138,822,695 | 123,810,428 | 6,931,620 | 8,080,647 |
| (Row Share) | (1.00) | (0.82) | (0.07) | (0.12) | (1.00) | (0.89) | (0.05) | (0.06) |
| [Column Share] | [1.00] | [1.00] | [1.00] | [1.00] | [1.00] | [1.00] | [1.00] | [1.00] |
| Knowledge Category | Any | Non-STEM | STEM-Related | STEM | Any | Non-STEM | STEM-Related | STEM |
| Computer | 235 | 164 | 14 | 57 | 56,052,661 | 45,740,066 | 2,567,078 | 7,745,517 |
| | (1.00) | (0.70) | (0.06) | (0.24) | (1.00) | (0.82) | (0.05) | (0.14) |
| | [0.44] | [0.38] | [0.39] | [0.92] | [0.40] | [0.37] | [0.37] | [0.96] |
| Mathematics | 273 | 191 | 23 | 59 | 67,329,561 | 54,510,845 | 5,818,659 | 7,000,057 |
| | (1.00) | (0.70) | (0.08) | (0.22) | (1.00) | (0.81) | (0.09) | (0.10) |
| | [0.51] | [0.44] | [0.64] | [0.95] | [0.49] | [0.44] | [0.84] | [0.87] |
| Engineering | 99 | 57 | 1 | 41 | 14,349,550 | 7,741,400 | 124,780 | 6,483,370 |
| | (1.00) | (0.58) | (0.01) | (0.41) | (1.00) | (0.54) | (0.01) | (0.45) |
| | [0.19] | [0.13] | [0.03] | [0.66] | [0.10] | [0.06] | [0.02] | [0.80] |
| Physics | 38 | 10 | 5 | 23 | 4,169,615 | 1,466,130 | 722,650 | 1,980,835 |
| | (1.00) | (0.26) | (0.13) | (0.61) | (1.00) | (0.35) | (0.17) | (0.48) |
| | [0.07] | [0.02] | [0.14] | [0.37] | [0.03] | [0.01] | [0.10] | [0.25] |
| Chemistry | 44 | 9 | 14 | 21 | 5,256,267 | 829,340 | 3,082,032 | 1,344,895 |
| | (1.00) | (0.20) | (0.32) | (0.48) | (1.00) | (0.16) | (0.59) | (0.26) |
| | [0.08] | [0.02] | [0.39] | [0.34] | [0.04] | [0.01] | [0.44] | [0.17] |
| Biology | 46 | 9 | 26 | 11 | 5,956,832 | 314,690 | 4,991,702 | 650,440 |
| | (1.00) | (0.20) | (0.57) | (0.24) | (1.00) | (0.05) | (0.84) | (0.11) |
| | [0.09] | [0.02] | [0.72] | [0.18] | [0.04] | [0.00] | [0.72] | [0.08] |
| Any STEM | 365 | 271 | 33 | 61 | 86,945,353 | 72,362,546 | 6,628,570 | 7,954,237 |
| | (1.00) | (0.74) | (0.09) | (0.17) | (1.00) | (0.83) | (0.08) | (0.09) |
| | [0.69] | [0.63] | [0.92] | [0.98] | [0.63] | [0.58] | [0.96] | [0.98] |

*Notes:* The row share (reported in parentheses) for non-STEM *occupations* gives the non-STEM share of those Census occupation codes where the given knowledge category is considered as "important" to the occupation. The row share for non-STEM *workers* reports the same after weighting each occupation by its 2019 employment as derived from OES data. The column share (reported in brackets) for non-STEM occupations gives the share of non-STEM occupations where the given knowledge category is considered as "important" to the occupation. Counts of occupation codes or employment levels from which the shares are based appear above the reported shares. A given knowledge category is considered important if the average evaluation of O*NET respondents on the knowledge questionnaire yields a value above 3, which is the threshold value which defines the knowledge as important on the five-point scale (with a 4 and 5 for "very important" and "extremely important", respectively). The "Any STEM" row reports the share of occupations/workers where the importance of at least one of the six STEM knowledge categories is considered important. We use the definition of STEM occupations that is used by the US Census and many other federal agencies. Table based on merged O*NET and OES 2019 data and converted from SOC-level to 2010 Census occupation code level. Resulting data contain 531 Census occupation codes with employment totaling 138,822,695 workers, representing 95% of employment given in OES 2019 data. Unlike SOC codes in OES data, Census occupation codes do not include fields of study for postsecondary teachers, resulting in all 1.5 million postsecondary teachers being classified as non-STEM. OES data exclude employment in the following (NAICS) industries: "Agriculture, forestry, fishing and hunting" (110000), "Private households" (814100), "Public Administration" (920000), and 'Unclassified" (990000). OES also excludes data from self-employed workers.

Table 7. Top Five R&D-Intensive Industries in US (2017)

| NAICS* | NAICS Title | R&D Expenditures (Millions USD) [Share of US R&D] | R&D Intensity (R&D/Sales) | R&D Employment (Thousands) | R&D Share of Industry Employment |
|---|---|---|---|---|---|
| 5417 | Scientific Research and Development Services | 17,321 [4.3%] | 25.1% | 86 | 30.4% |
| 5112 | Software Publishers | 34,264 [8.6%] | 14.9% | 134 | 23.4% |
| 3254 | Pharmaceutical and Medicine Manufacturing | 66,202 [16.5%] | 14.2% | 127 | 24.5% |
| 334 | Computer and Electronic Manufacturing | 78,575 [19.6%] | 11.3% | 258 | 21.5% |
| 5415 | Computer Systems Design and Related Services | 13,327 [3.3%] | 8.8% | 78 | 17.1% |

*Notes*: R&D intensity is defined as the cost of R&D performed by R&D-performing companies within the industry divided by their net sales. Data are from the NSF's 2017 *Business Research and Development Survey* (BRDS) as reported in National Science Board (2020) (`https://ncses.nsf.gov/pubs/nsb20203/u-s-business-r-d#key-characteristics-of-domestic-business-r-d-performance`). R&D expenditures are from Table 4-9 and R&D intensity and employment are from Table 4-10.
* All NAICS codes are given at 4-digit level except Computer and Electronic Manufacturing (NAICS 334) for which data is only available at the 3-digit level.

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E.2 Method for Decomposing Changes in Group Differences Over Time . . . . . . . . . 80

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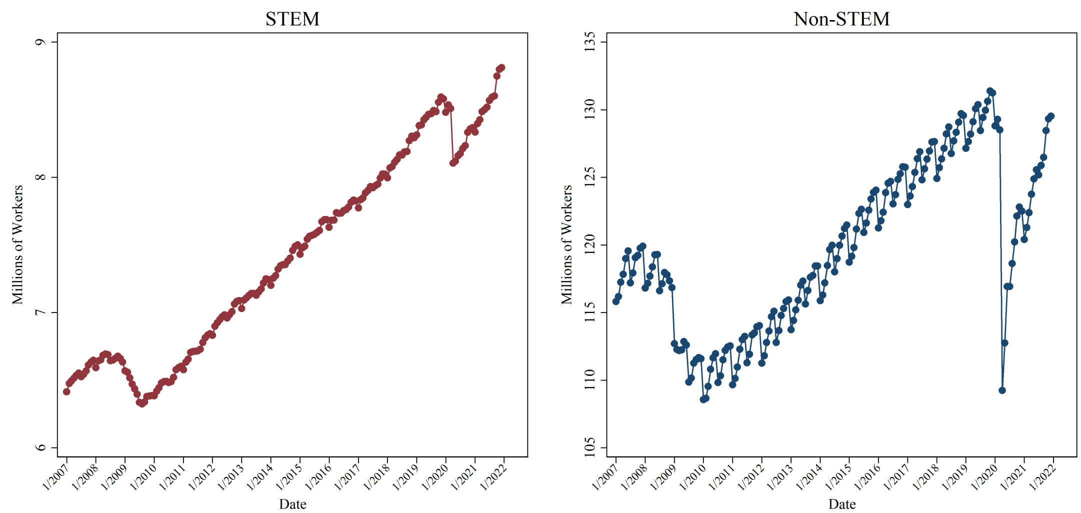
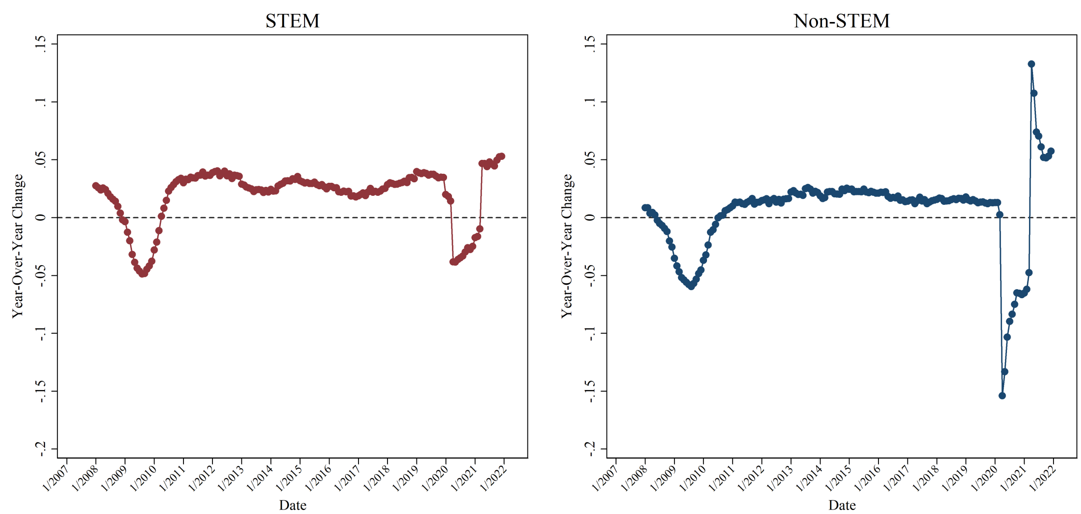
# A Supplementary Figures and Tables

Figure A.1. Monthly Employment in STEM and Non-STEM Occupations

**A. Level**

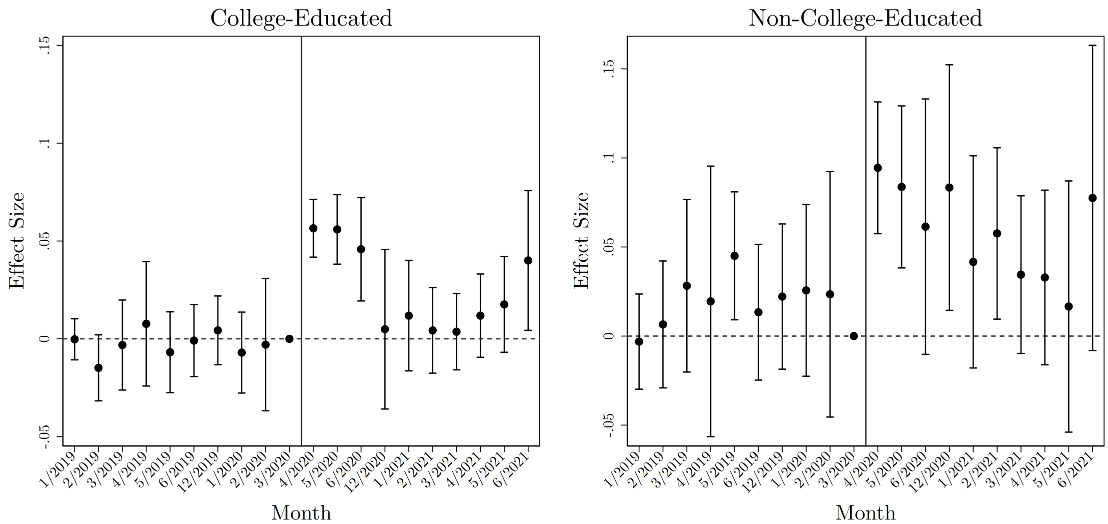



**B. Year-Over-Year Change**




*Notes*: STEM employment calculated by multiplying monthly QCEW employment for each four-digit NAICS industry by its STEM-share of employment as calculated using annual OES data and the US Census Bureau's definition of STEM occupations. The following NAICS occupations in QCEW data are excluded due to missing data in OES: "Agriculture, forestry, fishing and hunting" (110000), "Private households" (814100), "Public Administration" (920000), and 'Unclassified" (990000). OES data also excludes data from self-employed workers. STEM-related occupations are defined as non-STEM and the STEM-share of industry employment for months during 2021 is calculated using OES 2020 data.

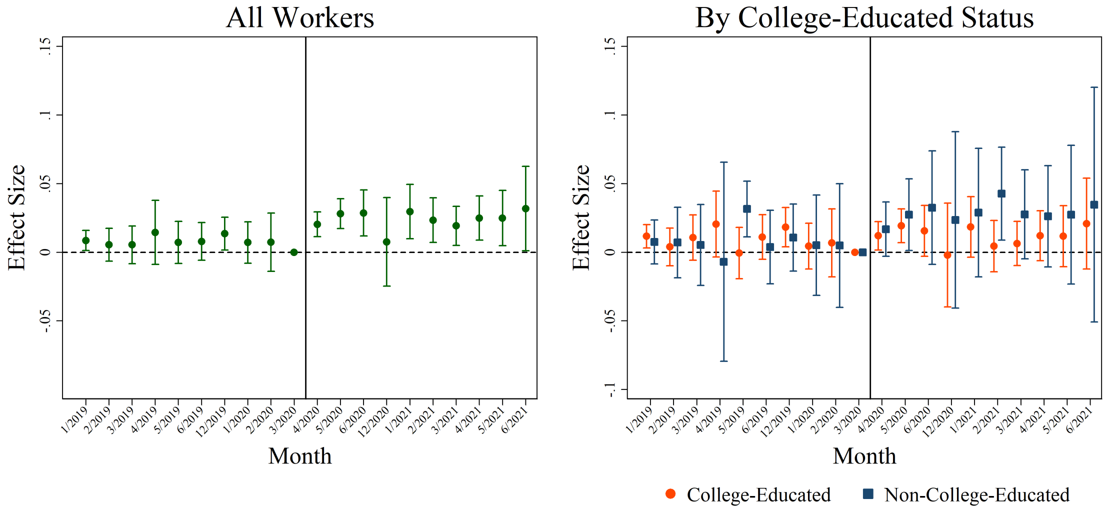
Figure A.2. STEM vs. Non-STEM Employment Rate Event Study by Education



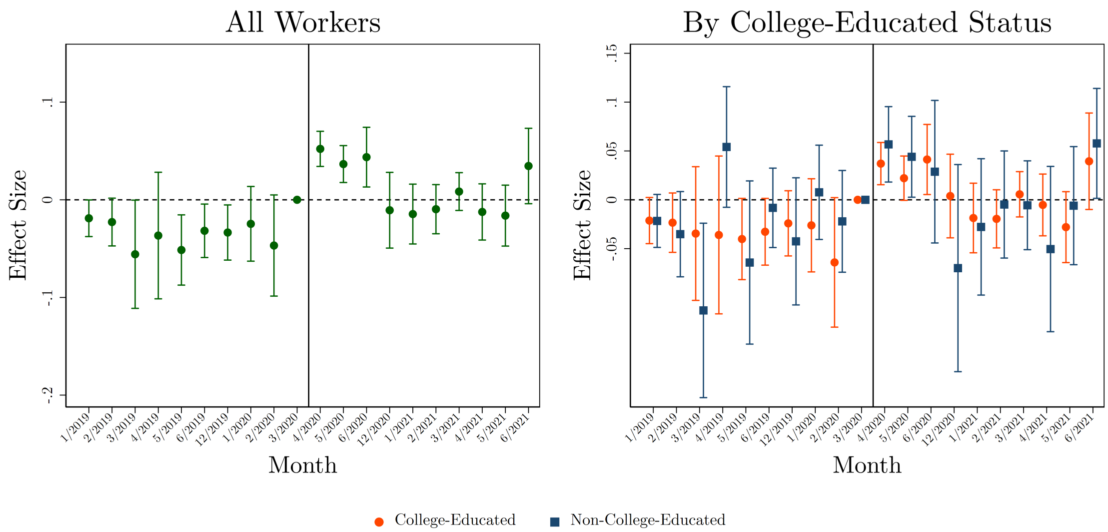

*Notes*: See notes to Figure 2. Event study shows the gap between STEM and non-STEM employment rates relative to that observed in March 2020 (last pre-pandemic month) with 95% confidence bands. Robust standard errors allow for clustering at person level.

Figure A.3. STEM vs. Non-STEM Labor Force Participation Rate and Work Hours Event Studies

**A. Labor Force Participation**

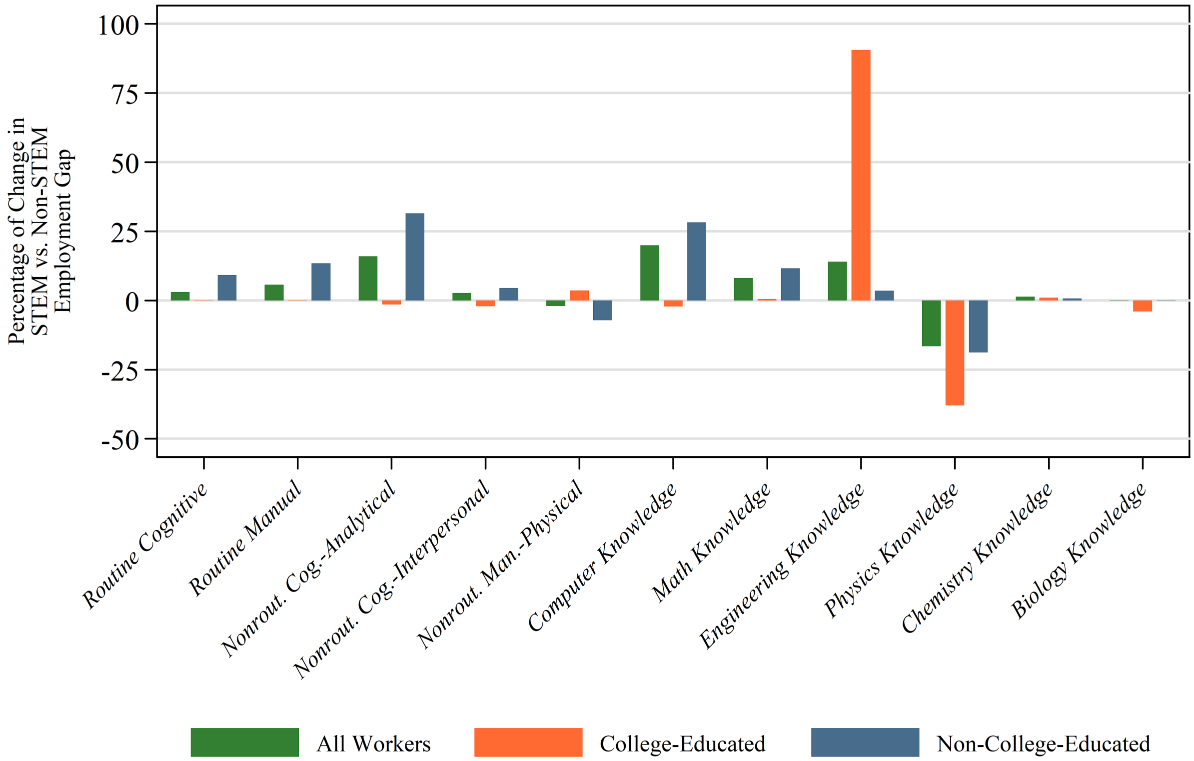



**B. Work Hours**




*Notes*: See notes to Figure 3. Event study shows the gap between STEM and non-STEM labor force participation rates and mean weekly work hours relative to that observed in March 2020 (last pre-pandemic month) with 95% confidence bands. Robust standard errors allow for clustering at person level.

Figure A.4. Employment Decomposition Results for Task Intensity and STEM Knowledge Covariates




*Notes*: See notes to Figure 5. This figure gives a more detailed account as to which task intensities and which fields of STEM knowledge are the most important drivers of STEM employment resiliency.

# Table A.1. Summary Statistics for College-Educated Workers

## A. Employment Regression Sample

| Period: | Pre-Pandemic | | Pandemic | |
|---|---|---|---|---|
| Group: | STEM | Non-STEM | STEM | Non-STEM |
| Employed | 0.97 | 0.94 | 0.94 | 0.88 |
| In Labor Force | 0.98 | 0.96 | 0.96 | 0.94 |
| Age | 42.16 | 43.87 | 42.88 | 44.50 |
| Female | 0.27 | 0.56 | 0.26 | 0.56 |
| White | 0.64 | 0.71 | 0.65 | 0.71 |
| Black | 0.07 | 0.10 | 0.06 | 0.10 |
| Asian | 0.22 | 0.09 | 0.22 | 0.09 |
| Hispanic | 0.06 | 0.09 | 0.06 | 0.09 |
| Other Race(s) | 0.02 | 0.02 | 0.02 | 0.02 |
| Foreign-Born | 0.29 | 0.17 | 0.29 | 0.17 |
| Married | 0.68 | 0.67 | 0.70 | 0.68 |
| Child (at home) | 0.48 | 0.51 | 0.51 | 0.52 |
| Female x Child | 0.12 | 0.29 | 0.12 | 0.29 |
| Disability Status | 0.02 | 0.03 | 0.02 | 0.02 |
| Highest Degree: BA | 0.61 | 0.63 | 0.59 | 0.62 |
| Highest Degree: MA/Prof | 0.32 | 0.33 | 0.33 | 0.33 |
| Highest Degree: PhD | 0.07 | 0.04 | 0.07 | 0.05 |
| Potential Experience | 19.23 | 21.04 | 19.92 | 21.64 |
| Large Employer | 0.67 | 0.56 | 0.70 | 0.55 |
| In Metro Area | 0.95 | 0.92 | 0.96 | 0.92 |
| In City Center | 0.34 | 0.31 | 0.34 | 0.31 |
| Cumulative Cases/100k | 0.00 | 0.00 | 4493.76 | 4518.65 |
| Cumulative Deaths/100k | 0.00 | 0.00 | 86.18 | 87.74 |
| New Cases/100k Last Week | 0.00 | 0.00 | 83.43 | 85.55 |
| New Deaths/100k Last Week | 0.00 | 0.00 | 2.37 | 2.54 |
| Physical Activity | 0.44 | 0.46 | 0.44 | 0.47 |
| Personal Proximity | 0.25 | 0.55 | 0.25 | 0.55 |
| Remote Work Index (RWI) | 0.53 | 0.38 | 0.53 | 0.38 |
| Essential Job Share | 0.30 | 0.41 | 0.30 | 0.41 |
| Routine Cognitive | -0.51 | -0.47 | -0.50 | -0.46 |
| Routine Manual | -0.81 | -0.81 | -0.81 | -0.80 |
| Non-Routine Cog.-Analytical | 1.25 | 0.50 | 1.24 | 0.49 |
| Non-Routine Cog.-Interpersonal | -0.06 | 0.80 | -0.06 | 0.79 |
| Non-Routine Man.-Physical | -0.86 | -0.77 | -0.87 | -0.76 |
| Educ Required: BA | 0.71 | 0.51 | 0.71 | 0.51 |
| Educ Required: MA | 0.19 | 0.07 | 0.18 | 0.07 |
| Educ Required: PhD/Prof | 0.04 | 0.08 | 0.05 | 0.08 |
| Computer Knowledge | 1.86 | 0.20 | 1.86 | 0.19 |
| Engineering Knowledge | 1.80 | -0.41 | 1.81 | -0.40 |
| Math Knowledge | 1.12 | 0.10 | 1.12 | 0.10 |
| Physics Knowledge | 0.97 | -0.37 | 0.97 | -0.37 |
| Chemistry Knowledge | 0.16 | -0.24 | 0.14 | -0.25 |
| Biology Knowledge | -0.00 | 0.20 | -0.02 | 0.19 |
| *N* | 6815 | 43531 | 6817 | 42052 |
| Person Count: | (1941) | (12159) | (1950) | (12439) |

## B. Work Hours Regression Sample

| Period: | Pre-Pandemic | | Pandemic | |
|---|---|---|---|---|
| Group: | STEM | Non-STEM | STEM | Non-STEM |
| Employed | 1.00 | 1.00 | 1.00 | 1.00 |
| Weekly Work Hours | 41.15 | 40.73 | 40.76 | 39.55 |
| Age | 42.21 | 43.63 | 42.83 | 44.28 |
| Female | 0.25 | 0.54 | 0.25 | 0.54 |
| White | 0.64 | 0.72 | 0.65 | 0.71 |
| Black | 0.07 | 0.10 | 0.06 | 0.10 |
| Asian | 0.22 | 0.08 | 0.22 | 0.09 |
| Hispanic | 0.06 | 0.09 | 0.06 | 0.09 |
| Other Race(s) | 0.02 | 0.02 | 0.02 | 0.02 |
| Foreign-Born | 0.29 | 0.16 | 0.29 | 0.16 |
| Married | 0.69 | 0.68 | 0.70 | 0.69 |
| Child (at home) | 0.49 | 0.52 | 0.52 | 0.53 |
| Female x Child | 0.11 | 0.28 | 0.12 | 0.29 |
| Disability Status | 0.02 | 0.02 | 0.02 | 0.02 |
| Highest Degree: BA | 0.60 | 0.62 | 0.59 | 0.61 |
| Highest Degree: MA/Prof | 0.33 | 0.34 | 0.33 | 0.33 |
| Highest Degree: PhD | 0.08 | 0.05 | 0.08 | 0.06 |
| Potential Experience | 19.25 | 20.76 | 19.85 | 21.38 |
| Large Employer | 0.67 | 0.57 | 0.70 | 0.57 |
| In Metro Area | 0.95 | 0.92 | 0.96 | 0.92 |
| In City Center | 0.34 | 0.31 | 0.33 | 0.31 |
| Cumulative Cases/100k | 0.00 | 0.00 | 4521.09 | 4643.74 |
| Cumulative Deaths/100k | 0.00 | 0.00 | 86.81 | 89.77 |
| New Cases/100k Last Week | 0.00 | 0.00 | 83.99 | 86.25 |
| New Deaths/100k Last Week | 0.00 | 0.00 | 2.38 | 2.47 |
| Physical Activity | 0.44 | 0.46 | 0.44 | 0.46 |
| Personal Proximity | 0.25 | 0.55 | 0.25 | 0.55 |
| Remote Work Index (RWI) | 0.54 | 0.39 | 0.54 | 0.39 |
| Essential Job Share | 0.29 | 0.42 | 0.30 | 0.42 |
| Routine Cognitive | -0.50 | -0.47 | -0.50 | -0.46 |
| Routine Manual | -0.81 | -0.84 | -0.81 | -0.82 |
| Non-Routine Cog.-Analytical | 1.25 | 0.55 | 1.25 | 0.55 |
| Non-Routine Cog.-Interpersonal | -0.05 | 0.84 | -0.06 | 0.83 |
| Non-Routine Man.-Physical | -0.87 | -0.80 | -0.88 | -0.79 |
| Educ Required: BA | 0.71 | 0.53 | 0.71 | 0.53 |
| Educ Required: MA | 0.18 | 0.07 | 0.18 | 0.07 |
| Educ Required: PhD/Prof | 0.04 | 0.08 | 0.05 | 0.08 |
| Computer Knowledge | 1.87 | 0.22 | 1.87 | 0.21 |
| Engineering Knowledge | 1.81 | -0.39 | 1.82 | -0.39 |
| Math Knowledge | 1.14 | 0.13 | 1.13 | 0.12 |
| Physics Knowledge | 0.99 | -0.37 | 0.98 | -0.37 |
| Chemistry Knowledge | 0.17 | -0.24 | 0.14 | -0.25 |
| Biology Knowledge | -0.00 | 0.21 | -0.02 | 0.21 |
| *N* | 6215 | 36695 | 6264 | 35655 |
| Person Count: | (1824) | (10792) | (1834) | (11042) |

*Notes*: Tables report survey-weighted means for college-educated workers in STEM and non-STEM occupations in the pre-pandemic period (before the April 2020 CPS survey) and pandemic period for the employment and work hour regression samples. See notes to Table 1. For employment sample, all differences in means between STEM and non-STEM worker characteristics significant at the 5% level except for "Other Race(s)" (pre-pandemic), "Married" (pre-pandemic), "Highest Degree: MA/Prof," "Routine Manual" (pre-pandemic), "Child (at home)" (pandemic), "Disability Status" (pandemic), and all included measures of statewide COVID-19 cases and deaths except "New Deaths/100k Last Week". For work hours sample, all differences in means between STEM and non-STEM worker characteristics significant at the 5% level except for "Other Race(s)" (pre-pandemic), "Married" (pre-pandemic), "Highest Degree: MA/Prof," "Routine Manual" (pandemic), "Child (at home)" (pandemic), "Disability Status," and all included measures of statewide COVID-19 cases and deaths except "New Deaths/100k Last Week".

Table A.2. Summary Statistics for Non-College-Educated Workers

## A. Employment Regression Sample

| Period: | Pre-Pandemic | | Pandemic | |
|---|---|---|---|---|
| Group: | STEM | Non-STEM | STEM | Non-STEM |
| Employed | 0.94 | 0.91 | 0.87 | 0.80 |
| In Labor Force | 0.97 | 0.95 | 0.94 | 0.89 |
| Age | 45.08 | 44.87 | 45.53 | 45.41 |
| Female | 0.20 | 0.45 | 0.18 | 0.45 |
| White | 0.74 | 0.60 | 0.75 | 0.60 |
| Black | 0.06 | 0.13 | 0.04 | 0.13 |
| Asian | 0.05 | 0.04 | 0.05 | 0.04 |
| Hispanic | 0.14 | 0.21 | 0.14 | 0.22 |
| Other Race(s) | 0.02 | 0.03 | 0.03 | 0.03 |
| Foreign-Born | 0.10 | 0.20 | 0.08 | 0.19 |
| Married | 0.65 | 0.59 | 0.65 | 0.59 |
| Child (at home) | 0.45 | 0.49 | 0.43 | 0.50 |
| Female x Child | 0.09 | 0.24 | 0.06 | 0.24 |
| Disability Status | 0.07 | 0.05 | 0.06 | 0.05 |
| Highest Degree: BA | 0.00 | 0.00 | 0.00 | 0.00 |
| Highest Degree: MA/Prof | 0.00 | 0.00 | 0.00 | 0.00 |
| Highest Degree: PhD | 0.00 | 0.00 | 0.00 | 0.00 |
| Potential Experience | 26.02 | 26.22 | 26.44 | 26.73 |
| Large Employer | 0.64 | 0.44 | 0.63 | 0.43 |
| In Metro Area | 0.89 | 0.84 | 0.89 | 0.84 |
| In City Center | 0.25 | 0.24 | 0.24 | 0.25 |
| Cumulative Cases/100k | 0.00 | 0.00 | 4709.67 | 4433.05 |
| Cumulative Deaths/100k | 0.00 | 0.00 | 81.87 | 81.71 |
| New Cases/100k Last Week | 0.00 | 0.00 | 82.50 | 79.34 |
| New Deaths/100k Last Week | 0.00 | 0.00 | 2.12 | 2.25 |
| Physical Activity | 0.50 | 0.65 | 0.51 | 0.65 |
| Personal Proximity | 0.26 | 0.56 | 0.27 | 0.56 |
| Remote Work Index (RWI) | 0.49 | 0.27 | 0.48 | 0.27 |
| Essential Job Share | 0.29 | 0.45 | 0.29 | 0.45 |
| Routine Cognitive | -0.37 | -0.05 | -0.33 | -0.06 |
| Routine Manual | -0.58 | 0.00 | -0.58 | -0.00 |
| Non-Routine Cog.-Analytical | 1.07 | -0.39 | 1.02 | -0.38 |
| Non-Routine Cog.-Interpersonal | -0.31 | -0.00 | -0.38 | 0.01 |
| Non-Routine Man.-Physical | -0.68 | 0.10 | -0.67 | 0.09 |
| Educ Required: BA | 0.50 | 0.14 | 0.47 | 0.14 |
| Educ Required: MA | 0.22 | 0.01 | 0.20 | 0.01 |
| Educ Required: PhD/Prof | 0.00 | 0.00 | 0.00 | 0.00 |
| Computer Knowledge | 1.97 | -0.32 | 1.98 | -0.32 |
| Engineering Knowledge | 1.85 | -0.32 | 1.86 | -0.31 |
| Math Knowledge | 0.84 | -0.19 | 0.78 | -0.20 |
| Physics Knowledge | 0.81 | -0.28 | 0.82 | -0.27 |
| Chemistry Knowledge | -0.02 | -0.15 | -0.03 | -0.15 |
| Biology Knowledge | -0.16 | -0.19 | -0.18 | -0.19 |
| *N* | 2204 | 65264 | 1980 | 59642 |
| Person Count: | (616) | (18300) | (590) | (17957) |

## B. Work Hours Regression Sample

| Period: | Pre-Pandemic | | Pandemic | |
|---|---|---|---|---|
| Group: | STEM | Non-STEM | STEM | Non-STEM |
| Employed | 1.00 | 1.00 | 1.00 | 1.00 |
| Weekly Work Hours | 41.44 | 39.69 | 40.80 | 38.14 |
| Age | 44.68 | 44.79 | 45.18 | 45.36 |
| Female | 0.20 | 0.43 | 0.17 | 0.44 |
| White | 0.74 | 0.62 | 0.77 | 0.62 |
| Black | 0.06 | 0.12 | 0.03 | 0.12 |
| Asian | 0.05 | 0.03 | 0.04 | 0.03 |
| Hispanic | 0.15 | 0.21 | 0.14 | 0.21 |
| Other Race(s) | 0.02 | 0.03 | 0.02 | 0.03 |
| Foreign-Born | 0.10 | 0.18 | 0.07 | 0.18 |
| Married | 0.65 | 0.61 | 0.64 | 0.60 |
| Child (at home) | 0.46 | 0.50 | 0.42 | 0.50 |
| Female x Child | 0.08 | 0.22 | 0.05 | 0.23 |
| Disability Status | 0.07 | 0.04 | 0.06 | 0.04 |
| Highest Degree: BA | 0.00 | 0.00 | 0.00 | 0.00 |
| Highest Degree: MA/Prof | 0.00 | 0.00 | 0.00 | 0.00 |
| Highest Degree: PhD | 0.00 | 0.00 | 0.00 | 0.00 |
| Potential Experience | 25.61 | 26.12 | 26.10 | 26.66 |
| Large Employer | 0.65 | 0.45 | 0.63 | 0.44 |
| In Metro Area | 0.90 | 0.83 | 0.89 | 0.83 |
| In City Center | 0.25 | 0.23 | 0.25 | 0.24 |
| Cumulative Cases/100k | 0.00 | 0.00 | 4786.24 | 4673.42 |
| Cumulative Deaths/100k | 0.00 | 0.00 | 83.50 | 84.75 |
| New Cases/100k Last Week | 0.00 | 0.00 | 83.17 | 79.49 |
| New Deaths/100k Last Week | 0.00 | 0.00 | 2.04 | 2.06 |
| Physical Activity | 0.50 | 0.64 | 0.51 | 0.64 |
| Personal Proximity | 0.26 | 0.55 | 0.26 | 0.55 |
| Remote Work Index (RWI) | 0.49 | 0.28 | 0.49 | 0.28 |
| Essential Job Share | 0.29 | 0.47 | 0.29 | 0.46 |
| Routine Cognitive | -0.39 | -0.04 | -0.36 | -0.06 |
| Routine Manual | -0.59 | -0.02 | -0.60 | -0.03 |
| Non-Routine Cog.-Analytical | 1.08 | -0.34 | 1.05 | -0.33 |
| Non-Routine Cog.-Interpersonal | -0.30 | 0.03 | -0.37 | 0.04 |
| Non-Routine Man.-Physical | -0.70 | 0.09 | -0.70 | 0.07 |
| Educ Required: BA | 0.52 | 0.15 | 0.50 | 0.16 |
| Educ Required: MA | 0.22 | 0.01 | 0.20 | 0.01 |
| Educ Required: PhD/Prof | 0.00 | 0.00 | 0.00 | 0.00 |
| Computer Knowledge | 2.02 | -0.27 | 2.04 | -0.27 |
| Engineering Knowledge | 1.86 | -0.29 | 1.87 | -0.28 |
| Math Knowledge | 0.83 | -0.14 | 0.78 | -0.15 |
| Physics Knowledge | 0.78 | -0.25 | 0.80 | -0.25 |
| Chemistry Knowledge | -0.07 | -0.15 | -0.08 | -0.15 |
| Biology Knowledge | -0.19 | -0.18 | -0.21 | -0.18 |
| *N* | 1886 | 49635 | 1686 | 45200 |
| Person Count: | (547) | (14923) | (522) | (14628) |

*Notes*: Tables report survey-weighted means for non-college-educated workers in STEM and non-STEM occupations in the pre-pandemic period (before the April 2020 CPS survey) and pandemic period for the employment and work hour regression samples. See notes to Table 1. For employment sample, all differences in means between STEM and non-STEM worker characteristics significant at the 5% level except for "Age," "Potential Experience," "In City Center", "Biology Knowledge," "Other Race(s)" (pandemic), "Disability Status" (pandemic), and all included measures of statewide COVID-19 cases and deaths except "Cumulative Cases/100k Last Week." For work hours sample, all differences in means between STEM and non-STEM worker characteristics significant at the 5% level except for "Age," "In City Center", "Biology Knowledge," and all included measures of statewide COVID-19 cases and deaths.

Table A.3. Impact of COVID-19 on Non-STEM Employment: Models by Domain of STEM Knowledge

| Sample: | College-Educated Non-STEM | | Non-College-Educated Non-STEM | |
|---|---|---|---|---|
| Dep. Var.: Employed | (1) | (2) | (1) | (2) |
| *Panel A. Key Variable: Importance of Computer Knowledge to Occupation* | | | | |
| Comp_know x Pandemic (Apr-Jun 2020) | 0.0359*** | 0.0160* | 0.0277*** | 0.00781 |
| | (0.00702) | (0.00694) | (0.00461) | (0.00518) |
| Comp_know x Pandemic (Dec-Jun 2021) | 0.0139$^{+}$ | 0.00808 | 0.00890$^{+}$ | 0.00185 |
| | (0.00772) | (0.00764) | (0.00524) | (0.00597) |
| *Panel B. Key Variable: Importance of Math Knowledge to Occupation* | | | | |
| Math_know x Pandemic (Apr-Jun 2020) | 0.0264*** | 0.0137* | 0.0186*** | 0.00876$^{+}$ |
| | (0.00494) | (0.00538) | (0.00436) | (0.00453) |
| Math_know x Pandemic (Dec-Jun 2021) | 0.00724 | 0.00428 | 0.00406 | -0.00131 |
| | (0.00540) | (0.00581) | (0.00489) | (0.00505) |
| *Panel C. Key Variable: Importance of Engineering Knowledge to Occupation* | | | | |
| Eng_know x Pandemic (Apr-Jun 2020) | 0.0138** | 0.00902$^{+}$ | 0.0216*** | 0.0108* |
| | (0.00522) | (0.00548) | (0.00447) | (0.00509) |
| Eng_know x Pandemic (Dec-Jun 2021) | 0.00195 | 0.00161 | 0.00462 | -0.00127 |
| | (0.00598) | (0.00614) | (0.00483) | (0.00551) |
| *Panel D. Key Variable: Importance of Physics Knowledge to Occupation* | | | | |
| Phys_know x Pandemic (Apr-Jun 2020) | 0.00251 | 0.00744 | 0.0183*** | 0.0120* |
| | (0.00538) | (0.00616) | (0.00483) | (0.00551) |
| Phys_know x Pandemic (Dec-Jun 2021) | 0.00726 | 0.00692 | 0.00683 | 0.00221 |
| | (0.00551) | (0.00644) | (0.00508) | (0.00573) |
| *Panel E. Key Variable: Importance of Chemistry Knowledge to Occupation* | | | | |
| Chem_know x Pandemic (Apr-Jun 2020) | 0.00464 | 0.00988$^{+}$ | -0.00870$^{+}$ | -0.00426 |
| | (0.00391) | (0.00542) | (0.00490) | (0.00531) |
| Chem_know x Pandemic (Dec-Jun 2021) | 0.00868* | 0.00979 | -0.00385 | -0.00578 |
| | (0.00416) | (0.00614) | (0.00516) | (0.00568) |
| *Panel F. Key Variable: Importance of Biology Knowledge to Occupation* | | | | |
| Bio_know x Pandemic (Apr-Jun 2020) | 0.0146*** | 0.0152** | 0.0201*** | 0.00550 |
| | (0.00306) | (0.00480) | (0.00496) | (0.00561) |
| Bio_know x Pandemic (Dec-Jun 2021) | 0.0142*** | 0.0182*** | 0.00985$^{+}$ | 0.00603 |
| | (0.00299) | (0.00524) | (0.00517) | (0.00599) |
| *N* | 85583 | 85583 | 124906 | 124906 |
| *Demographics-by-Pandemic* | No | Yes | No | Yes |
| *Educational Attainment-by-Pandemic* | No | Yes | No | Yes |
| *Location-by-Pandemic* | No | Yes | No | Yes |
| *RWI- & Essential Job-by-Pandemic* | No | Yes | No | Yes |
| *Education Requirement-by-Pandemic* | No | Yes | No | Yes |

*Notes:* All knowledge variables are standardized (zero mean and unit variance) across occupations. See Table 2 notes for additional details. Control sets not listed are excluded from all regressions. Robust standard errors clustered at individual-level are in parentheses. Regressions are weighted using CPS basic monthly weights. $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

# B Data Appendix

## B.1 Variable Definitions

Cumulative COVID-19 cases and deaths represent all cases and deaths in a respondent's state as of the day prior to the CPS survey reference week. New COVID-19 cases and deaths represent cases and deaths in a respondent's state during the week prior to the CPS survey reference week. Data on COVID-19 cases and deaths by state are compiled by the New York Times from state and local governments and health departments and can be accessed here: https://github.com/nytimes/covid-19-data/blob/master/us-states.csv. State population data are from the US Census Bureau and can be accessed here: https://www.census.gov/data/tables/time-series/demo/popest/2010s-state-total.html#par_textimage.

Remote work feasibility is measured by a continuous occupation-level Remote Work Index (RWI) that takes on values between zero and one, where higher values of RWI correspond to occupations where remote work is more feasible. RWI is constructed using O*NET data and is based on the degrees to which jobs require performing physical activities at one's workplace ("Physical Activity") and job tasks in close proximity to other people ("Personal Proximity"). See Appendix D for details on the construction of RWI using O*NET data as well as validation that it is closely correlated with the probability that respondents actually report teleworking due to the COVID-19 pandemic.

The share of essential workers in each occupation is calculated using the list of essential industries (4-digit NAICS) provided in the appendix to Tomer and Kane (2020), which are derived from the Department of Homeland Security (DHS) designation of essential infrastructure workers, created early in the pandemic. We merge this with 2019 OES data to obtain the employment level of each industry-occupation pair, and then calculate the share of essential workers in each SOC occupation by taking an employment-weighted average of the essential industry indicator variable across all industries employing workers in the given occupation. We then convert SOC codes to OCC codes by taking an employment-weighted average of the shares across all SOC codes contained within each OCC code.

Minimum education requirements of occupations are from BLS data available at https://www.bls.gov/oes/2019/may/education_2019.xlsx. The degree to which each occupation requires the performance of routine and non-routine tasks is based on O*NET-based standardized measures (i.e., mean zero and unit variance at the occupation level) developed in Acemoglu and Autor (2011). Similarly, the STEM knowledge variables are standardized measures based on the O*NET Knowledge questionnaire which asks respondents how important each knowledge category is to the performance of one's job. "Child" is an indicator variable equal to one if the respondent has a child of any age living at home. Disability status is an indicator variable for if the respondent reported any of the following types of disabilities: hearing, vision, difficulty remembering, physical difficulty, disability limiting mobility, or personal care difficulty. "Large Employer" represents whether a person's pre-pandemic employer employed at least 500 workers.

## B.2 Full CPS Monthly Data vs. CPS Analytical Sample vs. QCEW-OES Data

We utilize monthly person-level data from the Bureau of Labor Statistics' *Current Population Survey* (CPS) to analyze the impact of the COVID-19 pandemic on the labor market outcomes of STEM and non-STEM workers. An important issue to note is that the quality of the CPS as a nationally-representative survey may have declined during the COVID-19 pandemic. First, the COVID-19 pandemic led to a significant drop in response rates during the early months of the pandemic, especially for incoming rotation groups which normally receive in-person interviews.[51] Between March and June of 2020, Ward and Edwards (2020) find that the average month-over-month CPS nonresponse rate increased by 62% and that the size of newly-entering cohorts shrunk by 37% relative to the prior 18 months, which led to a 17% reduction in the overall sample size of the CPS.[52] Furthermore, Ward and Edwards (2020) find that attrition was associated with a shift in the demographics of the CPS sample and that these changes may effect estimates of subgroup unemployment rates.[53]

Therefore, we limit our analytical sample to the set of individuals who participated in the March 2020 CPS Annual Social and Economic Supplement (ASEC), who were employed at some point during 2019, who were between the ages of 25 and 65, and who were also observed at least once both before and in or after the April 2020 monthly CPS survey (i.e., both before and during the pandemic).[54] We limit to individuals observed both before and after the pandemic to guard against results being driven by differences in respondents sampled before and after the pandemic and also to limit the degree to which nonresponse bias—which was particularly concentrated among those first entering the CPS survey during the pandemic period—can influence our results.[55]

[51] See `https://cps.ipums.org/cps/covid19.shtml` for more details on how the pandemic impacted CPS data collection. The CPS follows a 4-8-4 rotating sampling scheme, meaning that new (potential) respondents enter the survey in each month, and that each respondent is surveyed for four consecutive months, out of the survey for eight months, and then surveyed again for four months (`https://www.census.gov/programs-surveys/cps/technical-documentation/methodology.html`)

[52] Ward and Edwards (2020) note that cohorts that were in the middle of a four-month spell at the onset of the COVID-19 pandemic suffered smaller declines in their response rate relative to those first entering or re-entering the survey during the COVID-19 pandemic.

[53] See also Heffetz and Reeves (2020) who investigate other sources of bias in CPS unemployment estimates and Rothbaum and Bee (2020) who find changing response patterns by demographics in the 2020 CPS ASEC.

[54] We limit to individuals in the March ASEC that were employed at some point during 2019 so that we can associate each respondent with an occupation—that being the one they report having occupied in their longest job during 2019 (using IPUMS CPS variable `occ10ly`). This may raise concerns as we are implicitly selecting our sample on the basis of the value taken by an outcome of interest (employment) in the pre-pandemic period. This could potentially bias our results towards finding employment losses during 2020 (and thus during the pandemic period). However, this possible bias appears negligible in our case as in Figure 2 we do not observe significant drops in employment in the months during 2020 just prior to the pandemic relative to their levels the year prior. Additionally, we limit our sample to those between the ages 25-65, which limits the scope of such a bias due to retirement; our results may even be conservative estimates of employment losses due to the pandemic if the pandemic induced an increased rate of retirement among those 65 and over.

[55] The only group included in our analytical sample that was first surveyed during the COVID-19 pandemic are those first entering the sample in March 2020; those entering in later months are excluded as they do not appear in

Figure 2 shows an immediate drop in the employment rate of both STEM and non-STEM workers in the analytical sample after the onset of the pandemic, with non-STEM workers appearing to have fared worse than STEM workers regardless of college-educated status. The employment rate of both STEM and non-STEM workers bottomed out in April 2020 and then began to recover, with the rate of recovery appearing to slow over time. How do these employment patterns compare to those in full CPS monthly data? In Panels A and B of Figure B.1, we plot 1) the level of STEM and non-STEM employment as derived from the full monthly CPS data using basic monthly survey weights and 2) the number of CPS respondents underlying the employment calculations.[56] Panel B shows a similar employment pattern to that found in our analytical sample: non-STEM employment falls precipitously to its trough in April 2020 and then recovers, with this recovery slowing over time. In contrast, Panel A shows an employment pattern for STEM workers that is drastically different than what is seen in our analytical sample. Instead of STEM employment hitting a trough in April 2020 and then recovering during the pandemic period, full CPS monthly data shows STEM employment achieving its highest level since 2018 in June 2020, hitting a trough in September 2020, and then recovering in December 2020 before heading back down in January 2021 and fluctuating thereafter. In Figure B.2 we see that full monthly CPS data implies that STEM employment saw positive year-over-year changes in employment in eight out of the first twelve months of the pandemic, whereas results using the CPS analytical sample show consistent year-over-year decreases in STEM employment for these same months. As expected after a year of recovery, the CPS analytical sample shows positive year-over-year changes for employment for STEM and non-STEM workers starting in April 2021. While full CPS shows a similar pattern for non-STEM workers, the pattern for STEM workers actually shows negative and decreasing year-over-year changes in STEM employment starting in April 2021. Rather than reflecting the true dynamics of the STEM labor market, the results using full CPS monthly data, especially during the beginning months of the pandemic, are likely to suffer from nonresponse bias. Figure B.1 shows that the number of respondents dropped significantly in March 2020, with further decreases occurring through June 2020 for non-STEM and unemployed/NILF respondents and through July 2020 for STEM respondents. The number of respondents subsequently recovered through October 2020 for STEM and non-STEM workers before again trending downward.

Are the employment patterns in the analytical sample likely to reflect broader US STEM labor market trends? To test whether the employment trends of STEM and non-STEM workers in our analytical sample are generalizable to the broader US STEM labor force, we use monthly data on industry employment (four-digit NAICS) from the Bureau of Labor Statistics' *Quarterly Census of Employment and Wages* (QCEW) combined with the STEM-share of employment in each industry calculated using annual OES data (which gives industry employment counts by occupation) to calculate monthly STEM and non-STEM employment, and then compare year-

any pre-pandemic months.

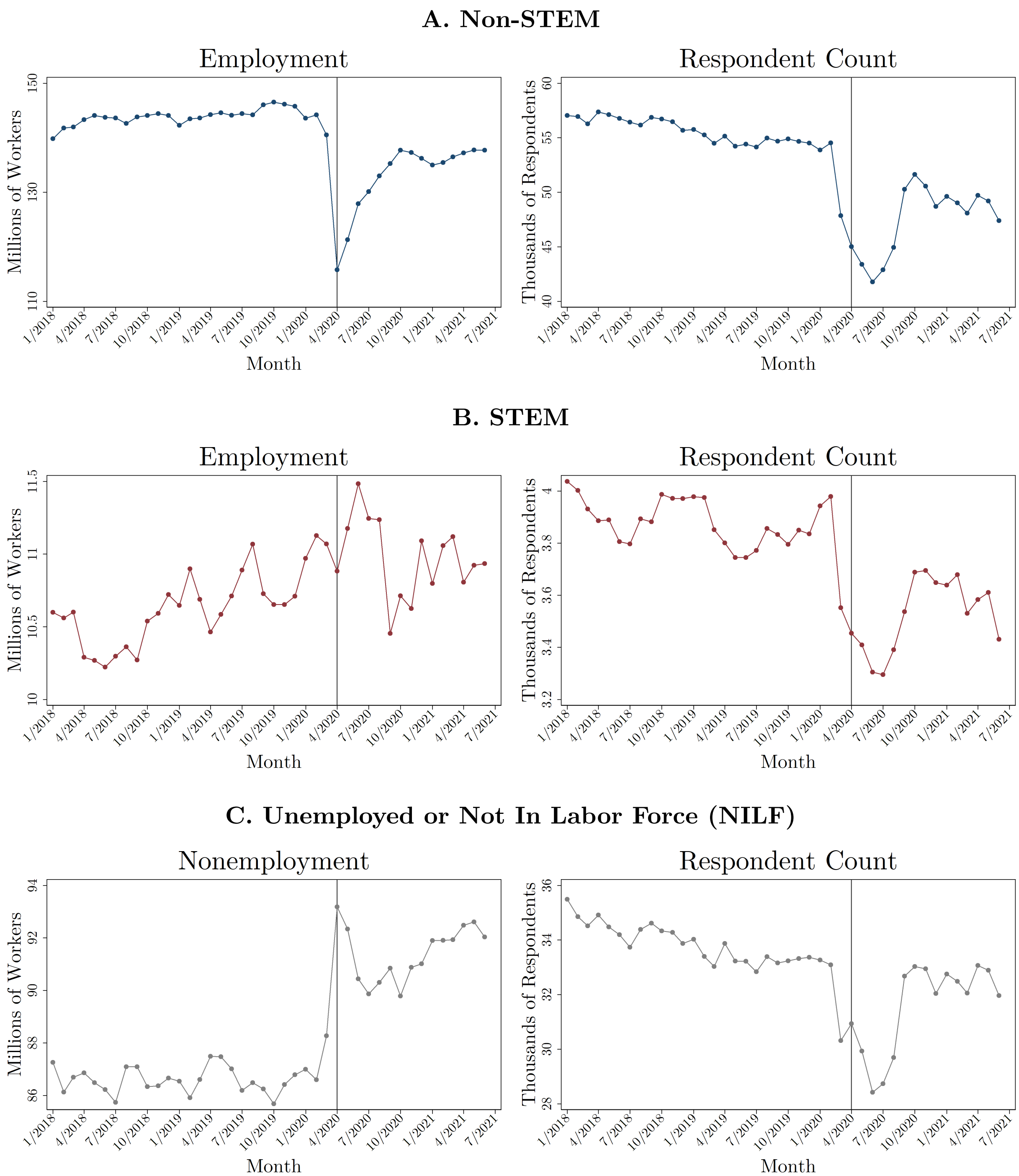
[56]In Panel C, we show the number of unemployed or NILF workers and associated respondents.

over-year changes in STEM and non-STEM employment calculated using QCEW-OES data and the CPS analytical sample in Figure B.3.[57] Figure B.3 shows that the dynamics during the first quarter of the pandemic period as implied by QCEW-OES data and analytical sample results are quite similar, with both STEM and non-STEM workers suffering year-over-year employment losses of similar magnitude, and with non-STEM employment suffering greater rates of year-over-year declines compared to STEM employment.[58] Both data sources show similar speeds of recovery in year-over-year STEM and non-STEM employment in subsequent months. The similarity between the labor market dynamics of the CPS analytical sample and those found using QCEW-OES data gives us some confidence that our CPS analytical sample reflects broad US STEM and non-STEM labor market trends.

[57]The following NAICS occupations in QCEW data are excluded due to lack of coverage in OES data: "Agriculture, forestry, fishing and hunting" (110000), "Private households" (814100), "Public Administration" (920000), and 'Unclassified" (990000). OES data also excludes data from self-employed workers. STEM-related occupations are defined as non-STEM and the STEM-share of industry employment for months during 2021 is calculated using OES 2020 data which is the latest data available. QCEW data is based on administrative data collected from mandatory state unemployment insurance (UI) reports—known as Quarterly Contributions Reports (QCRs)—sent from employers to their state. A significant advantage of the QCEW over survey-based estimates of employment during the COVID-19 pandemic is that response rates have remained high: in March (June) 2020, QCEW obtained reports from 90.8% (91.8%) of establishments which represented 96.8% (97.5%) of US employment (see https://www.bls.gov/cew/response-rates/cew-response-rates-establishments.htm and https://www.bls.gov/cew/response-rates/cew-response-rates-employment.htm). For comparison purposes, in March (June) 2019, QCEW obtained reports from 92.0% (92.5%) of establishments which represented 97.6% (97.9%) of US employment in those months. See https://www.bls.gov/opub/hom/cew/data.htm for additional details on QCEW data. A shortcoming of using QCEW-OES is that we can only capture annual variations in the STEM share of workers in each industry so that we will be unable to detect if the COVID-19 pandemic impacted the STEM share of workers in each industry month-to-month.

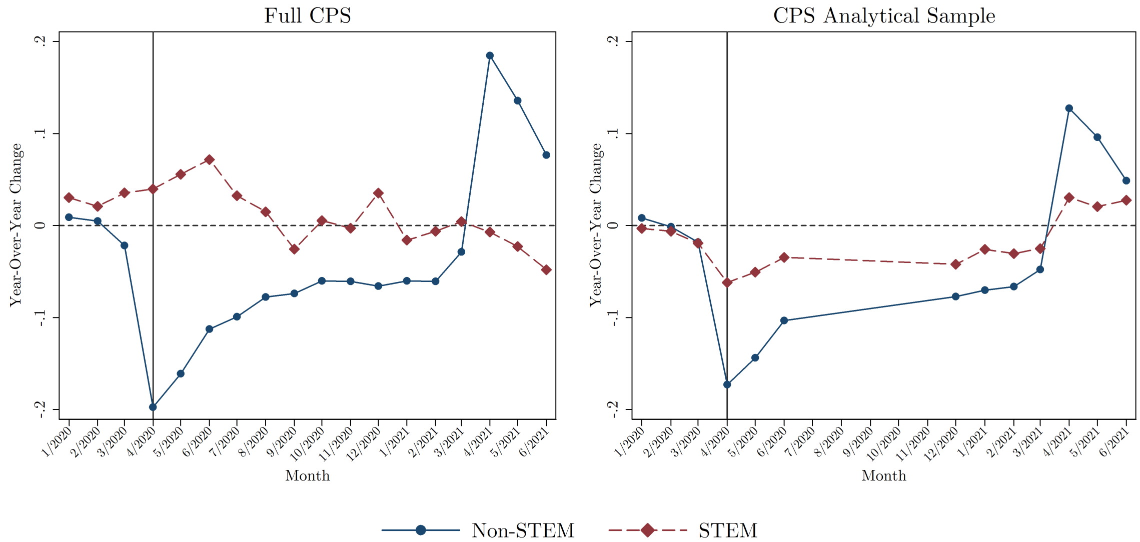
[58]Slight differences might be explained due to differences in the occupation codes used in OES and CPS data. OES data uses SOC codes, which are more detailed than the Census occupation codes ("OCC") included in CPS data. In CPS data, we are unable to identify STEM "postsecondary" teachers from non-STEM postsecondary teachers, and so follow the US Census Bureau's classification by labeling postsecondary teachers as non-STEM in CPS data. However, in QCEW-OES data we are able to identify postsecondary teachers in different fields and classify each as STEM or non-STEM.

Figure B.1. CPS Monthly Employment and Respondent Counts by STEM Status of Occupation



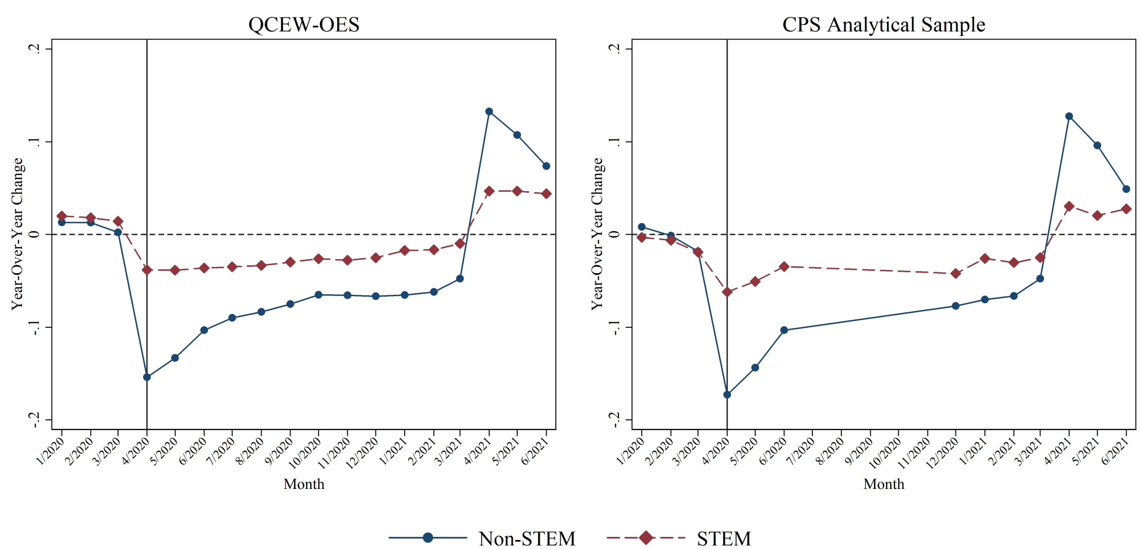

*Notes*: CPS basic monthly weights used to calculate employment and unemployment. Respondent counts are unweighted.

Figure B.2. Year-Over-Year Changes in Employment by STEM Status of Occupation: Full CPS vs. CPS Analytical Sample




*Notes*: CPS basic monthly weights used to calculate employment and unemployment.

Figure B.3. Year-Over-Year Changes in Employment by STEM Status of Occupation: QCEW-OES data vs. CPS Analytical Sample




*Notes*: QCEW-OES STEM employment calculated by multiplying monthly QCEW employment for each four-digit NAICS industry by its STEM-share of employment as calculated using annual OES data and the US Census Bureau's definition of STEM occupations. The following NAICS occupations in QCEW data are excluded due to missing data in OES: "Agriculture, forestry, fishing and hunting" (110000), "Private households" (814100), "Public Administration" (920000), and 'Unclassified" (990000). OES data also excludes data from self-employed workers. STEM-related occupations are defined as non-STEM.

## C Sources of STEM Employment Resiliency

Having observed a relative resiliency of STEM over non-STEM employment during both the Great Recession and COVID-19 recession in Figure 1, we now discuss possible reasons for STEM employment resiliency during recessions. We draw on previous studies of employment disparities during recessions to motivate the factors considered and show how STEM and non-STEM workers differ across these various dimensions. In Section 2 we exploit the COVID-19 labor market shock to empirically assess the relative importance of each factor in explaining STEM employment resiliency generally.

**Demographics** Young people, men, racial/ethnic minorities, and those with less education typically suffer greater rates of employment loss during recessionary periods including the Great Recession (Elsby, Hobijn, and Şahin, 2010; Hoynes, Miller, and Schaller, 2012). During the COVID-19 recession, women with young children, minorities, and immigrants have suffered worse employment effects (Papanikolaou and Schmidt, 2020; Borjas and Cassidy, 2020; Montenovo et al., 2020; Alon et al., 2021). Figure C.2 shows that STEM workers are about half as likely as non-STEM workers to be female, Black, or Hispanic, and are over three times as likely to be Asian. Given these sizable differences between STEM and non-STEM workers, it is possible that demographic disparities play some role in explaining STEM employment resiliency during recessions.

**Educational Attainment** The relative resiliency of STEM over non-STEM employment during the Great Recession and COVID-19 recession is due in part to the greater educational attainment of the average STEM worker. Figure C.1 shows that 70% of workers employed in STEM occupations have at least a college degree compared to 30% of non-STEM workers. In past recessions (including the Great Recession), employment fell much less among college-educated workers than among workers with less than a college degree (Elsby, Hobijn, and Şahin, 2010; Hoynes, Miller, and Schaller, 2012), and a similar pattern has been seen in the COVID-19 recession (Montenovo et al., 2020).

**Employer Industry and Size** Figure C.4 shows that STEM workers are more likely than non-STEM workers to work in industry sectors (two-digit NAICS) such as Professional, Scientific, and Technical Services (54) and Information (51), and less likely to work in sectors such as Retail Trade (44-45) and Accommodation and Food Services (72) which were most affected by business shutdowns and stay-at-home orders during the pandemic.[59] Table C.1 shows the top 15 industries (four-digit NAICS) by STEM share of employment (Panel A) and STEM employment level (Panel B).[60] Figure C.5 shows that workers in STEM occupations are more likely than workers in non-

[59] About 35% of STEM workers are employed in Professional, Scientific, and Technical Services, 16% are employed in Information, and 15% are employed in Manufacturing. Non-STEM workers are more dispersed across sectors, with 15% in Health Care and Social Assistance, 11% in Retail Trade, and 10% in Accommodation and Food Services. 2019 OES data includes nonfarm establishments only, and so agricultural employment is likely understated.

[60] Recent studies (e.g., Decker et al., 2020; Bai et al., 2021) follow Hecker (2005) in defining high-tech industries based on the industry's STEM-share of employment.

STEM occupations to be employed in large firms, which may be better able to survive economic downturns compared to smaller firms.[61]

**Geographic Location** The magnitude of the employment effects facing workers during recessions might depend on location, possibly due to state-specific economic policies, and whether workers live in metropolitan areas or city centers. At the onset of the COVID-19 pandemic, workers in different regions of the United States were subject to different levels of exposure to COVID-19, as well as state-level and city-level pandemic mitigation policies which likely impacted employment. Those living in densely-populated areas likely faced greater potential exposure to COVID-19, and so may have been subject to worse employment outcomes compared to those in densely-populated areas during previous recessions. If STEM and non-STEM workers are differentially concentrated in different states and cities throughout the US, this could lead to differences in employment outcomes during recessions.

**Remote Work Feasibility** Another possible reason for STEM workforce resiliency during the COVID-19 pandemic is the greater remote work feasibility of STEM occupations. To measure remote work feasibility, we use O*NET data to construct a continuous occupation-level Remote Work Index (RWI) that takes on values between zero and one, where higher values of RWI correspond to occupations where remote work is more feasible.[62] Since workers in essential jobs (e.g., nursing, grocery store clerks, etc.) were likely to continue employment regardless of remote work feasibility, we also construct a measure of the share of essential workers in each occupation using OES data. Figure C.3 shows that workers in STEM occupations are more likely to have greater remote work feasibility, while workers in non-STEM occupations are more likely to be in essential jobs (i.e., work in essential industries).[63]

**Non-routine and Cognitive Task Intensity of Work** Hershbein and Kahn (2018) find that the Great Recession restructured production towards routine-biased technologies, which led to persistent labor market "upskilling" years after the Great Recession. Jaimovich and Siu (2020) find that the jobless recoveries associated with the last three recessions were due to job losses in occupations characterized by routine work.[64] The COVID-19 pandemic may further accelerate

[61] Haltiwanger, Jarmin, and Miranda (2013) defines large firms as those with 500 workers and above. Other employer characteristics (e.g., firm age, R&D intensity) could matter as well, but we focus on employer industry and size due to the availability of detailed industry identifiers and employer size measures in CPS data (which likely correlate with other employer characteristics).

[62] RWI is based on the degrees to which jobs require performing physical activities at one's workplace ("Physical Activity") and job tasks in close proximity to other people ("Personal Proximity"). See Appendix D for details on the construction of RWI using O*NET data as well as validation that RWI is highly correlated with whether CPS analytical sample members reported teleworking from home due to the COVID-19 pandemic.

[63] According to occupation-level data weighted by 2019 OES employment, the mean RWI of STEM and non-STEM workers is 0.51 and 0.29, respectively, while the mean essential share is 0.34 and 0.43. See Appendix B.1 for details on construction of the essential share of workers in each occupation.

[64] As Jaimovich and Siu (2020) explain, jobless recoveries refer to a phenomenon of recent recessions where "aggregate employment declines for years following the turning point in aggregate income and output".

routine-biased technological change (RBTC) as firms reconfigure their workplaces during the pandemic. For each occupation we construct O*NET-based measures for the task intensity of work for five types of tasks, defined by Acemoglu and Autor (2011) as routine cognitive (RC), routine manual (RM), non-routine cognitive-analytical (NRC-A), non-routine cognitive-interpersonal (NRC-I), and non-routine manual-physical (NRM-P).[65] Figure C.6 shows the distribution of these occupation-level measures, comparing STEM and non-STEM occupations. STEM occupations are more likely to involve non-routine cognitive-analytic skills, while non-STEM occupations are more likely to involve routine tasks and non-routine manual-physical tasks. Thus, STEM employment resiliency might be due to the lesser degree of routine task intensity and greater degree of nonroutine cognitive-analytic task intensity in STEM occupations compared to non-STEM occupations.

**Education Requirements for the Job** STEM employment resiliency might also be explained by the greater share of STEM workers in occupations requiring higher levels of education. Figure C.7 shows that 70% of workers in STEM occupations work in an occupation requiring at least a Bachelor's degree, while only 30% of non-STEM workers are employed in such jobs.[66] Abel and Deitz (2018) similarly finds that recent college graduates with STEM degrees had among the lowest rates of underemployment (i.e., the share working in jobs not normally requiring a college degree) after the Great Recession. Just as workers with greater educational attainment and whose work entails nonroutine cognitive-analytical tasks, workers in jobs with greater education requirements may be harder to replace (with other workers or with technology) and so are more likely to remain employed during economic downturns.

**STEM Knowledge on the Job** Beyond education requirements in general, STEM knowledge in particular might be a source of employment resiliency during recessions. Previous studies find that employment of young college educated workers who graduate with degrees earning higher wage premiums, such as STEM degrees, is less affected by the business cycle at graduation (Altonji, Kahn, and Speer, 2016), and that recessions induce enrolled college students to increasingly select STEM majors (Shu, 2016; Liu, Sun, and Winters, 2019; Blom, Cadena, and Keys, 2021). It is plausible that all workers who utilize STEM knowledge as part of their job, and not just recent college graduates with STEM degrees, enjoy greater employment resiliency during recessions. Jobs in which STEM knowledge is important may be relatively protected in downturns if the demand for STEM knowledge is less cyclical than for other kinds of human capital.

[65] Each variable is standardized to have mean zero and a standard deviation of one at the occupation level. See the data appendix to Acemoglu and Autor (2011) for the definition of each category. Chernoff and Warman (2020) use these categories to identify jobs with high automation potential during the COVID-19 pandemic. See `https://time.com/5876604/machines-jobs-coronavirus/` for a discussion of the different types of jobs that have been subject to increasing automation during the COVID-19 pandemic.

[66] The breakdown of education requirements by STEM status is similar to the breakdown of education attained shown in Figure C.1 and they are correlated, but educational attainment and educational requirements are different concepts, the latter closer to the idea of education utilization on the job.

To explore the hypothesis that STEM knowledge in work provides for greater employment resiliency in recessions, we use O*NET data to construct occupation-level measures of the importance of knowledge in the following STEM categories: 1) computer knowledge, 2) engineering knowledge, 3) mathematics knowledge, 4) physics knowledge, 5) chemistry knowledge, and 6) biology knowledge.[67] The measures are derived from survey questions asking respondents how important knowledge in each area is to the performance of one's job, regardless of whether one's job is classified as a STEM occupation. The measures are standardized to have mean zero and unit standard deviation across occupations.

Figure C.8 shows that while workers in STEM occupations are more likely to have higher levels of STEM knowledge on the job, there is considerable overlap between workers in STEM and non-STEM occupations in the importance of STEM knowledge on the job.[68] It is important to note that each distribution in Figure C.8 gives the STEM knowledge importance probability distribution for workers *within* a given occupational classification (i.e., STEM or non-STEM)—while the proportion of STEM occupations where STEM knowledge is important exceeds the proportion of non-STEM jobs where STEM knowledge is important, the number of workers in non-STEM occupations in the US economy far exceeds the number of workers in STEM occupations so that there are in fact more non-STEM workers than STEM workers employed in jobs where STEM knowledge is important. To show this, Table 6 gives the share and number of STEM, STEM-related, and non-STEM occupations and workers for jobs where STEM knowledge on the job is important.[69] While we categorize STEM-related occupations (primarily healthcare occupations) as non-STEM in the rest of our analysis, here we break them out as a separate group in order to examine the importance of STEM knowledge on the job for non-STEM occupations that are not STEM-related. We find that workers in these non-STEM occupations constitute (74%) of all workers in occupations where at least one of the six selected fields of STEM knowledge is important on the job, and that well over half (72 million out of 124 million) of workers in non-STEM occupations work in a job where at least one of the six selected fields of STEM knowledge is important.[70]

[67] O*NET data provide measures of how important STEM knowledge is to each occupation, regardless of its classification as a STEM or non-STEM occupation. We use the term "STEM knowledge" to denote this set of six knowledge categories, rather than as a single type of knowledge. Aggregating across knowledge categories to produce a single index measure for the importance of STEM-types of knowledge is complicated by the fact that some occupations may utilize a single type of category intensely (e.g., pure mathematicians) while other fields may utilize multiple categories intensely (e.g., biochemists, material science engineers). While the latter occupations are more interdisciplinary, it is arguable whether they are more intensive than pure mathematicians in the use of a STEM-type of knowledge. It might also be argued that mathematics is a more fundamental type of STEM knowledge which is a prerequisite for knowledge in other fields and so should be given higher weight. Given such complications, we maintain the distinctions between the six STEM knowledge categories rather than aggregating to a single metric.

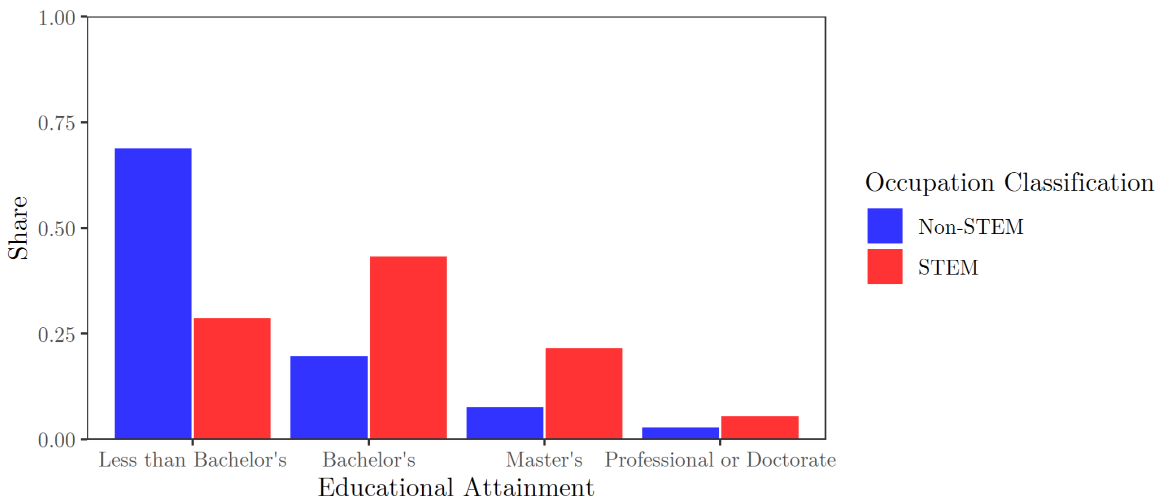
[68] The large overlap between STEM and non-STEM workers in importance of biology and chemistry knowledge on the job is partly due to our classification of "STEM-related" occupations, which are primarily healthcare-related, as non-STEM.

[69] A given knowledge category is considered important if the average evaluation of O*NET respondents on the knowledge questionnaire yields a value above 3, which is the threshold value which defines the knowledge as important on the five-point scale (with a 4 and 5 for "very important" and "extremely important", respectively).

[70] See notes to Table 6 for total number of occupation codes and employment for each occupational classification. Only one STEM occupation (Psychologists) and three STEM-related occupations (Occupational therapists, Recre-

For concreteness, Table C.2 and Table C.3 list the top 15 STEM and non-STEM occupations in terms of importance of STEM knowledge on the job, for each of the STEM knowledge domains.[71] Both tables produce broadly sensible lists, keeping in mind that these are measures of the *importance* of STEM knowledge on the job, and not to the *level* of STEM knowledge required for the job.[72] While some occupations in Table C.3 require a college education (e.g., financial analysts), many non-STEM occupations ranking the highest in terms of importance of STEM knowledge do not require a Bachelor's degree. National Science Board (2019) refers to such occupations as the "Skilled Technical Workforce" (STW) and find that workers in these occupations typically have higher pay and employment rates compared to other non-college-educated workers.

Figure C.1. Educational Attainment



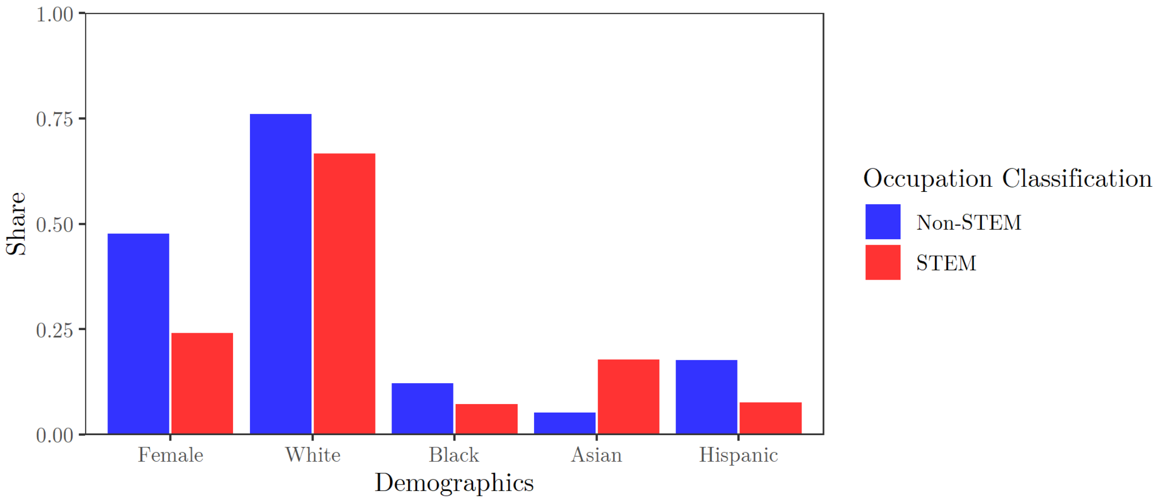

*Notes*: Bars report the share of STEM (Non-STEM) workers who have the given level of educational attainment. Educational attainment by occupation is from BLS data which can be downloaded at https://www.bls.gov/emp/tables/educational-attainment.htm. Employment in each Census occupation code is derived from 2019 OES data.

ational therapists, and Speech-language pathologists) fall in occupations where none of the six categories of STEM knowledge scores at least a 3 on the O*NET knowledge importance measure.

[71] Here, as in the rest of the paper, we classify STEM-related occupations together with non-STEM occupations.

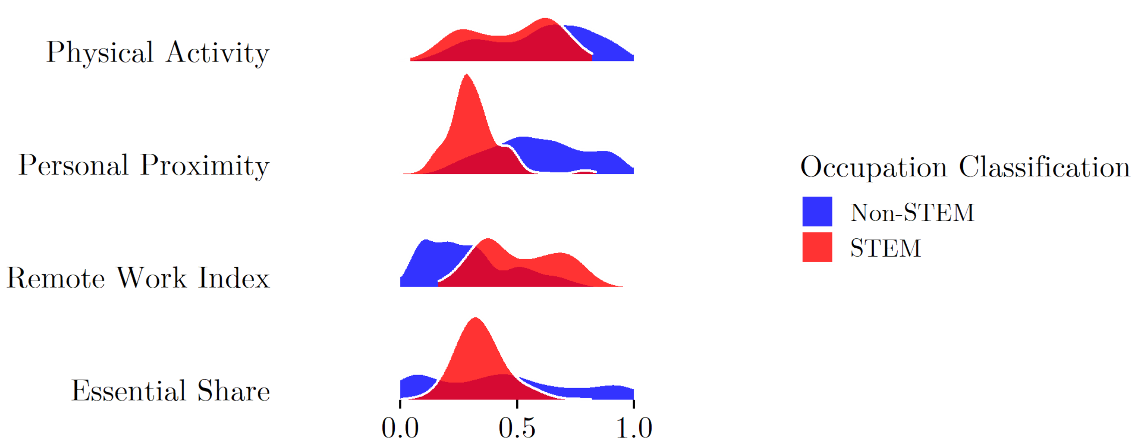
[72] The minimum education requirement for each occupation, discussed above, captures the level of knowledge required to perform an occupation. In regression analysis, we control for minimum education requirement, so our estimate of the effect of "STEM knowledge on the job" is based on variation among workers in occupations with the same minimum educational requirement.

Figure C.2. Demographics



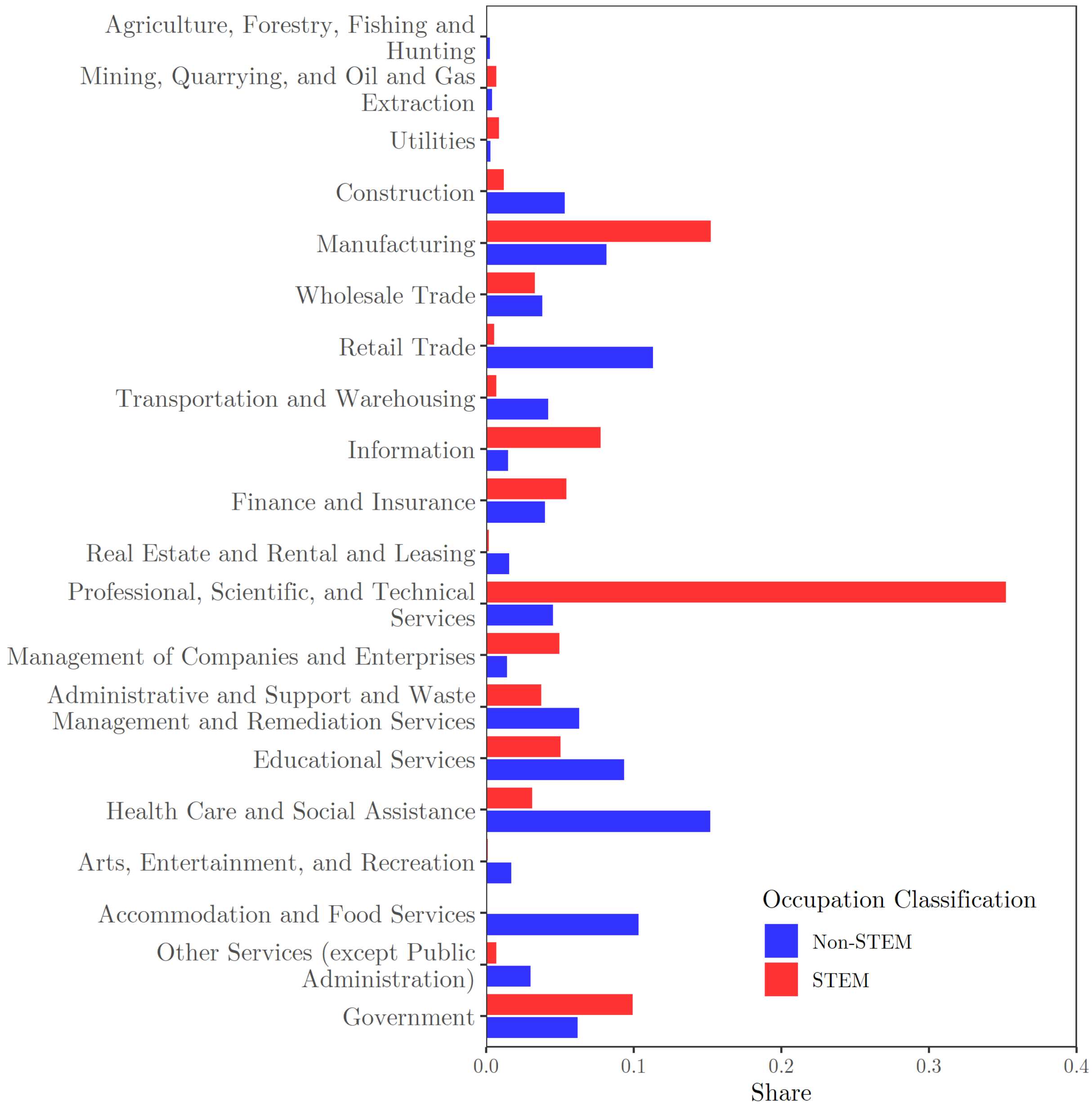

*Notes*: Bars report the share of STEM (Non-STEM) workers with the given demographic characteristic. Bars across race groups (White, Black, and Asian) do not sum to one as data excludes other race groups. Persons of Hispanic ethnicity may be of any race. Demographic share of each occupation is weighted by employment. Data is derived from 2019 CPS data and available from the BLS at https://www.bls.gov/cps/aa2019/cpsaat11.htm.

Figure C.3. Remote Work Feasibility and Essential Worker Share of Occupation



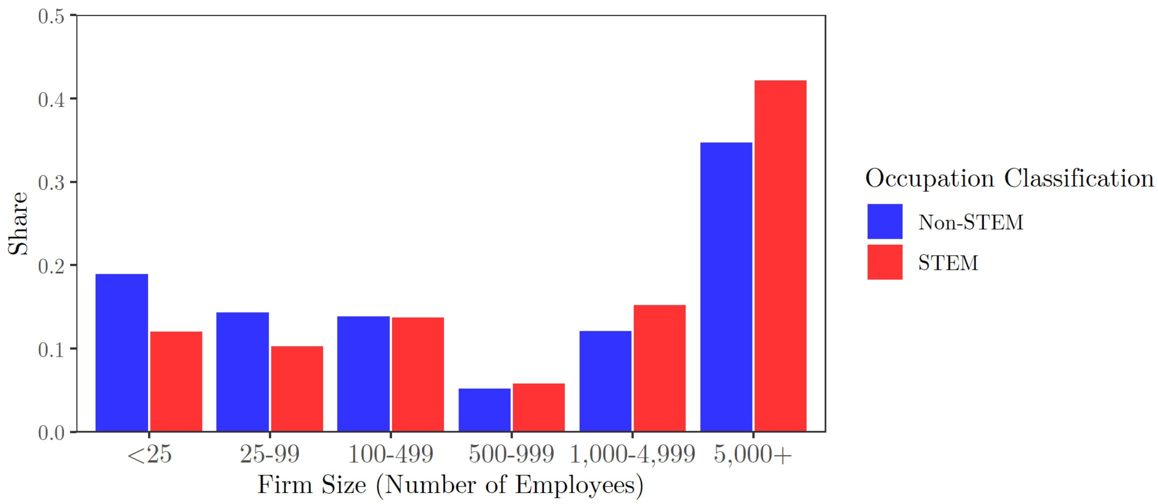

*Notes*: Density plots of O*NET-based variables giving the degree to which a worker's job relies on conducting physical activities at one's workplace ("Physical Activity"), the degree to which a worker must perform job tasks in close proximity to other people ("Personal Proximity"), and a Remote Work Index (RWI) constructed as one minus the maximum of the Physical Activity and Personal Proximity of the occupation. For each occupation, we measure the proportion of workers employed in essential industries as identified in Tomer and Kane (2020) ("Essential Share") and plot the corresponding density plots. See Appendix D for more details on the construction of Physical Activity, Personal Proximity, and RWI, and see Appendix B.1 for details on construction of Essential. Density plots are weighted by employment in each Census occupation code using 2019 OES data.

Figure C.4. Employer Industry



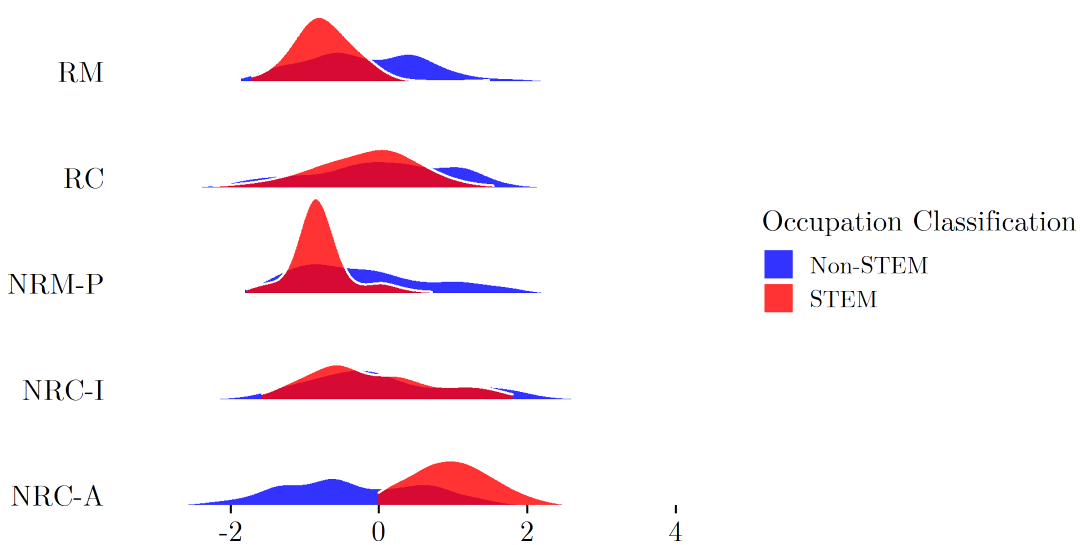

*Notes*: Bars report the share of STEM (non-STEM) workers who work in each industry. Occupation-by-industry (nonfarm establishment) employment is from 2019 OES data.

Figure C.5. Employer Size



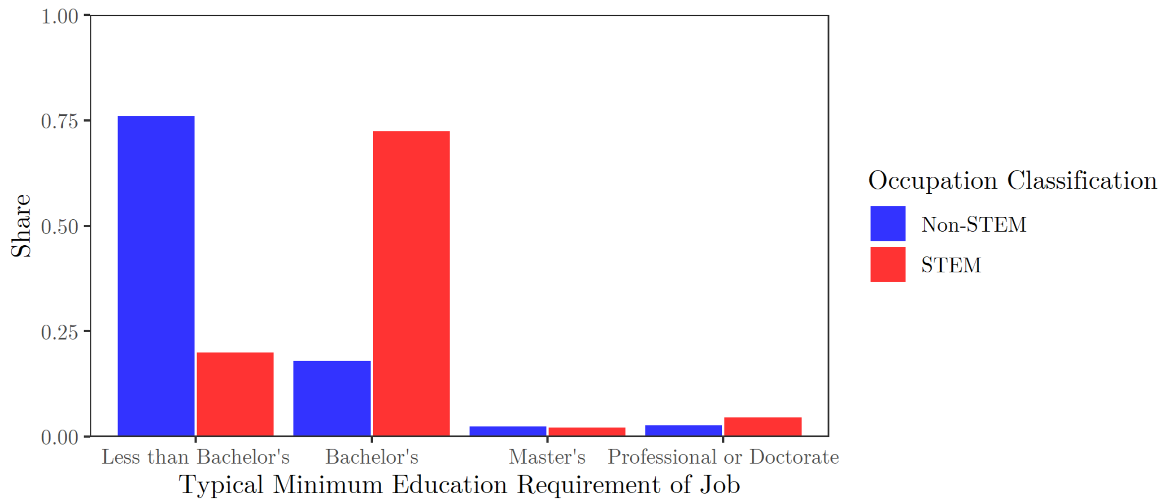

*Notes*: Bars report the share of STEM (non-STEM) workers who work in firms of each size. Industry employment by firm size data from the Census Bureau's *Statistics of U.S. Businesses* (SUSB) which is sourced from the Business Register (BR); data available at `https://www.census.gov/data/tables/2018/econ/susb/2018-susb-annual.html`. Occupation-by-industry (nonfarm establishment) employment is from 2018 OES data and is used to calculate the STEM-share of employment in each industry.

Figure C.6. Nonroutine and Cognitive Task Intensity of Work



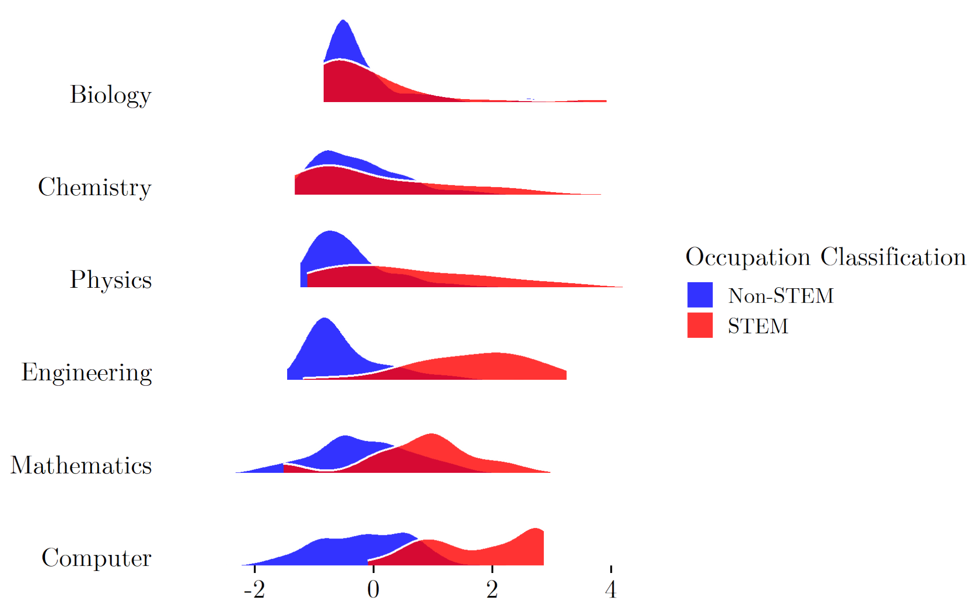

*Notes*: Density plots of O*NET-based standardized variables giving task measures for five task categories defined in Acemoglu and Autor (2011)—routine manual (RM), routine cognitive (RC), non-routine manual-physical (NRM-P), non-routine cognitive-interpersonal (NRC-I), and non-routine cognitive-analytical (NRC-A). Each variable has zero mean and unit variance across the set of all occupations. Density plots are weighted by employment in each Census occupation code using 2019 OES data.

Figure C.7. Education Required for the Job




*Notes*: Bars report the share of STEM (non-STEM) workers who work in an occupation with the given level of education typically required for the job. Typical minimum education requirements for occupations is from BLS data which can be downloaded at `https://www.bls.gov/oes/2019/may/education_2019.xlsx`. Employment in each Census occupation code is derived from 2019 OES data.

Figure C.8. Importance of STEM Knowledge for the Job




*Notes*: Density plots of O*NET-based standardized variables giving the importance of each type of STEM knowledge to each Census occupation. Each knowledge variable has zero mean and unit variance across the set of all occupations. Density plots are weighted by employment in each Census occupation code using 2019 OES data.

Table C.1. Top 15 Industries by STEM Employment

| NAICS (4-digit) | NAICS Title | STEM Share of Industry Employment (OES 2019) | STEM Employment (Thousands of Workers) |
|---|---|---|---|
| ***Panel A. Top 15 Industries by STEM Share of Own Employment in 2019*** | | | |
| 5415* | Computer Systems Design and Related Services | 0.64 | 1434 |
| 5417* | Scientific Research and Development Services | 0.60 | 456 |
| 5413* | Architectural, Engineering, and Related Services | 0.57 | 907 |
| 5112* | Software Publishers | 0.56 | 281 |
| 3341* | Computer and Peripheral Equipment Manufacturing | 0.52 | 813 |
| 5182* | Data Processing, Hosting, and Related Services | 0.46 | 170 |
| 3342* | Communications Equipment Manufacturing | 0.39 | 31 |
| 3345* | Navigational, Measuring, Electromedical, and Control Instruments Manufacturing | 0.39 | 165 |
| 3344* | Semiconductor and Other Electronic Component Manufacturing | 0.35 | 130 |
| 3364* | Aerospace Product and Parts Manufacturing | 0.34 | 182 |
| 5211 | Monetary Authorities - Central Bank | 0.32 | 1.5 |
| 3343 | Audio and Visual Equipment Manufacturing | 0.29 | 5.5 |
| 5191 | Other Information Services | 0.29 | 130 |
| 2111 | Oil and Gas Extraction | 0.28 | 38 |
| 3254* | Pharmaceutical and Medicine Manufacturing | 0.28 | 90 |
| ***Panel B. Top 15 Industries by STEM Employment in February 2020*** | | | |
| 5415* | Computer Systems Design and Related Services | 0.64 | 1434 |
| 5413* | Architectural, Engineering, and Related Services | 0.57 | 907 |
| 6113 | Colleges, Universities, and Professional Schools | 0.16 | 476 |
| 5417* | Scientific Research and Development Services | 0.60 | 456 |
| 5511 | Management of Companies and Enterprises | 0.18 | 436 |
| 5416 | Management, Scientific, and Technical Consulting Services | 0.21 | 325 |
| 5112* | Software Publishers | 0.56 | 281 |
| 5613 | Employment Services | 0.06 | 214 |
| 3364* | Aerospace Product and Parts Manufacturing | 0.34 | 182 |
| 5182* | Data Processing, Hosting, and Related Services | 0.46 | 170 |
| 5241 | Insurance Carriers | 0.14 | 168 |
| 3345* | Navigational, Measuring, Electromedical, and Control Instruments Manufacturing | 0.39 | 165 |
| 5173 | Telecommunications | 0.22 | 138 |
| 6221 | General Medical and Surgical Hospitals | 0.02 | 136 |
| 5191 | Other Information Services | 0.29 | 130 |

*Notes*: No other industries than those listed in Panel A have a STEM-share of own employment exceeding 25%. STEM-share of employment is calculated using 2019 OES data and the US Census Bureau's definition of STEM occupations. Industry employment based on seasonally-adjusted QCEW February 2020 data. We use * to denote the following four-digit NAICS which are typically classified as high-tech in the literature (e.g., Decker et al., 2020; Bai et al., 2021): 3254, 3341, 3342, 3344, 3345, 3364, 5112, 5161, 5179, 5181, 5182, 5413, 5415, 5417. As noted in Decker et al. (2020), this classification originates with Hecker (2005) who classified industries as high-tech on the basis of each industry's STEM-share of employment.

Table C.2. Top 15 STEM Occupations by Importance of STEM Knowledge

| Rank | Computer | Math | Engineering |
|---|---|---|---|
| 1 | Computer hardware engineers | Actuaries | Chemical engineers |
| 2 | Network & computer systems administrators | Astronomers & physicists | Computer hardware engineers |
| 3 | Software developers, applications, & systems software | Mathematicians | Biomedical engineers |
| 4 | Computer programmers | Chemical engineers | Nuclear engineers |
| 5 | Computer support specialists | Operations research analysts | Mechanical engineers |
| 6 | Computer & information systems managers | Economists | Aerospace engineers |
| 7 | Computer & information research scientists | Computer hardware engineers | Electrical & electronics engineers |
| 8 | Electrical & electronics engineers | Nuclear engineers | Agricultural engineers |
| 9 | Database administrators | Mechanical engineers | Civil engineers |
| 10 | Astronomers & physicists | Mining & geological engineers, including mining safety engineers | Environmental engineers |
| 11 | Web developers | Civil engineers | Engineers, all other |
| 12 | Biomedical engineers | Agricultural engineers | Mining & geological engineers, including mining safety engineers |
| 13 | Computer network architects | Surveyors, cartographers, & photogrammetrists | Astronomers & physicists |
| 14 | Information security analysts | Biomedical engineers | Marine engineers & naval architects |
| 15 | Computer systems analysts | Marine engineers & naval architects | Petroleum engineers |
| **Rank** | **Physics** | **Chemistry** | **Biology** |
| 1 | Astronomers & physicists | Chemical engineers | Biological scientists |
| 2 | Nuclear engineers | Chemists & materials scientists | Medical scientists |
| 3 | Atmospheric & space scientists | Materials engineers | Biological technicians |
| 4 | Chemical engineers | Chemical technicians | Agricultural & food scientists |
| 5 | Mechanical engineers | Agricultural & food scientists | Biomedical engineers |
| 6 | Biomedical engineers | Biomedical engineers | Agricultural engineers |
| 7 | Materials engineers | Agricultural & food science technicians | Conservation scientists & foresters |
| 8 | Agricultural engineers | Nuclear engineers | Agricultural & food science technicians |
| 9 | Marine engineers & naval architects | Environmental engineers | Environmental scientists & geoscientists |
| 10 | Aerospace engineers | Biological scientists | Environmental engineers |
| 11 | Computer hardware engineers | Medical scientists | Natural science managers |
| 12 | Engineers, all other | Mechanical engineers | Miscellaneous life, physical, & social science technicians |
| 13 | Civil engineers | Architectural & engineering managers | Physical scientists, all other |
| 14 | Nuclear technicians | Petroleum engineers | Statisticians |
| 15 | Petroleum engineers | Agricultural engineers | Chemical engineers |

*Notes*: Ranking based on O*NET-based standardized variables giving the importance of each type of STEM knowledge to each Census occupation.

Table C.3. Top 15 Non-STEM Occupations by Importance of STEM Knowledge

| Rank | Computer | Math | Engineering |
|---|---|---|---|
| 1 | Computer Operators | Cost Estimators | Electrical & electronics installers & repairers, transportation equipment |
| 2 | Avionics Technicians | Lodging managers | Construction managers |
| 3 | Computer, automated teller, & office machine repairers | Tool & die makers | Electrical & electronics repairers, industrial & utility |
| 4 | TV, video, & motion picture camera operators & editors | Financial analysts | Tool & die makers |
| 5 | Technical writers | Cabinetmakers & bench carpenters | Cost estimators |
| 6 | Desktop publishers | Statistical assistants | Electronic home entertainment equipment installers & repairers |
| 7 | Electrical & electronics installers & repairers, transportation equipment | Millwrights | Avionics technicians |
| 8 | Broadcast & sound engineering technicians & radio operators | Boilermakers | Wind turbine service technicians |
| 9 | Artists & related workers | Sales representatives, services, all other | Industrial & refractory machinery mechanics |
| 10 | Radio & telecommunications equipment installers & repairers | Layout workers, metal & plastic | Broadcast & sound engineering technicians & radio operators |
| 11 | Statistical assistants | Market research analysts & marketing specialists | First-line supervisors of mechanics, installers, & repairers |
| 12 | Other education, training, & library workers | Carpenters | Model makers & patternmakers, wood |
| 13 | Lodging managers | Financial specialists, all other | Manufactured building & mobile home installers |
| 14 | Electrical & electronics repairers, industrial & utility | Buyers & purchasing agents, farm products | Architects, except naval |
| 15 | Motion picture projectionists | Fabric & apparel patternmakers | Construction & building inspectors |

| Rank | Physics | Chemistry | Biology |
|---|---|---|---|
| 1 | Nurse anesthetists | Nurse anesthetics | Veterinarians |
| 2 | Radiation therapists | Water & water treatment plants & system operators | Nurse anesthetists |
| 3 | Commercial divers | Pharmacists | Optometrists |
| 4 | Diagnostic related technologists & technicians | Chemical processing machine setters, operators, & tenders | Physicians & surgeons |
| 5 | Heating, A/C, & refrigeration mechanic & installers | Other healthcare practitioners & technical occupations | Nurse practitioners |
| 6 | Elevator installer & repairers | Plating & coating machine setters, operators, & tenders, metal & plastic | Nurse midwives |
| 7 | Wind turbine service technicians | Veterinarians | Fish & game wardens |
| 8 | Electrical & electronics repairers, industrial and utility | Optometrists | Dietitians & nutritionists |
| 9 | Physical therapists | Firefighters | Physician assistants |
| 10 | Electricians | Physician assistants | Chiropractors |
| 11 | Aircraft pilots & flight engineers | Licensed practical & licensed vocational nurses | Water & water treatment plants & system operators |
| 12 | Optometrists | Semiconductor processors | Farmers, ranchers, & other agricultural managers |
| 13 | Millwrights | Crushing, grinding, polishing, mixing, & blending workers | Other healthcare practitioners & technical occupations |
| 14 | Electrical & electronics installers & repairers, transportation equipment | Dieticians & nutritionists | Physical therapists |
| 15 | Computer control programmers & operators | Nurse practitioners | Registered nurses |

*Notes*: Ranking based on O*NET-based standardized variables giving the importance of each type of STEM knowledge to each Census occupation.

# D Constructing and Validating a Remote Work Index (RWI)

We characterize the remote work capacity/feasibility of occupations using data from the Department of Labor's *Occupational Information Network* (O*NET).[73] O*NET data is based on the survey responses of workers within different occupations defined by SOC codes, with workers answering questions pertaining to their work activities and work context. We use responses to the O*NET question items found in Table D.1 to construct two metrics: "Physical Activity", which measures the degree to which a worker's job relies on conducting physical activities at one's workplace (e.g., controlling machines, inspecting equipment, monitoring processes, etc.) and "Personal Proximity", which measures the degree to which a worker must perform job tasks in close proximity to other people.[74] To link these metrics with CPS data, we convert Physical Activity and Personal Proximity from the finer SOC coding system to the broader Census occupation codes ("OCC") present in CPS data. We do this by calculating employment-weighted means of Physical Activity and Personal Proximity for all SOC codes contained within each OCC code, where employment weights are based on employment numbers contained in the Bureau of Labor Statistics' *Occupation Employment Statistics* (OES) 2019 data.[75] We then normalize Physical Activity and Personal Proximity to fall within the unit interval.[76]

Physical Activity and Personal Proximity represent two dimensions that are likely to determine a worker's ability to carry out work remotely.[77] The top panel of Figure D.1 shows that these metrics vary both within and between STEM, STEM-Related, and non-STEM occupations: on average, STEM occupations appear to be the most capable of remote work as STEM occu-

[73] See Dingel and Neiman (2020) and Mongey, Pilossoph, and Weinberg (2021) for a similar approach. We utilize data files from the O*NET 25.0 Database.

[74] The value of Physical Activity and Personal Proximity for a given occupation is chosen as the maximum value across all questions under its heading found in Table D.1, and then is scaled to lie within the unit interval.

[75] In 2019, BLS began a partial transition of OES occupation codes from SOC 2010 to SOC 2018 codes, utilizing a hybrid SOC system during the first part of the transition (see `https://www.bls.gov/oes/soc_2018.htm` for details). We utilize the crosswalk found at `www.bls.gov/oes/oes_2019_hybrid_structure.xlsx` to facilitate linkage of OES 2019 data and ONET 25.0 data which uses SOC 2010 occupation codes.

[76] Mongey, Pilossoph, and Weinberg (2021) validate their O*NET-based measures they call "low work-from-home" and "physical proximity" using measures of the share of hours worked from home and the share of hours worked alone, respectively, from the Bureau of Labor Statistics' *American Time Use Survey* (ATUS). See Mongey, Pilossoph, and Weinberg for details. We reproduce Figure 2 from Mongey, Pilossoph, and Weinberg (2021) for our metrics using data from the ATUS 2019 microdata files in Figure D.2.

[77] Some examples can help to clarify the distinct nature of these two aspects (Physical Activity and Personal Proximity) which reflect the ability or ease of carrying out or transitioning to remote work: "secondary school teachers", for example, score below the median on Physical Activity but above the median on Personal Proximity because they typically work in close contact with students in the classroom. Workers in these types of occupations may be able to transition to working from home, but since their job is typically carried out in high personal proximity, are likely to face nontrivial transition costs to doing so. "Chemists and materials scientists" are an example of a high Physical Activity and low Personal Proximity occupation—these workers likely require equipment located at a lab to carry out their work but can potentially do so in a socially-distanced manner since this does not require high personal proximity. An example of an occupation which scores low on both Physical Activity and Personal Proximity is "Economists", an occupation typically well-suited to remote work. We would expect workers in occupations scoring high on both Physical Activity and Personal Proximity, such as "flight attendants", to be among those most vulnerable to the negative economic impacts of the pandemic.

pations are associated with lower Physical Activity and Personal Proximity than STEM-related and non-STEM occupations.[78] STEM-related occupations are associated with the highest Personal Proximity; many STEM-related occupations are health service providers such as "dental hygienists" and "emergency medical technicians and paramedics," and so this makes sense. The Personal Proximity of non-STEM jobs lies between that of STEM and STEM-related jobs, but achieves the maximum value of Physical Activity, which indicates that even though these jobs may not require as close physical proximity to others as STEM-related jobs, the machines and materials located at one's workplace tend to be more vital for being able to carry out any of one's job tasks. The correlation between Physical Activity and Personal Proximity among STEM occupations is 0.22, among STEM-related occupations is 0.53, and among non-STEM occupations is 0.14. The absence of a uniformly strong correlation between these two measures supports the notion that these metrics are measuring two distinct characteristics of occupations, each of which plays a role in determining remote work feasibility.

We combine our measures of Physical Ability and Personal Proximity to form a single Remote Work Index (RWI) that we use to control for the impact of remote work feasibility on pandemic era changes in labor market outcomes, and to explore the extent to which differences in the remote work feasibility of STEM and non-STEM occupations explain differences in pandemic period outcomes. We construct RWI based on the intuition that occupations that require conducting physical activities at one's workplace ("Physical Activity") *or* performing job tasks in close proximity to other people ("Personal Proximity") are less feasible for remote work. Therefore, for each occupation, we construct RWI by first taking the maximum value between Physical Activity and Personal Proximity, and then subtracting this value from one. The bottom panel of Figure D.1 shows the distribution of Physical Activity, Personal Proximity, and RWI for STEM, STEM-related, and non-STEM occupations. Based on RWI, STEM occupations appear to be the most remote work feasible, followed by STEM-related and then non-STEM occupations.[79]

Starting in May 2020, the Bureau of Labor Statistics began asking CPS respondents 1) whether they had teleworked or worked from home in the last four weeks due to the COVID-19 pandemic and 2) whether they were unable to work at any time during the last four weeks because their employer had lost business or closed due to the COVID-19 pandemic.[80] In Figure D.9 we find a positive relationship between RWI and the share of workers in each occupation who report teleworking any time in the last four weeks due to the COVID-19 pandemic, while there is a negative relationship

[78] Occupations are classified according to the US Census Bureau's "STEM, STEM-related, and non-STEM Occupation Code List 2010" which can be found at https://www2.census.gov/programs-surveys/demo/guidance/industry-occupation/stem-census-2010-occ-code-list.xls.

[79] See Figure D.3, Figure D.4, and Figure D.5 for a break-down of STEM occupations by Physical Activity, Personal Proximity, and RWI, respectively. Similarly, see Figure D.6, Figure D.7, and Figure D.8 for a break-down of STEM-related occupations by Physical Activity, Personal Proximity, and RWI, respectively.

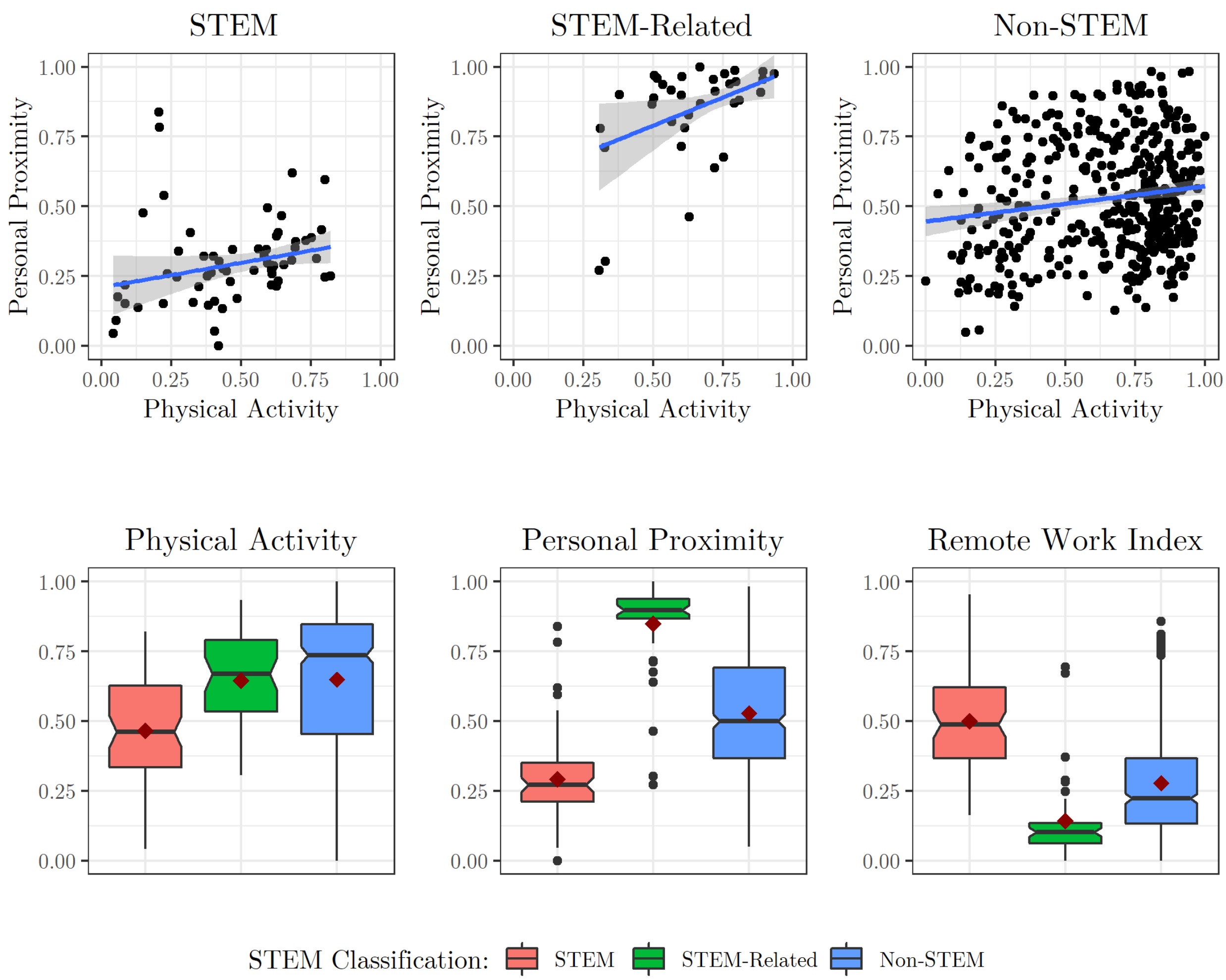
[80] See https://www.bls.gov/covid19/measuring-the-effects-of-the-coronavirus-covid-19-pandemic-using-the-current-population-survey.htm for additional COVID-19 related questions added to the CPS in May 2020.

between RWI and the share of workers who "lost work" due to their employer losing business.[81] We can also see that a subset of occupations that are more heavily associated with essential industries "clump" at zero for the share teleworking and the share who lost work across a range of values for RWI, as might be expected.[82] In Table D.2, we report results from person-month level regressions where the dependent variable in Panel A is whether the person teleworked in the given month due to COVID (conditional on being employed) and in Panel B whether the person had lost work during the last month due to their employer losing business due to COVID-19. After controlling for the education attained by workers and typically required for their job, demographics, and location, RWI maintains its strong relationship with both these outcomes. We also find that workers in STEM occupations were more likely than those in non-STEM to telework and less likely to lose work due to COVID-19 during May through June 2020. We view these results as a further validation of our RWI metrics—not only is RWI a significant predictor of pandemic era employment and hours (results available on request), but also is predictive of whether an individual actually teleworked or lost work explicitly for COVID-19 related reasons.

[81] The correlation between RWI and the share teleworking in May 2020 and May 2021 is 0.63 and 0.56, respectively. while the correlation with the share who "lost work" is -0.27 and -0.10, respectively. The samples include observations from the "Employment Regression Sample" who are observed in May 2020 or May 2021, respectively.

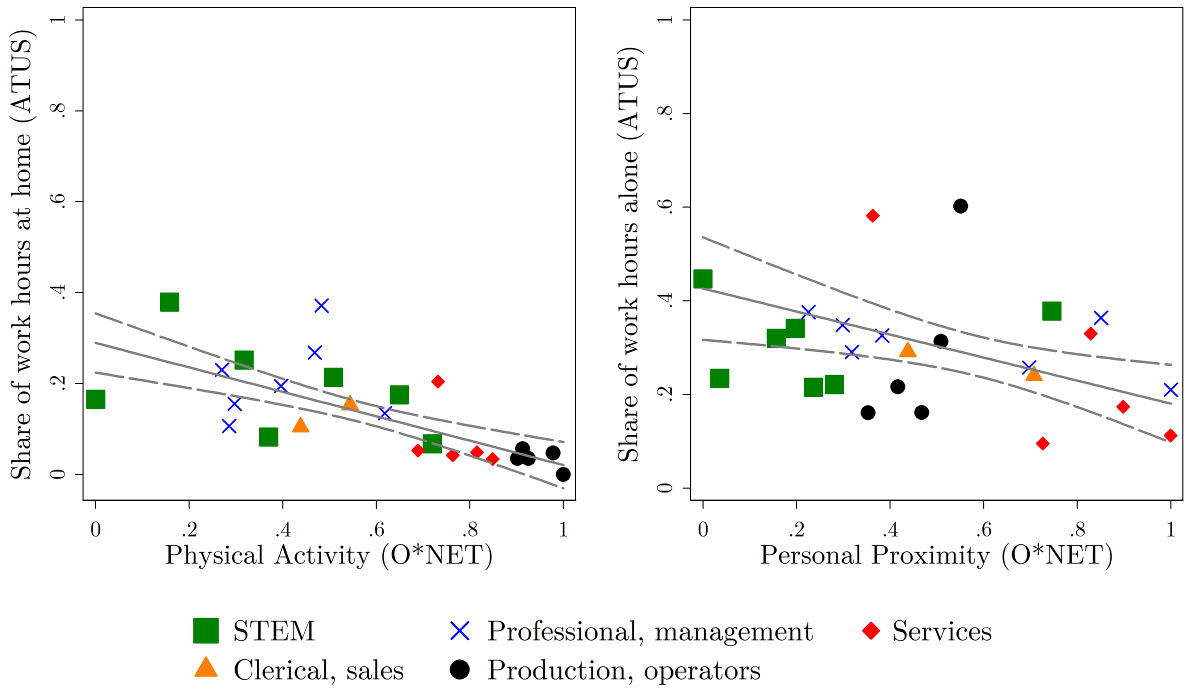
[82] See Appendix B.1 for discussion of how we measure the degree to which an occupation is "essential".

Figure D.1. Physical Activity, Personal Proximity, and Remote Work Index (RWI) of Occupations by STEM Classification



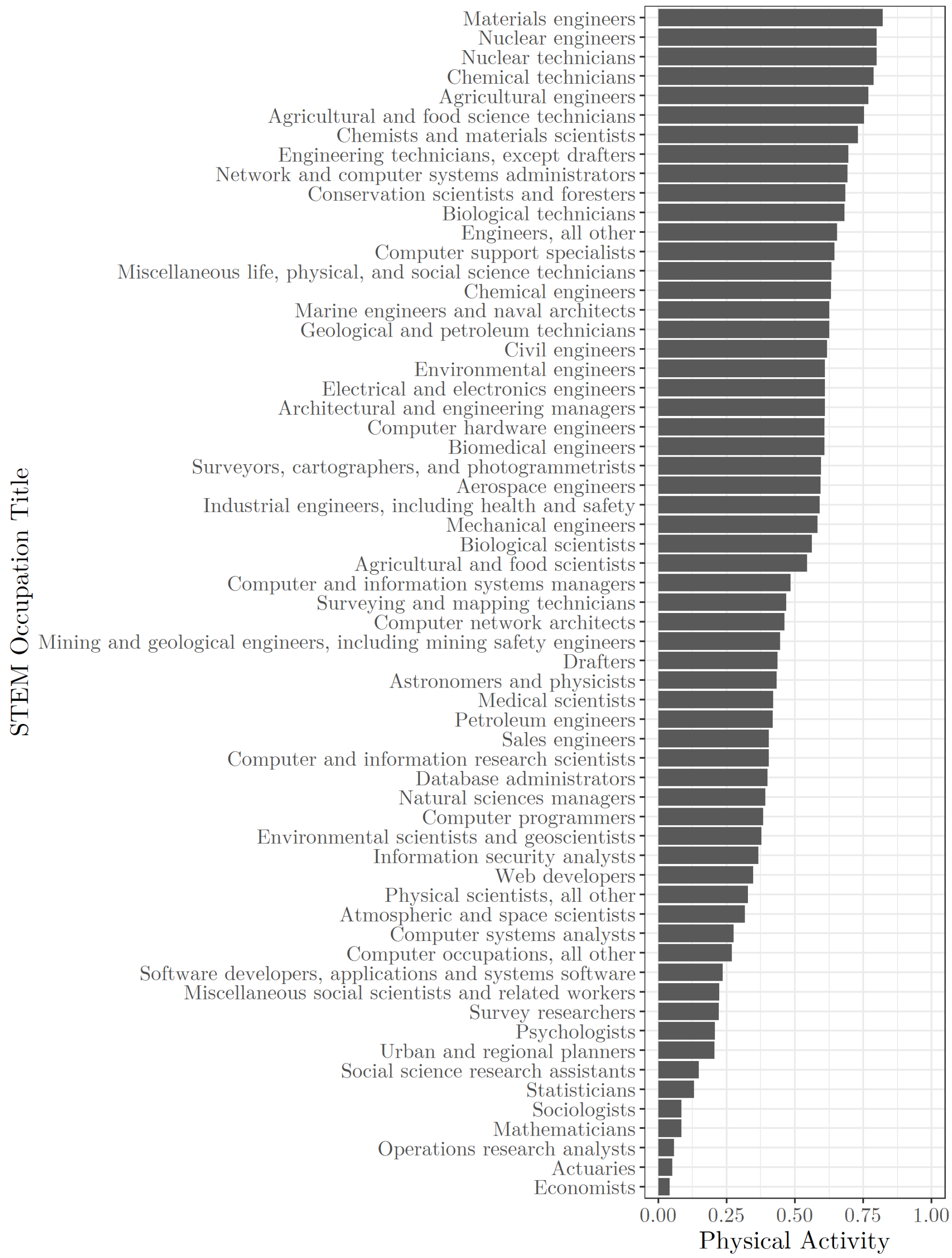

*Notes*: The top panel of this figure plots the Physical Activity and Personal Proximity of each occupation by STEM status classification. The correlation between Physical Activity and Personal Proximity among STEM occupations is 0.22, among STEM-related occupations is 0.53, and among non-STEM occupations is 0.14. Line of best fit produced from a regression of Personal Proximity on Physical Activity, with the associated 95% confidence interval based on robust standard errors. The bottom panel shows boxplots for Physical Activity, Personal Proximity, and the Remote Work Index (RWI) by STEM classification of occupation. For each occupation, RWI is equal to one minus the maximum of Physical Activity and Personal Proximity. Notches centered at the median approximate the 95% confidence interval for the median. The lower and upper hinges of the boxplot correspond to the 25th and 75th percentiles (first and third quartiles), respectively. The red point represents the mean value of Physical Activity, Personal Proximity, and RWI, respectively, within each STEM classification. The upper (lower) whisker extends from the 75th (25th) percentile to the largest (smallest) value that is no further than 1.5 times the inter-quartile range (distance between first and third quartile). Points in black represent occupations whose value of RWI lies outside the range of the whiskers.

Figure D.2. Comparing O*NET-based Physical Activity and Personal Proximity Measures to ATUS



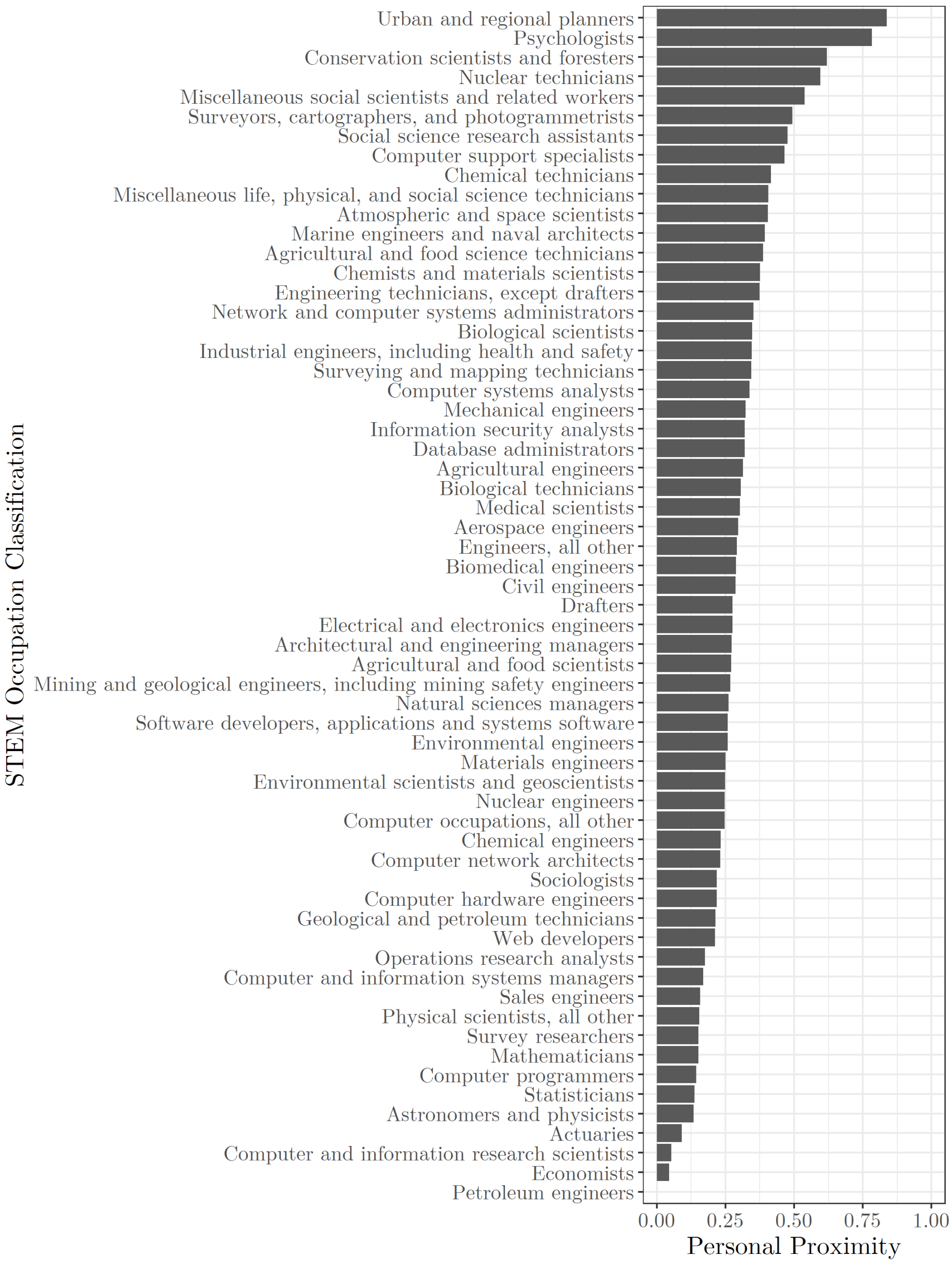

*Notes*: This figure reproduces Figure 2 from Mongey, Pilossoph, and Weinberg (2021) using our Physical Activity and Personal Proximity metrics. The correlation between Physical Activity and the ATUS measure of work from home is -0.67, and the correlation between Personal Proximity and the ATUS measure of share of time spent working alone is -0.28. We separate STEM occupations into their own group using the Census classification of STEM occupations — these occupations were previous classified as "Professional, management, technology" in Mongey, Pilossoph, and Weinberg (2021). We use ATUS 2019 to construct this figure.

Figure D.3. Physical Activity by STEM Occupation



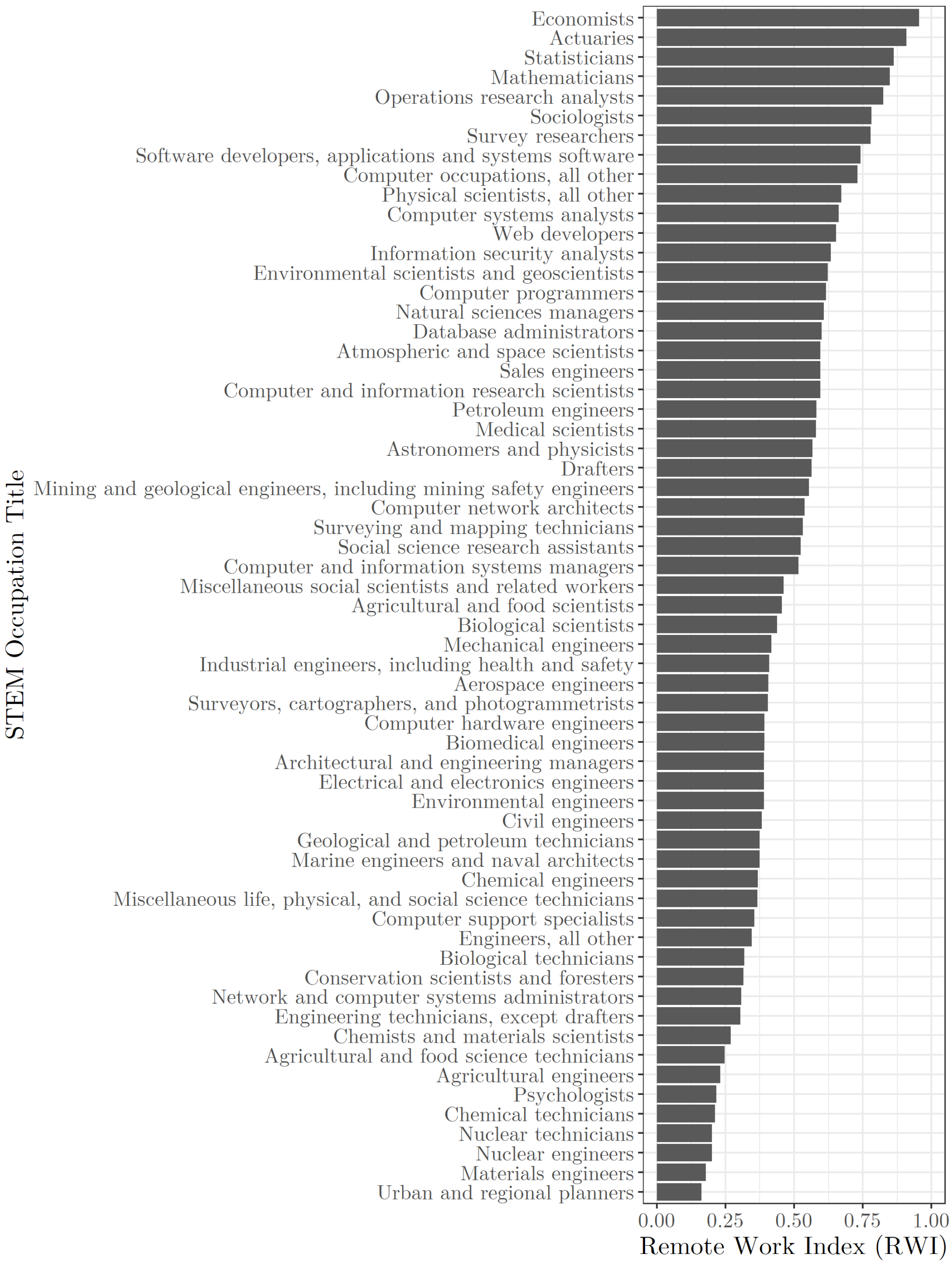

*Notes*: This figures plots the Physical Activity measure for each STEM occupation as defined by the US Census Bureau's "STEM, STEM-related, and Non-STEM Occupation Code List 2010."

Figure D.4. Personal Proximity by STEM Occupation



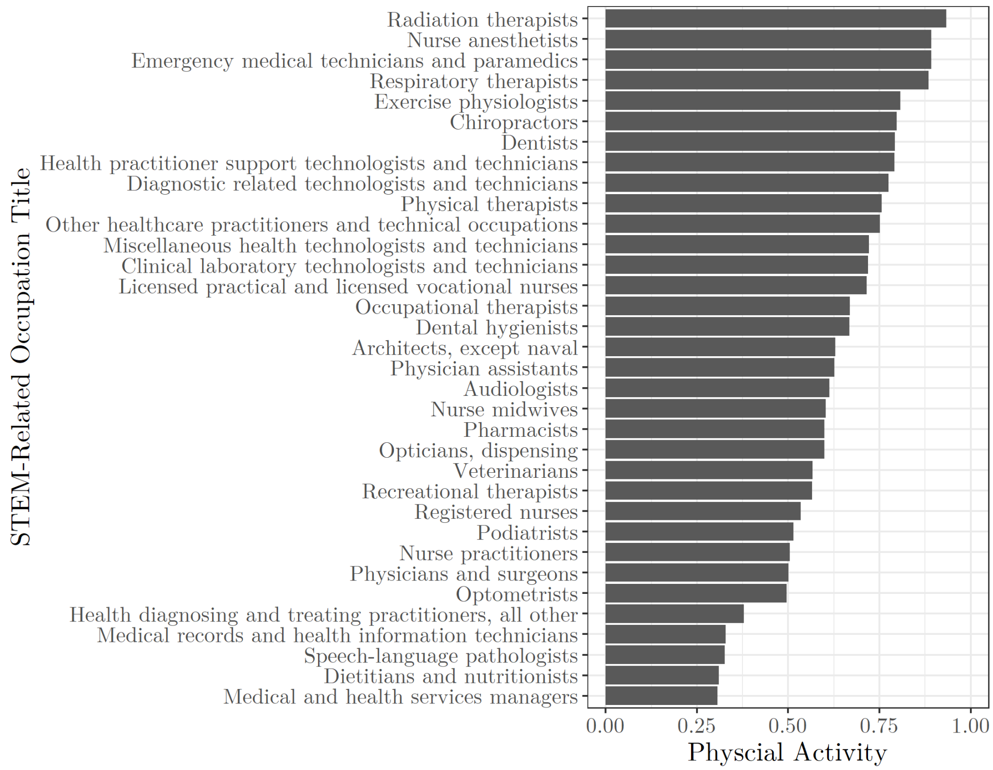

*Notes*: This figures plots the Personal Proximity measure for each STEM occupation as defined by the US Census Bureau's "STEM, STEM-related, and Non-STEM Occupation Code List 2010."

Figure D.5. Remote Work Index (RWI) by STEM Occupation



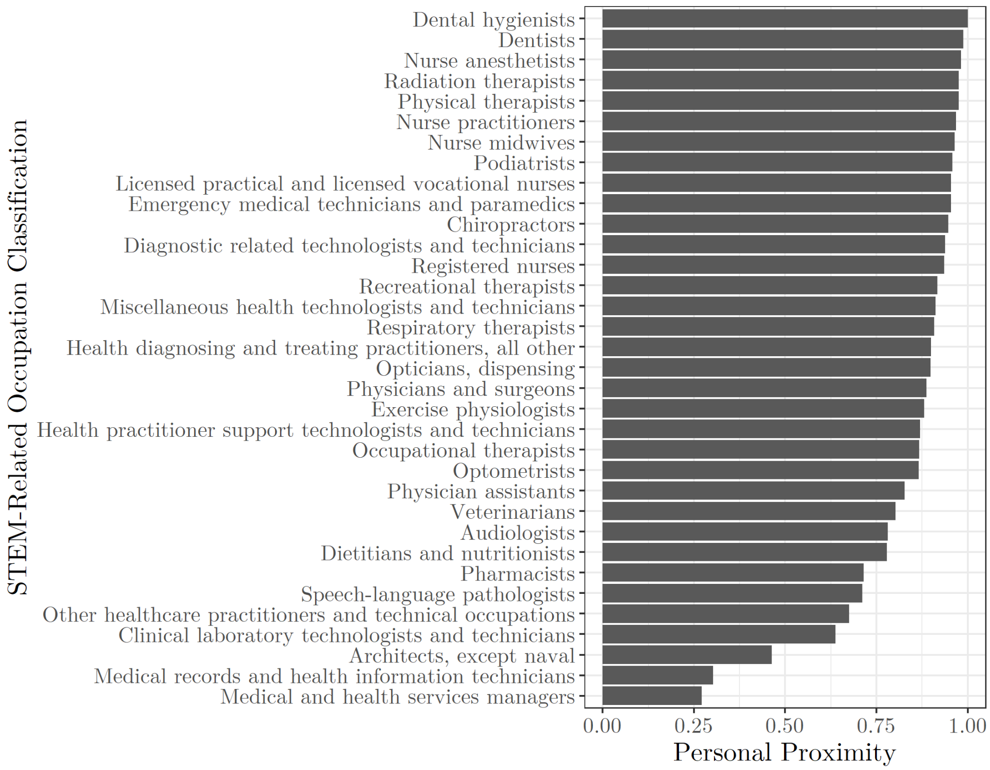

*Notes*: This figures plots the Remote Work Index (RWI) for each STEM occupation as defined by the US Census Bureau's "STEM, STEM-related, and Non-STEM Occupation Code List 2010."

Figure D.6. Physical Activity by STEM-Related Occupation



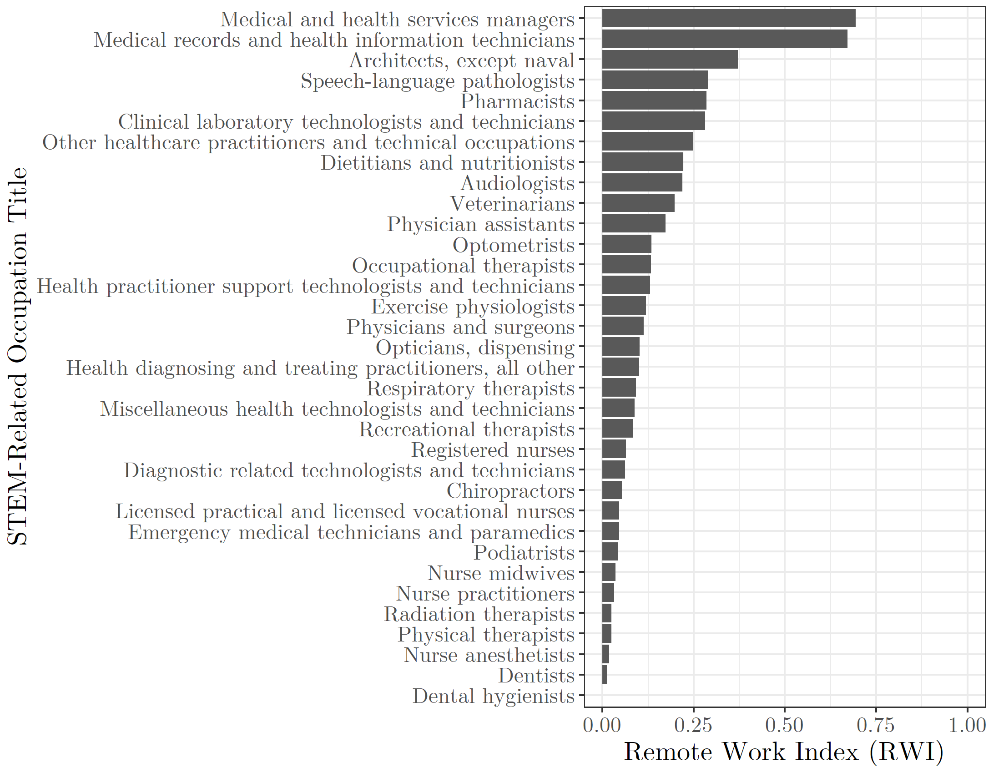

*Notes*: This figures plots the Physical Activity measure for each STEM-related occupation as defined by the US Census Bureau's "STEM, STEM-related, and Non-STEM Occupation Code List 2010."

Figure D.7. Personal Proximity by STEM-Related Occupation



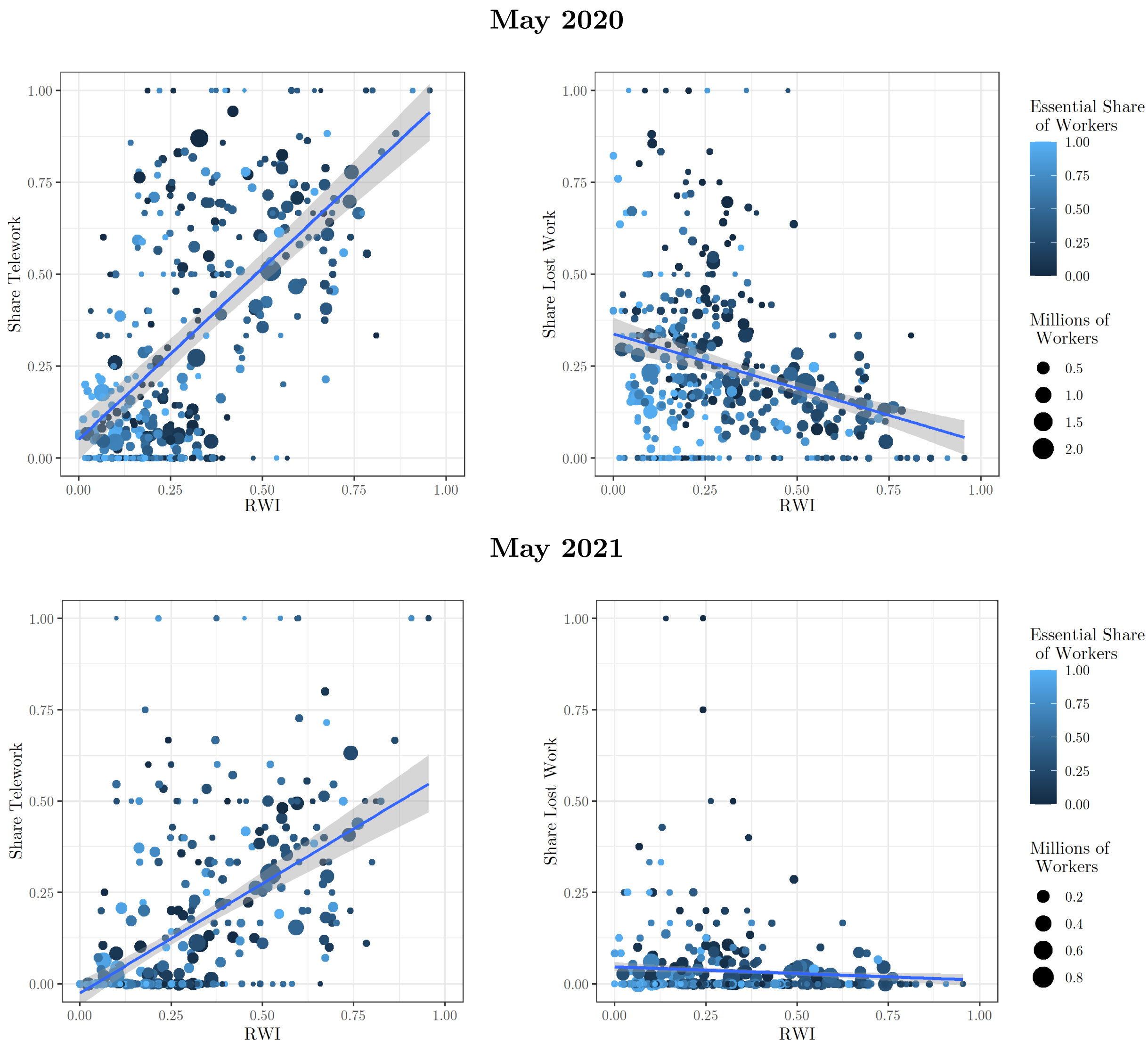

*Notes*: This figures plots the Personal Proximity measure for each STEM-related occupation as defined by the US Census Bureau's "STEM, STEM-related, and Non-STEM Occupation Code List 2010."

Figure D.8. Remote Work Index (RWI) by STEM-Related Occupation




*Notes*: This figures plots the Remote Work Index (RWI) for each STEM-Related occupation as defined by the US Census Bureau's "STEM, STEM-related, and Non-STEM Occupation Code List 2010."

Figure D.9. Share of Workers Who Teleworked or Lost Work due to COVID-19 by RWI




*Notes*: Sample includes observations from the "Employment Regression Sample" who are observed in May 2020 and May 2021, respectively. The leftward plots in this figure show the share of employed workers in each occupation who report teleworking at any time in the last four weeks due to the COVID-19 pandemic by RWI. The correlation in May 2020 and May 2021 is 0.63 and 0.56, respectively. The rightward plots in this figure show the share of workers in each occupation who report that they were unable to work at any time during the last four weeks because their employer closed or lost business due to the COVID-19 pandemic by RWI. The correlation in May 2020 and December 2021 is -0.27 and -0.10, respectively. Each point on the figure represents an occupation, with the size of each point determined by the number of workers in each occupation calculated using survey weights. The color of each point is based on the share of workers in that occupation that work in an essential industry as defined by Tomer and Kane (2020). Line of best fit in each panel produced from a weighted regression of the share of workers teleworking and who "lost work", respectively, on RWI, with the associated 95% confidence interval based on robust standard errors. OES 2019 data used to measure the number of workers in each industry by occupation.

Table D.1. O*NET Question Items Used to Compute Physical Activity and Personal Proximity

| O*NET Questionnaire | Question Number | Question Title |
|---|---|---|
| *Physical Activity* | | |
| Work Activities | 4 | Inspecting Equipment, Structures, or Materials |
| Work Activities | 16 | Performing General Physical Activities |
| Work Activities | 17 | Handling and Moving Objects |
| Work Activities | 18 | Controlling Machines and Processes |
| Work Activities | 20 | Operating Vehicles, Mechanized Devices, or Equipment |
| Work Activities | 22 | Repairing and Maintaining Mechanical Equipment |
| Work Activities | 23 | Repairing and Maintaining Electronic Equipment |
| *Personal Proximity* | | |
| Work Activities | 29 | Assisting and Caring for Others |
| Work Activities | 32 | Performing for or Working Directly with the Public |
| Work Context | 21 | Physical Closeness to Other People When Performing Job |

*Notes*: Work Activity questions ask how important each activity (given by the question title) is to the performance of one's current job. Responses follow a five-point scale ranging from the activity being "Not Important" to "Extremely Important" to the performance of a worker's current job. The single question we use from the Work Context survey asks how physically close one is to other people when one performed their current job. Responses follow a five-point scale ranging from "I don't work near other people (beyond 100 ft.)" to "Very close (near touching)." The value of Physical Activity and Personal Proximity for a given occupation is chosen as the maximum value across all questions under the metrics heading found in this table, and then is scaled to lie within the unit interval.

Table D.2. Teleworking by STEM Status and Remote Work Index

| Sample: | Full Sample | College-Educated | Non-College-Educated | STEM | College-Educated STEM |
|---|---|---|---|---|---|
| *Panel A. Telework (Conditional on Employed)* | | | | | |
| STEM | 0.0869*** | 0.0408* | 0.197*** | | |
| | (0.0164) | (0.0186) | (0.0374) | | |
| STEM x (Dec-Jun 2021) | 0.0628** | 0.0917*** | -0.0538 | | |
| | (0.0195) | (0.0224) | (0.0438) | | |
| RWI | 0.485*** | 0.467*** | 0.465*** | 0.168$^{+}$ | 0.197* |
| | (0.0230) | (0.0327) | (0.0330) | (0.0904) | (0.0971) |
| RWI x (Dec-Jun 2021) | -0.0674* | 0.0184 | -0.162*** | 0.261* | 0.203$^{+}$ |
| | (0.0273) | (0.0399) | (0.0379) | (0.113) | (0.123) |
| Essential | -0.117*** | -0.244*** | -0.00343 | -0.136 | -0.0200 |
| | (0.0132) | (0.0215) | (0.0161) | (0.136) | (0.146) |
| Essential x (Dec-Jun 2021) | 0.119*** | 0.214*** | 0.0288 | 0.0338 | -0.0145 |
| | (0.0154) | (0.0260) | (0.0178) | (0.173) | (0.185) |
| $R^2$ | 0.289 | 0.221 | 0.148 | 0.203 | 0.167 |
| $N$ | 72148 | 33570 | 38578 | 6223 | 4892 |
| *Panel B. Unable to Work Because Employer Lost Business ("Lost Work")* | | | | | |
| STEM | -0.0819*** | -0.0655*** | -0.104*** | | |
| | (0.0107) | (0.0116) | (0.0268) | | |
| STEM x (Dec-Jun 2021) | 0.0623*** | 0.0463*** | 0.0928*** | | |
| | (0.0113) | (0.0122) | (0.0279) | | |
| RWI | -0.228*** | -0.207*** | -0.243*** | -0.133** | -0.101* |
| | (0.0186) | (0.0247) | (0.0291) | (0.0467) | (0.0460) |
| RWI x (Dec-Jun 2021) | 0.174*** | 0.142*** | 0.201*** | 0.0811$^{+}$ | 0.0549 |
| | (0.0197) | (0.0263) | (0.0309) | (0.0488) | (0.0505) |
| Essential | -0.205*** | -0.138*** | -0.255*** | 0.0906 | 0.129 |
| | (0.0126) | (0.0178) | (0.0175) | (0.0780) | (0.0802) |
| Essential x (Dec-Jun 2021) | 0.144*** | 0.0853*** | 0.187*** | -0.0840 | -0.137 |
| | (0.0133) | (0.0188) | (0.0186) | (0.0869) | (0.0885) |
| $R^2$ | 0.118 | 0.0911 | 0.136 | 0.0752 | 0.0808 |
| $N$ | 83120 | 36980 | 46140 | 6665 | 5175 |
| *Demographics-by-Pandemic* | Yes | Yes | Yes | Yes | Yes |
| *Educational Attainment-by-Pandemic* | Yes | Yes | Yes | Yes | Yes |
| *Location-by-Pandemic* | Yes | Yes | Yes | Yes | Yes |
| *RWI- & Essential Job-by-Pandemic* | Yes | Yes | Yes | Yes | Yes |
| *Education Requirement-by-Pandemic* | Yes | Yes | Yes | Yes | Yes |

*Notes:* See notes to Table 2 and see Section 2.2 for the definition of each set of controls. Sample includes individuals from our analytical sample who are observed in May 2020, June 2020, and December 2020 through June 2021. The dependent variable in Panel A is an indicator variable for if the CPS respondent reported that they had teleworked or worked from home in the last four weeks due to the COVID-19 pandemic. The dependent variable in Panel B is an indicator variable for if the CPS respondent reported that they were unable to work at any time during the last four weeks because their employer had lost business or closed due to the COVID-19 pandemic. Control sets not listed are excluded from all regressions. Robust standard errors clustered at individual-level are in parentheses. Regressions are weighted using CPS basic monthly weights. $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

# E Decomposition Method Details

## E.1 Method for Decomposing Group Differences at a Point in Time

The standard Oaxaca-Blinder decomposition for two groups $A$ and $B$ takes the following specification as given:

$$y_i^G = X_i \beta^G + \varepsilon_i^G, \quad G \in \{A, B\}, \tag{7}$$

where $y_i^G$ is the outcome for individual $i$ in group $G$, $X_i$ is a vector of explanatory variables determining the outcome for individuals of either group, $\beta^G$ is a vector of group-specific coefficients, and $E(\varepsilon_i^G) = 0$.[83] The goal is to decompose the difference in the mean of the outcome variable across two groups. After suppressing the individual index $i$, the difference in the mean outcomes between the two groups can be written as:

$$\begin{aligned} E(y^A) - E(y^B) &= E(X^A)\beta^A - E(X^B)\beta^B \\ &= \underbrace{\left[E(X^A) - E(X^B)\right]\beta^*}_{Explained} + \underbrace{E(X^A)\left[\beta^A - \beta^*\right] + E(X^B)\left[\beta^* - \beta^B\right]}_{Unexplained}, \end{aligned} \tag{8}$$

where $\beta^*$ is a reference coefficient vector.[84] We can estimate (8) by its sample analog where $\beta^*$ is estimated by the OLS estimates $\hat{\beta}^P$ from a pooled regression over both groups and $\beta_A$ and $\beta_B$ are estimated by OLS estimates from the group regressions given in (7):

$$\overline{y}^A - \overline{y}^B = \underbrace{\left[\overline{X}^A - \overline{X}^B\right]\hat{\beta}^P}_{Explained} + \underbrace{\overline{X}^A\left[\hat{\beta}^A - \hat{\beta}^P\right] + \overline{X}^B\left[\hat{\beta}^P - \hat{\beta}^B\right]}_{Unexplained},$$

where the "explained" part of this two-fold decomposition gives the magnitude of the mean differences in the outcome ($\overline{y}^A - \overline{y}^B$) explained by mean differences in the control variables each weighted by its marginal effect on the outcome of interest in a pooled regression over both groups.

Fortin, Lemieux, and Firpo (2011) note that an alternative measure of unexplained mean differences in outcomes between groups $A$ and $B$ can be given by the coefficient $\alpha_1$ on the group membership indicator in the following pooled specification:

$$E(y_i | X_i, D_{Bi}) = \alpha_0 + \alpha_1 D_{Bi} + X_i \beta^{**}, \tag{9}$$

[83] See Fortin, Lemieux, and Firpo (2011) for a detailed discussion of Oaxaca-Blinder and related decompositions.

[84] A reference coefficient vector is used so that the magnitude of the explained part of the decomposition is invariant to the specification of the base group. That is, if we decompose by taking $E(y^B) - E(y^A)$, instead, the explained part is given by $[E(X^B) - E(X^A)]\beta^* = -[E(X^A) - E(X^B)]\beta^*$. See Jann (2008) and Fortin, Lemieux, and Firpo (2011) for further discussion.

where $D_{Bi} = 1$ if individual $i$ belongs to the base group $B$ and $\beta^{**}$ is a vector of the group-invariant coefficients on the controls in $X_i$. This follows because (9) implies:

$$E(y_i|X_i, D_{Bi} = 1) - E(y_i|X_i, D_{Bi} = 0) = \underbrace{\left[E(X_i|D_{Bi} = 1) - E(X_i|D_{Bi} = 0)\right]\beta^{**}}_{Explained} + \alpha_1. \tag{10}$$

Fortin, Lemieux, and Firpo (2011) refer to this as a "regression-compatible" approach as it relies on assumptions that are common to a typical regression analysis where a group indicator variable is deemed sufficient to control for mean differences between groups unexplained by other factors and thus other factors are assumed to impact the outcomes of each group in the same way (as opposed to including interactions between these other factors and the group indicator to allow for group-specific effects). The explained part of the decomposition can be broken down into the portion explained by different subsets of controls. For example, partitioning the control set into $K$ categories, we can rewrite the explained part of the decomposition as:

$$\left[E(X_i|D_{Bi} = 1) - E(X_i|D_{Bi} = 0)\right]\beta^{**} = \sum_{k=1}^{K} \left[E(X_i^k|D_{Bi} = 1) - E(X_i^k|D_{Bi} = 0)\right]\beta^{**,k}, \tag{11}$$

where $X_i^k$ are the subset of controls included in partition $k$ and $\beta^{**,k}$ are the corresponding coefficients.

We utilize the regression-compatible approach given by (10) to decompose the mean differences in the labor market outcomes (employment, labor force participation, logarithm of work hours) between STEM and non-STEM workers in our analytical sample separately for two time periods: 1) the pre-pandemic period and 2) the first full quarter of the pandemic (April 2020 through June 2020) and three groups: 1) all workers, 2) college-educated (or above) workers, and 3) non-college-educated workers. To do this, we restrict our sample to the relevant time period and subsample and utilize the sample analog of (10) given by:

$$\overline{y}^{STEM} - \overline{y}^{NonSTEM} = \underbrace{\left[\overline{X}^{STEM} - \overline{X}^{NonSTEM}\right]\hat{\beta}^{P}}_{Explained} + \hat{\alpha_1}, \tag{12}$$

where $\hat{\alpha_1}$ is the OLS estimate of the coefficient on the STEM indicator when including controls in regression results reported in Table 2.[85] We also include a detailed decomposition by breaking down the explained part based on different groupings of control variables by utilizing the sample

[85]Interactions of controls with the pandemic indicators are naturally excluded since we estimate separate decompositions for the pre-pandemic and early pandemic period (i.e., there is no variability in the pandemic indicators within either period.)

analog of (11):

$$\left[\overline{X}^{STEM} - \overline{X}^{NonSTEM}\right]\hat{\beta}^{P} = \sum_{k=1}^{K}\left[\overline{X}^{STEM,k} - \overline{X}^{NonSTEM,k}\right]\hat{\beta}^{P,k}. \tag{13}$$

## E.2 Method for Decomposing Changes in Group Differences Over Time

For each group (all workers, college-educated workers, and non-college-educated workers), we carry out separate two-fold regression-compatible pooled Oaxaca-Blinder decompositions for two time periods: pre-pandemic and the first full quarter of the pandemic (April 2020 through June 2020).[86] Each time period's two-fold decomposition utilizes period-specific coefficients from a pooled regression, which is consistent with our regression approach above wherein we allowed the impact of our controls to vary over time (e.g., by controlling for demographic variables and their interactions with the pandemic time period indicators). We note that simply estimating a decomposition for the first quarter of the pandemic is not sufficient to decompose the effect of the COVID-19 recession on labor market outcomes during this period; this is because STEM workers also had an advantage in these outcomes before the COVID-19 pandemic, and so such a decomposition will be contaminated by decomposing the already extant difference in outcomes alongside period-specific differences brought on by the pandemic. To get at the decomposition of the effect unique to the first quarter of the pandemic, we utilize the "simple subtraction method" (SSM) which subtracts the decomposition for the pre-pandemic period ($\tau - 1$) from the decomposition for the first quarter of the pandemic ($\tau$).[87]

Denote $\Delta\overline{y}_{\tau} \equiv \left[\overline{y}_{\tau}^{STEM} - \overline{y}_{\tau}^{NonSTEM}\right]$ and $\Delta\overline{X}_{\tau} \equiv \left[\overline{X}_{\tau}^{STEM} - \overline{X}_{\tau}^{NonSTEM}\right]$. Then (12) implies that the change in differences between STEM and non-STEM labor market outcomes over time can be decomposed as:

$$\begin{aligned}\Delta\overline{y}_{\tau} - \Delta\overline{y}_{\tau-1} &= \left[\Delta\overline{X}_{\tau}\hat{\beta}_{\tau}^{P} + \hat{\alpha}_{1,\tau}\right] - \left[\Delta\overline{X}_{\tau-1}\hat{\beta}_{\tau-1}^{P} + \hat{\alpha}_{1,\tau-1}\right] \\ &= \underbrace{\left[\Delta\overline{X}_{\tau}\hat{\beta}_{\tau}^{P} - \Delta\overline{X}_{\tau-1}\hat{\beta}_{\tau-1}^{P}\right]}_{Explained} + \underbrace{\Delta\hat{\alpha}_{1}}_{Unexplained},\end{aligned} \tag{14}$$

where $\Delta\hat{\alpha}_1 \equiv [\hat{\alpha}_{1,\tau} - \hat{\alpha}_{1,\tau-1}]$ gives the change in the labor market advantage of STEM workers unexplained by other factors and corresponds to the coefficient $\hat{\delta}_1$ on STEM*Pandemic (Apr-Jun 2020) in our original regression specification (2) but where we exclude observations for after June 2020 from our analytical sample. Note that the explained part of (14) depends both on changes in the mean "endowments" of characteristics over time for each group and changes in the coefficients/returns associated with each of these characteristics. Table 1 shows that there is not much change in the characteristics of STEM and non-STEM workers in our analytical sample, which is

[86] Decompositions are estimated by the Stata package `oaxaca` using the `pooled` option (Jann, 2008).
[87] See Kröger and Hartmann (2021) for a discussion of this and related methods.

because we restrict our sample to a consistent sample of individuals who are observed both during and before the pandemic. Thus, differences in the returns to characteristics before and during the pandemic will be the driving force behind the explained part of (14) in our application.[88]

Following (13), we can further decompose the portion of the effect of the COVID-19 pandemic on differences in labor market outcomes between STEM and non-STEM workers among $K$ groups/partitions of controls as:

$$\Delta\overline{X}_{\tau}\hat{\beta}_{\tau}^{P} - \Delta\overline{X}_{\tau-1}\hat{\beta}_{\tau-1}^{P} = \sum_{k=1}^{K}\left[\Delta\overline{X}_{\tau}^{k}\hat{\beta}_{\tau}^{P,k} - \Delta\overline{X}_{\tau-1}^{k}\hat{\beta}_{\tau-1}^{P,k}\right]. \tag{15}$$

For clarity, consider two groups of controls: remote work feasibility and demographics, and suppose employment is the outcome of interest in the sample of all workers. Suppose the remote work feasibility group includes our Remote Work Index (RWI) as the only control in the group; then, the Oaxaca-Blinder coefficient on this single control will quite clearly represent the coefficient associated with the remote work feasibility group. Suppose demographics, on the other hand, is comprised of many controls. Then the Oaxaca-Blinder coefficient on this set of controls is the sum of the coefficients of all the individual controls within the group.

The percentage of the change in the gap in labor market outcomes between STEM and non-STEM workers explained by the full set of controls is calculated as $[(\Delta\overline{X}_{\tau}\hat{\beta}_{\tau}^{P} - \Delta\overline{X}_{\tau-1}\hat{\beta}_{\tau-1}^{P})/(\Delta\overline{y}_{\tau} - \Delta\overline{y}_{\tau-1})] * 100\%$ and the unexplained percentage is calculated as $[\Delta\hat{\alpha}_1/(\Delta\overline{y}_{\tau} - \Delta\overline{y}_{\tau-1})] * 100\%$ where the explained and unexplained percentage sum to 100%. The percentage of the change in the gap in labor market outcomes between STEM and non-STEM workers explained by controls in group $k$ is calculated as $[(\Delta\overline{X}_{\tau}^{k}\hat{\beta}_{\tau}^{P,k} - \Delta\overline{X}_{\tau-1}^{k}\hat{\beta}_{\tau-1}^{P,k})/(\Delta\overline{y}_{\tau} - \Delta\overline{y}_{\tau-1})] * 100\%$. Note that the explained percentage will exceed 100% (and the unexplained percentage will be negative) in cases where, after including all controls, the STEM advantage in outcomes disappears and is replaced with a STEM *disadvantage* in outcomes.[89] Additionally, the portion of the difference in outcomes explained by some groups of variables can be negative when, after controlling for such variables, the STEM advantage in outcomes increases.[90]

[88] This allays concerns with the simple subtraction method raised by Kim (2010).

[89] Such is the case when examining the differences in labor force participation between STEM and non-STEM non-college-educated workers that emerged during the first full quarter of the pandemic. Panel C of Table 2 shows that, without controls, STEM workers fared better than non-STEM workers during April 2020 through June 2020, but that after adding our full set of controls in Table 2, the coefficient on STEM*Pandemic (Apr-Jun 2020) is negative.

[90] Such is the case when controlling for the share of workers in one's occupation employed in essential industries; since non-STEM workers are more likely to be employed in essential industries, and since workers in essential industries tend to do better in terms of labor market outcomes, conditioning on this variable increases the STEM advantage in labor market outcomes.

## F Decomposition Results for Labor Force Participation and Work Hours

**Labor Force Participation** In Table F.1, Panel A and Panel B show that STEM workers held a 2.5 and 4.4 percentage point advantage over non-STEM workers in terms of labor force participation during the pre-pandemic period and early pandemic period, respectively, representing a 1.8 percentage-point increase in the STEM vs. non-STEM differential in labor force participation.[91] Panel B shows that our full set of covariates explains 109.4% of the increase in the STEM vs. non-STEM differential. Panel C shows that the most important factor in explaining the pandemic-driven increase in the STEM vs. non-STEM differential is remote work feasibility (50.3%), followed by industry (31.0%), demographics (26.3%), non-routine and cognitive task intensity of work (20.6%), STEM knowledge on the job (13.9%), and educational attainment (13.4%).

Table F.2 presents decomposition results for the college-educated and non-college-educated subsamples. Panel B shows that the full set of controls explains 282.6% of the change in the STEM vs. non-STEM differential in labor force participation, among college-educated and non-college-educated workers, respectively. Panel C shows that among college-educated workers, STEM knowledge on the job (176.7%) is the overwhelming factor in explaining the change in the STEM vs. non-STEM differential in labor force participation, followed by industry (56.4%) and remote work feasibility (52.7%), while among non-college-educated workers, demographics (73.8%) and remote work feasibility (50.6%) are the leading factors.[92] For both college-educated and non-college-educated workers, education requirements for the job has a smaller effect in explaining the STEM vs non-STEM differential in the pandemic period compared to the pre-pandemic period. Among college-educated workers, STEM knowledge on the job has a larger effect, while among non-college-educated workers, STEM knowledge on the job has a smaller effect, in explaining the STEM vs. non-STEM differential in the pandemic period compared to the pre-pandemic period.

**Work Hours** In Table F.3, Panel A and Panel B show that STEM workers held a 4.9% and 11.5% advantage over non-STEM workers in terms of work hours during the pre-pandemic period and early pandemic period, respectively,[93] and the STEM vs. non-STEM differential in work hours increased by 6.6% from the pre-pandemic period to the early pandemic period.[94] Panel B shows that the full set of covariates explains 69.7% of the increase in the STEM vs. non-STEM

[91] This corresponds to the coefficient estimate on *STEM*Pandemic (Apr-Jun 2020)* in the first column of Table 2 Panel B.

[92] Figure G.1 shows that, among non-college-educated workers, women with children, nonmarried persons, Blacks, and foreign-born workers were hit the hardest in terms of labor force participation during the early pandemic period, whereas only Asians experienced additional labor force participation reductions among the college-educated.

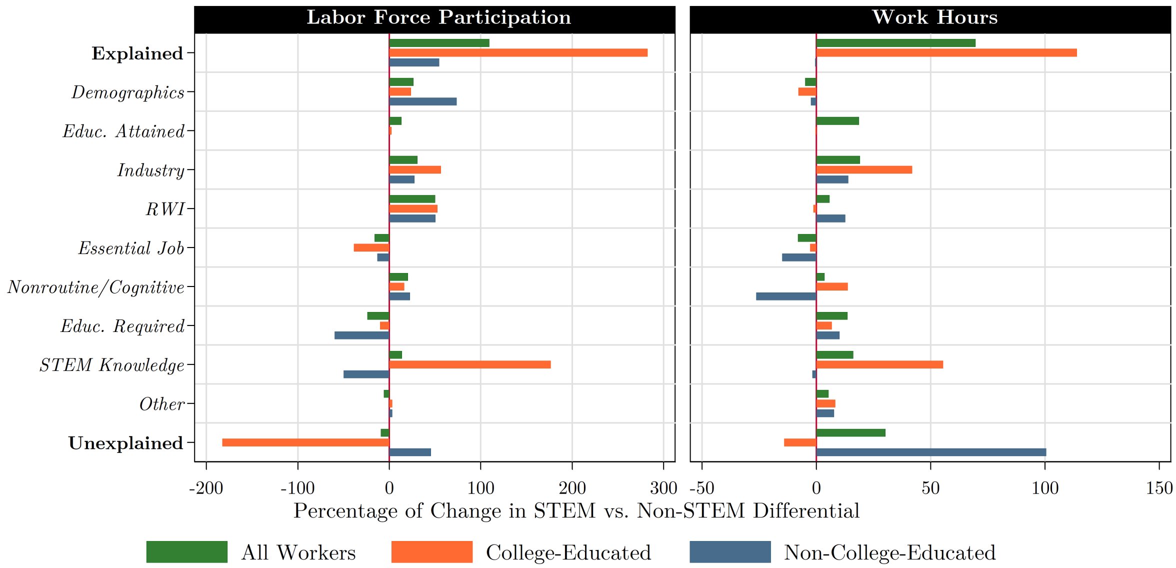
[93] These percentage differences are approximations based on $d\log(x) = dx/x$. The exact work hours advantage of STEM over non-STEM workers can be calculated as 5.0% and 12.2% in the pre-pandemic period and pandemic period, respectively.

[94] This corresponds to the coefficient estimate on *STEM*Pandemic (Apr-Jun 2020)* in the first column of Table 2 Panel C.

differential. Panel C shows that the main factors explaining the pandemic-driven increase in the STEM vs. non-STEM differential are industry (19.2%), educational attainment (18.7%), STEM knowledge on the job (16.2%), and education requirements for the job (13.7%).

Table F.4 presents decomposition results for the college-educated and non-college-educated subsamples. Panel B shows that the full set of covariates explains 114.0% of the change in the STEM vs. non-STEM differential in work hours among college-educated workers and explains none (-0.01%) of the change in the STEM vs. non-STEM differential among non-college-educated workers. Panel C shows that among college-educated workers, STEM knowledge on the job (55.4%) is the leading factor in explaining the change in the STEM vs. non-STEM differential in work hours, followed by industry (41.9%) and non-routine and cognitive task intensity of work (13.8%).

Figure F.1. Decomposition of the Relative Resiliency of STEM over Non-STEM Labor Force Participation and Work Hours at the Trough of the COVID-19 Recession into the Percentage Explained by Each Mechanism




*Notes*: This figure gives the decomposition results for the impact of the pandemic on the labor force participation and work hours gap between STEM and non-STEM workers during the first quarter of the pandemic (April 2020 through June 2020). It is the graphical representation of the Oaxaca-Blinder decomposition estimates reported in the fourth columns of Table F.1 and Table F.3 and the fourth and eighth columns of Table F.2 and Table F.4 which are expressed as percentages of the change in the total difference (explained + unexplained) in the labor force participation (work hours) between STEM and non-STEM workers after the onset of the pandemic. Oaxaca-Blinder decompositions estimated using Stata package `oaxaca` using the `pooled` option (Jann, 2008). "Demographics" includes all controls listed in Table 1 between and including "Age" and "Disability Status." "Educ. Attained" includes the highest degree obtained my the worker. "Industry" includes industry fixed effects. "RWI" includes only the remote work index and "Essential Job" includes only the share of workers in one's occupation working in essential industries. "Nonroutine/Cognitive" includes standardized variables for the degree to which a worker's occupation entails routine cognitive, routine manual, non-routine cognitive-analytical, non-routine cognitive-interpersonal, and non-routine manual-physical tasks. "Educ. Required" includes indicators for the typical minimum education required for the worker's occupation. "STEM Knowledge" includes standardized variables for the degree to which the following six types of STEM knowledge is important to a worker's occupation: 1) Computer knowledge, 2) Engineering knowledge, 3) Mathematics knowledge, 4) Physics knowledge, 5) Chemistry knowledge, and 6) Biology knowledge. "Other" includes whether employer is a large firm (over 500 employees), location, the measures of COVID-19 cases and deaths included in Table 1, and month and survey group indicators.

Table F.1. Decomposition of the Relative Resiliency of STEM over Non-STEM Labor Force Participation At the Trough of the COVID-19 Recession

| Sample: | All Workers | | | |
|---|---|---|---|---|
| | Pre-Pandemic | Pandemic | Difference | Share |
| *Panel A. Mean Labor Force Participation Rates* | | | | |
| STEM | 0.978 | 0.957 | -0.021 | |
| Non-STEM | 0.953 | 0.914 | -0.039 | |
| Difference | 0.025 | 0.044 | 0.018 | 1.000 |
| *Panel B. Overall Decomposition* | | | | |
| Explained | 0.043*** | 0.063*** | 0.020 | 1.094 |
| | (0.005) | (0.008) | | |
| Unexplained | -0.018*** | -0.019* | -0.002 | -0.094 |
| | (0.005) | (0.009) | | |
| *Panel C. Detailed Decomposition* | | | | |
| Demographics | 0.008*** | 0.013*** | 0.005 | 0.263 |
| | (0.001) | (0.002) | | |
| Educ. Attained | 0.000 | 0.003 | 0.002 | 0.134 |
| | (0.001) | (0.002) | | |
| Industry | 0.004* | 0.010** | 0.006 | 0.310 |
| | (0.002) | (0.003) | | |
| RWI | 0.003 | 0.012*** | 0.009 | 0.503 |
| | (0.002) | (0.003) | | |
| Essential Job | -0.001 | -0.004** | -0.003 | -0.160 |
| | (0.001) | (0.001) | | |
| Routine/Cognitive | 0.000 | 0.004 | 0.004 | 0.206 |
| | (0.004) | (0.006) | | |
| Educ. Required | 0.005* | 0.001 | -0.004 | -0.240 |
| | (0.002) | (0.004) | | |
| STEM Knowledge | 0.021*** | 0.024** | 0.003 | 0.139 |
| | (0.005) | (0.008) | | |
| Other | 0.002* | 0.000 | -0.001 | -0.061 |
| | (0.001) | (0.001) | | |
| *N* | 117814 | 52460 | | |

*Notes:* "Pre-pandemic" and "Pandemic" columns give results from two-fold regression-compatible pooled Oaxaca-Blinder decompositions of the difference in labor force participation between STEM and non-STEM workers in our analytical sample during the relevant period. Pandemic period only includes data for April 2020 through June 2020. "Difference" reports the difference between the decompositions in order to decompose the change in the gap in labor force participation between STEM and non-STEM workers that emerged after the onset of the pandemic. "Share" represents the share of the total change in the gap (explained + unexplained) in labor force participation between STEM and non-STEM workers. Oaxaca-Blinder decompositions estimated using Stata package `oaxaca` using the `pooled` option (Jann, 2008). Robust standard errors clustered at individual-level are in parentheses. "Demographics" includes all controls listed in Table 1 between and including "Age" and "Disability Status" (where age forms the basis of a quartic polynomial in potential experience). "RWI" includes only the remote work index, "Essential" includes only the share of workers in one's occupation working in essential industries. "Routine/Cognitive Task Intensities" includes standardized variables for the degree to which a worker's occupation entails routine cognitive, routine manual, non-routine cognitive-analytical, non-routine cognitive-interpersonal, and non-routine manual-physical tasks. "STEM Knowledge" includes standardized variables for the degree to which the following six types of STEM knowledge is important to a worker's occupation: 1) Computer knowledge, 2) Engineering knowledge, 3) Mathematics knowledge, 4) Physics knowledge, 5) Chemistry knowledge, and 6) Biology knowledge. "Industry" includes industry fixed effects. "Other" includes whether employer is a big firm (over 500 employees), location, the measures of COVID-19 cases and deaths included in Table 1, and month and survey group indicators. $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table F.2. Decomposition of the Relative Resiliency of STEM over Non-STEM Labor Force Participation at the Trough of the COVID-19 Recession, by Educational Attainment

| Sample: | College-Educated Workers | | | | Non-College-Educated Workers | | | |
|---|---|---|---|---|---|---|---|---|
| | Pre-Pandemic | Pandemic | Diff. | Share | Pre-Pandemic | Pandemic | Diff. | Share |
| *Panel A. Mean Labor Force Participation Rates* | | | | | | | | |
| STEM | 0.981 | 0.962 | -0.019 | | 0.971 | 0.939 | -0.031 | |
| Non-STEM | 0.964 | 0.937 | -0.027 | | 0.946 | 0.898 | -0.048 | |
| Difference | 0.016 | 0.025 | 0.008 | 1.000 | 0.025 | 0.042 | 0.016 | 1.000 |
| *Panel B. Overall Decomposition* | | | | | | | | |
| Explained | 0.022*** | 0.045*** | 0.023 | 2.826 | 0.061*** | 0.069*** | 0.009 | 0.545 |
| | (0.006) | (0.009) | | | (0.008) | (0.014) | | |
| Unexplained | -0.005 | -0.020+ | -0.015 | -1.826 | -0.035*** | -0.028 | 0.007 | 0.455 |
| | (0.006) | (0.010) | | | (0.010) | (0.017) | | |
| *Panel C. Detailed Decomposition* | | | | | | | | |
| Demographics | 0.005*** | 0.007** | 0.002 | 0.237 | 0.009*** | 0.021*** | 0.012 | 0.738 |
| | (0.001) | (0.002) | | | (0.002) | (0.003) | | |
| Educ. Attained | 0.000+ | 0.000+ | 0.000 | 0.024 | 0.000 | 0.000 | 0.000 | 0.000 |
| | (0.000) | (0.000) | | | | | | |
| Industry | 0.002 | 0.007+ | 0.005 | 0.564 | 0.007* | 0.012+ | 0.004 | 0.275 |
| | (0.002) | (0.004) | | | (0.003) | (0.007) | | |
| RWI | 0.001 | 0.005 | 0.004 | 0.527 | 0.007* | 0.015** | 0.008 | 0.506 |
| | (0.002) | (0.003) | | | (0.003) | (0.005) | | |
| Essential Job | -0.001 | -0.004** | -0.003 | -0.387 | -0.001 | -0.004 | -0.002 | -0.132 |
| | (0.001) | (0.001) | | | (0.001) | (0.002) | | |
| Routine/Cognitive | -0.003 | -0.001 | 0.001 | 0.163 | 0.001 | 0.005 | 0.004 | 0.226 |
| | (0.004) | (0.006) | | | (0.006) | (0.011) | | |
| Educ. Required | 0.005** | 0.004 | -0.001 | -0.101 | 0.002 | -0.008 | -0.010 | -0.599 |
| | (0.002) | (0.003) | | | (0.004) | (0.006) | | |
| STEM Knowledge | 0.011+ | 0.026** | 0.014 | 1.767 | 0.034*** | 0.026* | -0.008 | -0.500 |
| | (0.007) | (0.010) | | | (0.007) | (0.013) | | |
| Other | 0.001* | 0.002 | 0.000 | 0.031 | 0.002+ | 0.003 | 0.001 | 0.032 |
| | (0.001) | (0.001) | | | (0.001) | (0.002) | | |
| N | 50346 | 22822 | | | 67468 | 29638 | | |

*Notes:* "Pre-pandemic" and "Pandemic" columns give results from two-fold regression-compatible pooled Oaxaca-Blinder decompositions of the difference in labor force participation between STEM and non-STEM workers in our analytical sample during the relevant period. Pandemic period only includes data for April 2020 through June 2020. "Difference" reports the difference between the decompositions in order to decompose the change in the gap in labor force participation between STEM and non-STEM workers that emerged after the onset of the pandemic. "Share" represents the share of the total change in the gap (explained + unexplained) in labor force participation between STEM and non-STEM workers. Oaxaca-Blinder decompositions estimated using Stata package `oaxaca` using the `pooled` option (Jann, 2008). Robust standard errors clustered at individual-level are in parentheses. "Demographics" includes all controls listed in Table 1 between and including "Age" and "Disability Status" (where age forms the basis of a quartic polynomial in potential experience). "RWI" includes only the remote work index, "Essential" includes only the share of workers in one's occupation working in essential industries. "Routine/Cognitive Task Intensities" includes standardized variables for the degree to which a worker's occupation entails routine cognitive, routine manual, non-routine cognitive-analytical, non-routine cognitive-interpersonal, and non-routine manual-physical tasks. "STEM Knowledge" includes standardized variables for the degree to which the following six types of STEM knowledge is important to a worker's occupation: 1) Computer knowledge, 2) Engineering knowledge, 3) Mathematics knowledge, 4) Physics knowledge, 5) Chemistry knowledge, and 6) Biology knowledge. "Industry" includes industry fixed effects. "Other" includes whether employer is a big firm (over 500 employees), location, the measures of COVID-19 cases and deaths included in Table 1, and month and survey group indicators. $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table F.3. Decomposition of the Relative Resiliency of STEM over Non-STEM Work Hours at the Trough of the COVID-19 Recession

| Sample: | All Workers | | | |
|---|---|---|---|---|
| | Pre-Pandemic | Pandemic | Difference | Share |
| *Panel A. Mean Weekly Work Hours (log-units)* | | | | |
| STEM | 3.710 | 3.699 | -0.011 | |
| Non-STEM | 3.661 | 3.584 | -0.077 | |
| Difference | 0.049 | 0.115 | 0.066 | 1.000 |
| *Panel B. Overall Decomposition* | | | | |
| Explained | 0.100*** | 0.146*** | 0.046 | 0.697 |
| | (0.010) | (0.016) | | |
| Unexplained | -0.051*** | -0.031+ | 0.020 | 0.303 |
| | (0.011) | (0.018) | | |
| *Panel C. Detailed Decomposition* | | | | |
| Demographics | 0.025*** | 0.022*** | -0.003 | -0.049 |
| | (0.002) | (0.003) | | |
| Educ. Attained | 0.005* | 0.017*** | 0.012 | 0.187 |
| | (0.002) | (0.004) | | |
| Industry | 0.010* | 0.023*** | 0.013 | 0.192 |
| | (0.004) | (0.006) | | |
| RWI | 0.024*** | 0.027*** | 0.004 | 0.059 |
| | (0.004) | (0.006) | | |
| Essential Job | -0.010*** | -0.015*** | -0.005 | -0.081 |
| | (0.002) | (0.003) | | |
| Routine/Cognitive | -0.027*** | -0.024* | 0.002 | 0.037 |
| | (0.007) | (0.011) | | |
| Educ. Required | 0.004 | 0.013+ | 0.009 | 0.137 |
| | (0.004) | (0.007) | | |
| STEM Knowledge | 0.063*** | 0.074*** | 0.011 | 0.162 |
| | (0.009) | (0.015) | | |
| Other | 0.005*** | 0.009*** | 0.004 | 0.054 |
| | (0.001) | (0.002) | | |
| *N* | 94431 | 40340 | | |

*Notes:* "Pre-pandemic" and "Pandemic" columns give results from two-fold regression-compatible pooled Oaxaca-Blinder decompositions of the difference in log(work hours) between STEM and non-STEM workers in our analytical sample during the relevant period. Pandemic period only includes data for April 2020 through June 2020. "Difference" reports the difference between the decompositions in order to decompose the change in the gap in log(work hours) between STEM and non-STEM workers that emerged after the onset of the pandemic. "Share" represents the share of the total change in the gap (explained + unexplained) in log(work hours) between STEM and non-STEM workers. Oaxaca-Blinder decompositions estimated using Stata package `oaxaca` using the `pooled` option (Jann, 2008). Robust standard errors clustered at individual-level are in parentheses. "Demographics" includes all controls listed in Table 1 between and including "Age" and "Disability Status" (where age forms the basis of a quartic polynomial in potential experience). "RWI" includes only the remote work index, "Essential" includes only the share of workers in one's occupation working in essential industries. "Routine/Cognitive Task Intensities" includes standardized variables for the degree to which a worker's occupation entails routine cognitive, routine manual, non-routine cognitive-analytical, non-routine cognitive-interpersonal, and non-routine manual-physical tasks. "STEM Knowledge" includes standardized variables for the degree to which the following six types of STEM knowledge is important to a worker's occupation: 1) Computer knowledge, 2) Engineering knowledge, 3) Mathematics knowledge, 4) Physics knowledge, 5) Chemistry knowledge, and 6) Biology knowledge. "Industry" includes industry fixed effects. "Other" includes whether employer is a big firm (over 500 employees), location, the measures of COVID-19 cases and deaths included in Table 1, and month and survey group indicators. $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table F.4. Decomposition of the Relative Resiliency of STEM over Non-STEM Work Hours at the Trough of the COVID-19 Recession, by Educational Attainment

| Sample: | College-Educated Workers | | | | Non-College-Educated Workers | | | |
|---|---|---|---|---|---|---|---|---|
| | Pre-Pandemic | Pandemic | Diff. | Share | Pre-Pandemic | Pandemic | Diff. | Share |
| *Panel A. Mean Weekly Work Hours (log-units)* | | | | | | | | |
| STEM | 3.707 | 3.699 | -0.007 | | 3.720 | 3.698 | -0.023 | |
| Non-STEM | 3.674 | 3.614 | -0.060 | | 3.651 | 3.561 | -0.091 | |
| Difference | 0.033 | 0.085 | 0.052 | 1.000 | 0.069 | 0.137 | 0.068 | 1.000 |
| *Panel B. Overall Decomposition* | | | | | | | | |
| Explained | 0.098*** | 0.157*** | 0.059 | 1.140 | 0.081*** | 0.081** | -0.000 | -0.006 |
| | (0.014) | (0.020) | | | (0.016) | (0.028) | | |
| Unexplained | -0.064*** | -0.072** | -0.007 | -0.140 | -0.012 | 0.056+ | 0.068 | 1.006 |
| | (0.016) | (0.022) | | | (0.018) | (0.032) | | |
| *Panel C. Detailed Decomposition* | | | | | | | | |
| Demographics | 0.026*** | 0.022*** | -0.004 | -0.079 | 0.023*** | 0.022*** | -0.002 | -0.023 |
| | (0.003) | (0.004) | | | (0.004) | (0.005) | | |
| Educ. Attained | 0.002* | 0.002* | -0.000 | -0.004 | 0.000 | 0.000 | 0.000 | 0.000 |
| | (0.001) | (0.001) | | | | | | |
| Industry | 0.014** | 0.035*** | 0.022 | 0.419 | 0.007 | 0.016 | 0.009 | 0.139 |
| | (0.005) | (0.007) | | | (0.008) | (0.014) | | |
| RWI | 0.020*** | 0.019*** | -0.001 | -0.013 | 0.020*** | 0.029** | 0.009 | 0.127 |
| | (0.004) | (0.006) | | | (0.006) | (0.009) | | |
| Essential Job | -0.008*** | -0.009** | -0.001 | -0.027 | -0.013*** | -0.023*** | -0.010 | -0.149 |
| | (0.002) | (0.003) | | | (0.003) | (0.005) | | |
| Routine/Cognitive | -0.021** | -0.014 | 0.007 | 0.138 | -0.035** | -0.053** | -0.018 | -0.263 |
| | (0.008) | (0.011) | | | (0.011) | (0.020) | | |
| Educ. Required | 0.004 | 0.007 | 0.004 | 0.068 | -0.007 | -0.001 | 0.007 | 0.102 |
| | (0.003) | (0.005) | | | (0.007) | (0.013) | | |
| STEM Knowledge | 0.058*** | 0.087*** | 0.029 | 0.554 | 0.081*** | 0.080*** | -0.001 | -0.017 |
| | (0.014) | (0.021) | | | (0.013) | (0.024) | | |
| Other | 0.003* | 0.008** | 0.004 | 0.083 | 0.005* | 0.011* | 0.005 | 0.078 |
| | (0.002) | (0.003) | | | (0.003) | (0.005) | | |
| $N$ | 42910 | 19032 | | | 51521 | 21308 | | |

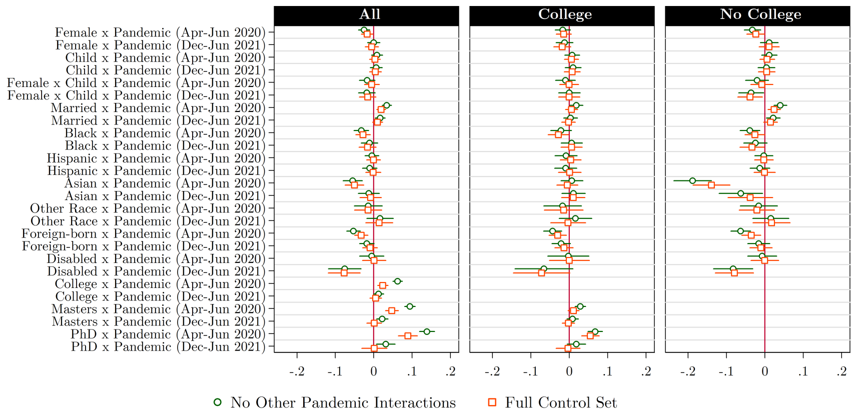
*Notes:* "Pre-pandemic" and "Pandemic" columns give results from two-fold regression-compatible pooled Oaxaca-Blinder decompositions of the difference in log(work hours) between STEM and non-STEM workers in our analytical sample during the relevant period. Pandemic period only includes data for April 2020 through June 2020. "Difference" reports the difference between the decompositions in order to decompose the change in the gap in log(work hours) between STEM and non-STEM workers that emerged after the onset of the pandemic. "Share" represents the share of the total change in the gap (explained + unexplained) in log(work hours) between STEM and non-STEM workers. Oaxaca-Blinder decompositions estimated using Stata package `oaxaca` using the `pooled` option (Jann, 2008). Robust standard errors clustered at individual-level are in parentheses. "Demographics" includes all controls listed in Table 1 between and including "Age" and "Disability Status" (where age forms the basis of a quartic polynomial in potential experience). "RWI" includes only the remote work index, "Essential" includes only the share of workers in one's occupation working in essential industries. "Routine/Cognitive Task Intensities" includes standardized variables for the degree to which a worker's occupation entails routine cognitive, routine manual, non-routine cognitive-analytical, non-routine cognitive-interpersonal, and non-routine manual-physical tasks. "STEM Knowledge" includes standardized variables for the degree to which the following six types of STEM knowledge is important to a worker's occupation: 1) Computer knowledge, 2) Engineering knowledge, 3) Mathematics knowledge, 4) Physics knowledge, 5) Chemistry knowledge, and 6) Biology knowledge. "Industry" includes industry fixed effects. "Other" includes whether employer is a big firm (over 500 employees), location, the measures of COVID-19 cases and deaths included in Table 1, and month and survey group indicators. $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

# G Demographic Disparities in the Impact of the Pandemic

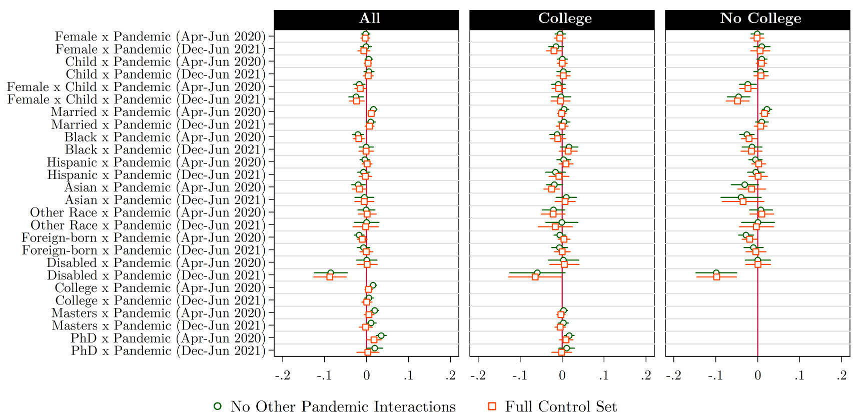
The extent to which COVID-19 has had disparate impacts on the employment of different demographic groups has received much attention. In Figure G.1 we plot estimated coefficients (and 95% confidence intervals) for demographic variables' interactions with the pandemic indicators corresponding to the full specification regressions reported in Table 2. The coefficient plots show that among non-college-educated workers the following groups experienced greater employment losses in the initial period of the pandemic: women, nonmarried persons, Blacks, Asians, and foreign-born persons. Among the college-educated, foreign-born workers and Blacks experienced greater employment losses, while those with doctoral degrees fared better in terms of employment in the initial period of the pandemic. Figure G.1 also shows that among the non-college-educated, women with children, nonmarried persons, Blacks, and foreign-born persons were more likely to drop out of the labor force, and among the college-educated, Asians were less likely to drop out of the labor force. Among all employed workers, nonmarried persons experienced a decrease in work hours, and among non-college-educated employed workers, foreign-born persons experienced a decrease in work hours while persons of other races experienced an increase in work hours. Our finding of greater employment losses for foreign-born workers is consistent with findings in Borjas and Cassidy (2020), and our finding of worse outcomes for women and minorities accords with other papers in the literature (e.g., Montenovo et al., 2020; Alon et al., 2021).

Figure G.1. Coefficient Plot for Demographics-by-Pandemic Effects

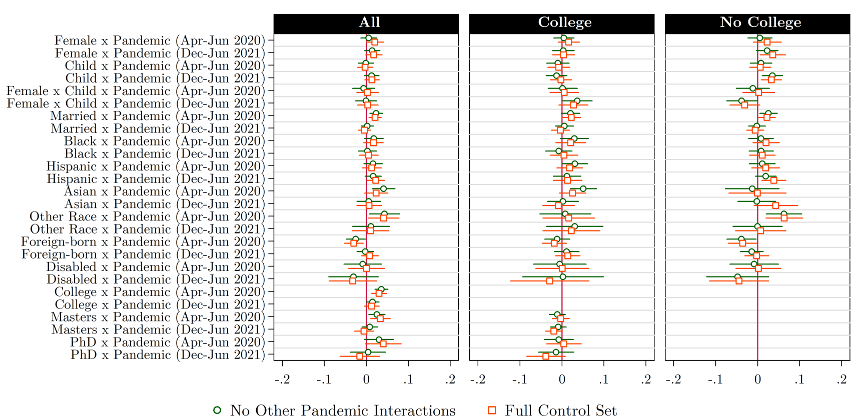
## A. Employment




## B. Labor Force Participation




## C. Work Hours




*Notes*: This figure plots the coefficient estimates and 95% confidence intervals for the demographic controls interacted with the pandemic indicator in the full specification regression results reported in Table 2. To provide a baseline for each estimate, we also plot estimates for a regression without any other controls interacted with pandemic, also excluding occupational characteristics such as STEM, RWI, and Essential from the specification. Robust standard errors are clustered at the person level.