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ABSTRACT

We study the effect of state reopening policies on a large set of labor market indicators through May 2020 to: (1) understand the recent increase in employment using longitudinal as well as cross-sectional data, (2) assess the likely trajectory of reemployment going forward, and (3) investigate the strength of job matches that were disrupted by COVID-19. Estimates from event studies and difference-in-difference regressions suggest that some of the recent increases in employment activity, as measured by cellphone data on work-related mobility, internet searches related to employment, and new and continuing unemployment insurance claims, were likely related to state reopenings, often predating actual reopening dates somewhat. We provide suggestive evidence that increases in employment stem from people returning to their prior jobs: reopenings are only weakly related to job postings, and longitudinal CPS data show that large shares of the unemployed-on-layoff and employed-but-absent in April who transitioned to employment in May remain in the same industry or occupation. Longitudinal CPS estimates further show declines in reemployment probabilities with time away from work. Taken together, these estimates suggest that employment relationships are durable in the short run, but raise concerns that employment gains requiring new employment matches may not be as rapid.

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1 Introduction

The May 2020 Employment Situation Summary showed that non-farm payroll employment rose by 2.5 million right after many states lifted their stay-at-home mandates and allowed certain non-essential businesses to reopen in a gradual manner (U.S. Bureau of Labor Statistics, 2020a). The small increase in employment is a welcome relief following the massive collapse in employment in March (fell by 701,000) and April (fell by 20.5 million), yet the May report was a surprise for most labor economists because the initial unemployment insurance claims data in the weeks leading up the May employment report did not seem to suggest a rebound.

In this paper, we study the dynamics of job loss and re-employment during the re-opening phase of the US response to the COVID-19 epidemic. Studying re-employment in the May Current Population Survey is critical for assessing the likely speed of recovery going forward and for learning about reemployment dynamics more generally.

We start by using high-frequency data to assess the ways in which American labor markets have started to re-open. Specifically, we use daily and weekly data to track work related physical mobility, employment related internet search activity, internet job postings, and unemployment insurance claims. In addition, we use data from multiple waves of the monthly basic Current Population Survey (CPS) to examine more conventional measures of labor market activity and to study the labor market transitions that occurred between April and May of 2020.

The paper is organized around three main questions. First, what can high-frequency labor market data tell us about the factors that are driving an improvement in the labor market and whether it is likely to continue? Second, how important were state policies related to re-opening in generating the increase in employment captured by the May CPS? Third, who was actually re-employed in May and what factors seemed to drive the increase. We form a longitudinal sample from the monthly CPS data in order to measure labor market transitions. This allows us to assess the extent to which people transitioned from unemployment to employment by finding new jobs vs by resuming their old jobs.

Estimates from event studies and difference-in-difference regressions suggest that the employment increases were likely related to state reopening policies. We find considerable evidence that the labor market response predates the policy response by roughly 5 days, which we tie to an announcement effect. Evidence from longitudinal CPS data and from job posting data suggests that most of the increase in employment came from people who resumed an existing employment relationship. Our evidence suggests that new hires may have played some role in the increase in employment, but are probably not the primary factor. Online job posting data from Burning Glass Technologies show that the return to work was associated with some increase in job postings, but the longitudinal CPS data show that most re-employed workers remain in the same occupation and industry as their previous job, suggesting that they returned to their previous employer.

We further show that reemployment probabilities decline dramatically with length of time unemployed, which suggests that worker-job matches may decline the longer they are apart. Thus, this analysis also provides a valuable window into the economics of the employment relationship. Traditional analyses of reemployment hazards focus on separating the causal effect of duration dependence, which gives the causal effect of time out of work on the probability of being reemployed, from the possibility of selection, as the distribution of unobserved characteristics may be different among the workers still not re-hired after a long time (i.e.if the most able workers get (re)hired first). Models of reemployment by the original employer must also address competing risks (e.g. of workers being hired by other employers).

Given that most rehiring appears in the May CPS to be by the original employers, at least initially, recovery from the COVID-19 pandemic will depend on the original employers' ability to resume business, and there is less scope for competing risks (i.e. of people being hired by other employers). To isolate the causal effect of duration, we would want to observe reemployment hazards for employers who reopen after different lengths of exogenously imposed closures (i.e. to be able to treat the length of closure as exogenous), which the current situation mimics to some extent. In the case of time / duration-varying heterogeneity, the concern is that the best workers will be reemployed in early phases, leaving the least attractive workers to be reemployed in later phases. Given the rapidity of employment reductions, the scope for time / duration-varying heterogeneity is likely to be small within most employers in the early phases. That problem is likely to become larger at later phases and there may well be differences across employers (e.g. if restaurants closed early, they may reopen later). Thus, the COVID-19 pandemic provides some opportunity to reduce confounding from time / duration-dependent heterogeneity and competing risks and partially isolate duration dependence, which is critical for understanding reemployment dynamics.

The large employment gains in the May report were surprising, in part, because of the the high level of initial UI claims in the weeks leading up to the May CPS. Our analysis helps to reconcile this difference by showing that there is still a tremendous amount of churn in labor markets (re-hiring and new unemployment happening at the same time). We make this point by looking at continuing UI claims and combining initial and continuing claims to generate a worker-based measure of gross employment flows. These show that many workers remain unemployed or became unemployed in May even as many others returned to work.

2 Related Research

The social science literature on COVID-19 and employment is evolving rapidly. Thus, an attempt at a literature review will likely be incomplete. However, this paper relates to several themes that have already emerged in other articles. One line of work examines the way in which the epidemic and social distancing policy responses have affected labor market outcomes overall, although none we are aware of have used matched CPS data through May to study reopenings. Lozano-Rojas et al. (2020) show that the historically unprecedented increase in initial unemployment claims in March 2020 was largely across the board, occurring in all states regardless of local epidemiological conditions or policy responses. Baek et al. (2020) come to a broadly similar conclusion with UI records, examining a longer time period. Campello et al. (2020) provide evidence on labor demand using job postings data from Linkup, although not as a function of state policy. They find that job postings decline about 2 weeks before the large rise in UI claims. They also find that job postings by small firms decline much more than job postings by large firms, that job postings decline more for high- than low-skilled jobs, and that job postings drop more in concentrated labor markets. Kahn et al. (2020) show a large drop in job vacancy postings in the second half of March. They report that, by early April, there were 30% fewer job postings than at the beginning of the year. These declines also largely happened across states, regardless of state policies or infection rates. While their primary focus is on expectations and consumer spending, Coibin et al. (2020) use custom data to show that lockdowns are related to worse labor markets, controlling for COVID-19 cases. Similar work is underway to analyze the economic effects of the epidemic in other countries (Adams-Prassl et al., 2020; Dasgupta and Murali, 2020; Rothwell and Van Drie, 2020).

Recent works study the effects of closures, but not reopenings, on particular sub-populations, often highlighting the role of job characteristics. We note there that reopenings and closures are likely to be asymmetric given the differences between terminating or freezing employment relationships and bringing workers back to work. Montenovo et al. (2020) study early labor market outcomes during the epidemic using CPS data from April 2020. They find high rates of recent unemployment that vary across groups, with particularly high job losses among younger workers, Hispanic workers, workers in non-essential industries, workers in jobs that are harder to perform remotely, and workers in jobs that require more face-to-face contact. Furthermore, they show a hump-shaped pattern in job losses by education. Dingel and Neiman (2020) and Mongey and Weinberg (2020) also study high work-from-home occupations. Leibovici et al. (2020) takes a similar approach to measure occupations with high interpersonal contact. Alon et al. (2020) find that the COVID-19 epidemic may have a larger economic effect on women than men, unlike in a "regular" recession. A number of researchers have sought to provide results at a higher frequency than the CPS. Blick and Blandin (2020) provide information on a number of demographic groups using data from the Real-Time Population Survey, which is conducted every other week. Cajner et al. (2020) use the payroll microdata from Automatic Data Processing, Inc (commonly known as ADP). Aaronson et al. (2020) build a forecasting model that uses Google searching activity for unemployment-related terms to predict weekly unemployment insurance claims, and find that unemployment insurance claims and Google searches for unemployment insurance both peak prior to stay-at-home orders. In this spirit, we draw on UI claims data as well as cell device mobility to workplaces in order to provide high-frequency information to augment our CPS analyses. However, note that Coibion et al. (2020) use data from an early-April household survey and find that unemployment rate may greatly exceed unemployment insurance claims.

Another line of work examines the effects of state and local social distancing policies on measures of mobility and interaction. Using cell phone data, Gupta et al. (2020) document a massive, nationwide decline in multiple measures of mobility outside the home. They also find evidence that early and information-focused state policies did lead to larger reductions in mobility. These reductions in time spent outside the home suggest that many people are experiencing work disruptions, and that those who can work remotely may be more able to maintain employment during the crisis.

This work relates as well to the large literature in labor and personnel economics of worker-firm relationships (e.g. Lazear and Oyer, 2013). At the macro level, in standard theory (e.g. Pissarides 2000), a matching function explains the relationship between the unemployment rates, hiring, and the job vacancy rates, such that when vacancies are low and unemployment is high, openings should be easier to fill. A rich empirical literature exists, due to availability of establishment- and firm-level matched data that enables the estimation of the individual and employer components of wages (eg Abowd and Kramarz 1999) and the hiring of new workers into vacancies (e.g. Davis et al 2013). Key insights from this literature that inform our work are that during and after the Great Recession, hiring fell faster in the recession and rose slower in recovery than standard models predict (Davis et al 2013) and that this can be reconciled with theory by taking into account that costs of creating vacancies are procyclical (Leduc and Liu, 2020).

This work relates as well to the large literature on the importance of worker-firm relationships and the consequences of disrupting productive job matches. For workers, sudden job losses have substantial negative long-term consequences on earnings (Jacobson et al., 1993), particularly during recessions (David and von Wachter, 2011; Farber, 2017). Recent evidence suggests earnings losses from job disruption are associated with loss of match-specific capital, which takes time to build (Lachowska et al., 2018). The process of forming and dissolving good job matches depends on costly search, and contributes both to the depth and dynamics of recession (Lise and Robin, 2017). The loss of productive workers is very costly to firms (Jäger and Heining, 2016) and they must go to great expense in replacing them (Friebel et al., 2019). Where typical recessions have a cleansing effect by targeting the least productive firms and jobs, the effects of the COVID-19 pandemic are largely unrelated to pre-pandemic productivity. Stabilization policies have therefore operated in part to preserve employment relationships both in the United States (Chetty et al., 2020) and abroad (Giupponi and Landais, 2018).

3 Data

3.1 State Activity Closure Data

We use data on state social distancing (closure) policies that were previously reported in Gupta et al. (2020). Basic information about the timing of state policy actions was originally collected by Washington University researchers (Fullman et al., 2020) and Boston University researchers (Raifman et al., 2020).

3.2 Reopening Policy Data

We use the timing of initial reopenings by state that were previously reported in Nguyen et al. (2020) (see Figure 1). We collected and coded data on state reopening policies, starting with the New York Times descriptions of each state's reopening policies and gathering additional information on the reopening schedules for each state through internet searches and states' guidance. South Carolina became the first state to reopen on April 20, 2020. All states took steps to reopen by June 1. We also tracked the date of official announcements by Governors regarding their detailed reopening plans. A typical state announces their detailed reopening plan about 4 days prior to the effective date of reopening (median).[1] This implementation period varies by state (the gap between orange and blue dots in Figure 1). We provide the information we have compiled from various sources on GitHub (https://github.com/nguyendieuthuy/ReOpeningPlans).

[1] There is one exception to this–in Illinois, the governor released a phased plan of reopenings on May 5, several days *after* the initial reopening on certain outdoor activities actually took place.

3.3 O*Net

The 2019 Occupational Information Network (O*Net) contains a module on characteristics of the Work Context, which reports summary measures of the tasks used in 968 (2010 SOC) occupations (O*NET National Center for O*NET Development (2020)). The data are gathered through surveys asking workers how often they perform particular tasks. This module is assembled by O*NET from survey questions asking workers about their need for face-to-face interaction with clients, customers, and co-workers. Other questions assess the reliance of each job on activities that could be performed remotely (i.e. from a worker's home). These measures are typically provided on a 1-5 scale, where 1 indicates that a task is performed rarely or is not important to the job, and 5 indicates that the task is performed regularly or is important to the job. Following Montenovo et al. (2020), we use indices of for face-to-face interactions and potential for remote work. We standardized these indices for the analysis. Montenovo et al. (2020) includes more details on how these indices are built.

3.4 Homeland Security Data on Essential Work

The U.S. Department of Homeland Security (DHS) issued guidance about critical infrastructure workers during the COVID-19 epidemic[2]. The DHS guidance outlines 14 categories that are defined as essential critical infrastructure sectors. We follow Blau et al. (2020)'s definition of essential industries, which matches the text descriptions to the NAICS 2017 four-digit industry classification from the U.S. Census Bureau[3], and to the CPS industry classification system. From the 287 industry categories at the four-digit level, 194 are identified as essential; these essential industries are found in 17 out of 20 NAICS sectors.

3.5 Weekly Initial Unemployment Insurance Claims

We also study the number of initial UI claims in each U.S. state, including Washington, DC, from the first week of 2019 to the week ending in May 30, 2020. We utilize the Department of Labor Weekly Claims Data (ETA 539), which provides state-by-week counts of the number of initial UI claims, as well as the number of continuing claims from prior weeks. The number of initial UI claims measures the total number of newly initiated claims in a given state/week, while the continuing weeks claimed is a number of all current claims in a state/week that were

[2]The list of critical infrastructure jobs is available at: https://www.cisa.gov/

[3]North American Industry Classification System. Available at https://www.census.gov/

initiated and certified in a previous week [4]. We focus on the number of new UI claims per covered worker, using the number of covered workers as of January 2020 as a fixed denominator to avoid changes in rates driven by changes in covered employment. Additionally, with this data we construct weekly outflows. This allows us to build a measure of net flows into the program, the difference between the number of people entering and exiting the program each week, assuming a 20% denial rate. This provides additional insight to the initial and continuing claims data. By estimating the net flows we can see the dynamics of claimants as they enter and exit the program.

3.6 Monthly Unemployment Insurance First Payment Delays

To get assess the timing of UI benefit provision we use the monthly first payment activity data (ETA 5159) and the monthly payment delay data (ETA 9050). While the ETA 5159 data provides a monthly count of total first payments made, the ETA 9050 provides the monthly count of those first payments that experienced a delay. These delayed cases are grouped by the number of weeks (1-11+) payments were delayed, with counts reported by the month in which the first payment was made (as opposed to when the claim was initiated). Given the attention paid to delays in the provision of unemployment insurance benefits, we use these data points to construct monthly measures of the amount of delay for first payments nationally and for states.

3.7 Work-Related Mobility Data

We extract work-related mobility from two cell signal aggregators: Google mobility and Safegraph. In the Google data, we use a day-by-state-level index of activity detected in work locations. In the Safegraph data, we focus on a state-by-day measure of the fraction of devices detected at locations that Safegraph has defined as likely to be the device owner's work location. The advantage of these data is that they are available at the daily level and provide a way for us to investigate whether employment followed a different trend in states

[4] Once a claim is filed it must go through a determination process (i.e. the acceptance/denial process). First, a monetary determination must be made on an initial claim. This process determines whether the claimant meets baseline wage and employment requirements for the program. Second, if the claimant's employer believes the claimant does not meet the separation requirements (i.e. that they quit their job or were fired for misconduct) they may begin a non-monetary determination process. If this happens, a claimant who met monetary requirements may still be denied (Anderson and Meyer, 2000; Vroman et al., 2017). We use monetary (ETA 218) and non-monetary determinations (ETA 207) data to estimate denial rates over the last decade, through the first quarter of 2020. Combined monetary and non-monetary separation denials create an overall denial rate for initial claims. This rate has been roughly 20% since 2015. Thus, we assume roughly 80% of all initial claims become certified and receive payment.

with early social distancing policies, a challenge in the CPS data given its monthly schedule. However, cell phone mobility data have not been widely used in labor economics research and their properties are not well understood. We view them as a proxy for time spent at a person's typical work location. These measures will not capture remote work, which has become more common during the epidemic. It is also likely that the quality of these measures could deteriorate when overall unemployment rates and job disruptions are high. After a protracted period of working from home or unemployment, many people will no longer have a meaningful, distinct workplace to serve as a reference point for work-related cell phone mobility measures. In the CPS, our concept of employment does not depend on whether it is done physically at a work location. Thus, we view the mobility data as supplementary to the CPS data.

3.8 Google Trends Data

We obtain information on day-by-state internet search behavior through the Google Trends API, which allows us to follow internet search queries across different terms, topics, and geographies, in a way that allows comparisons across time and place[5]. We pull data from queries related to unemployment and unemployment benefits as suggested in the Google Trends webpage and previously reported in Gupta et al. (2020) (see Figure 3). The final series represents the total number of searches across all search terms in a state per 10 million searches.

3.9 Job Vacancy Data

We use Burning Glass Technologies (BGT) data covering virtually all online job postings by US employers. BGT collects, cleans, and parses online job advertisements from approximately 40,000 job boards and websites (Deming and Kahn, 2018; Scrivner et al., 2020). We obtain weekly online job postings, by state, between June 22, 2019 and June 10, 2020. The job advertisements data is stratified by industry by state in this study. The measure is the number of weekly job postings per 100,000 state population.

3.10 Current Population Survey

We use data from the Basic Monthly CPS from January 2015 to May 2020, including all individuals aged 21 and above. There are between 76,000 and 97,000 observations per month.

[5] We access this using the *apiclient.discovery* package for Python and its function *getTimelinesForHealth*. For a thorough explanation of the different information available with Google Trends see www.medium.com

These surveys ask respondents about their labor market activities during a reference week that includes the 12th of the month (U.S. Census Bureau, 2019). Our primary measure of employment status is the share of the population that the CPS codes as being employed and at work. This measure excludes people who have a job but were temporarily absent[6]. Lozano-Rojas et al. (2020); Bogage (2020); Borden (2020) highlight the importance of properly coding people who are employed but absent for measuring employment status during the COVID-19 epidemic[7]. Given the importance that absence from work has gained during the epidemic, we also consider the outcome "Absent - Employed," which only includes those workers classified as absent from work but still employed during the Basic Monthly CPS.

In order to investigate factors associated with people's probability of reemployment, we create a longitudinal sample by matching respondents in the CPS from April to May in 2020. The matching scheme consists of two steps: First, we match individuals with identical household identifier and individual line number. Second, we delete matches where genders differ or ages differ by more than or equal to three years. For comparison, we also created two-period panels from March to April 2020 and from April to May in 2019. The matched samples cover 51,366 individuals from April to May 2020, 53,148 individuals from March to April 2020 and 61,581 individuals from April to May 2019.

4 Econometric Methods

We conduct three broad empirical analyses. First, we examine the connection between state reopening policies and labor markets using high frequency measures, including cell phone measures of work-related physical mobility,and Google trends data on work-related internet search activity. The cell phone and search data provide information at the day-by-state level. We use an event study model to analyze the immediate changes in work-related mobility around reopening events, defined as the announcement date so that we capture all anticipatory

[6]The CPS defines as "absent from job" all workers who were "temporarily absent from their regular jobs because of illness, vacation, bad weather, labor dispute, or various personal reasons, whether or not they were paid for the time off" (U.S. Census Bureau, 2019).

[7]First, some employers released workers intending to rehire them. Second, some workers may have requested leave from their schedule to provide dependent care or to care for a sick household member. Third, there was a misclassification problem during the data collection of the March and April 2020 CPS. Specifically, the BLS instructed surveyors to code those out of work due to the epidemic as recently laid off or unemployed, but U.S. Bureau of Labor Statistics (2020d), U.S. Bureau of Labor Statistics (2020b), U.S. Bureau of Labor Statistics (2020c) explain that surveyors appeared to code at least some of them in the employed-but-absent category. These factors contribute to a massive increase in the share of workers coded as "employed but absent" from work between February and April. In our sample, the employed-but-absent share rose by almost 150% from February to April, 2020.

behavior as well. Second, we examine the relationship between state reopening policies and initial unemployment claims, continuing unemployment claims, and job posting data using an event study model at the week-by-state level. These first two sets of analyses provide relatively high-frequency measures of labor-market-related activity, and they allow us to assess pre-trends and anticipation effects in considerable detail. However, these data are all aggregated and do not allow us to track individuals over time. We turn to the CPS to study more conventional measures of labor market performance, and to construct a longitudinal CPS sample that allows us to study employment transitions at the individual level between April and May 2020.

4.1 High-Frequency Data: Work-Related Mobility, Google Trends, Unemployment Insurance, and Job Posting

There is variation across states in the timing of reopening policies, and also in how long various closure mandates were in place before the state started reopening. In the analysis of work-related mobility and internet search data, the data are measured at the daily level and we model the effects of the policy for each day surrounding the reopening. The job posting data are weekly. In those data, we study the effects of the policy for each week surrounding the reopening announcement. We fit event study regression models with the following structure:

$$y_{st} = \sum_{a=-l}^{-2} \alpha_{Pa} 1\left(t = R_s + a\right) + \sum_{b=0}^{u} \beta_{Pb} 1\left(t = R_s + b\right) \; + \theta_s + \gamma_t + \epsilon_{st}$$

In the model, R_s represents the calendar day (week) when state s adopted a reopening policy. We set lower (l) and upper limits (u) for the event time coefficients following the availability of periods. For the daily analyses of mobility data and Google Trends data, we allow for a window of 20 days before and after policy. In the weekly analyses for job postings we follow up to 4 weeks prior to the policy change and 3 weeks after. θ_s is a set of state fixed effects, which are meant to capture fixed differences in the level of outcomes across states that are stable over the study period. γ_t is a set of daily or weekly time fixed effects, which capture trends in the outcome that are common across all states. ϵ_{st} is a residual error term. The α_{Pa} and β_{Pb} are event study coefficients that trace out deviations from the common trends that states experience in the days leading up to and following reopening policies. The reference period in the event study is one period before the adoption of the reopening policy. α_{Pa} traces out differential pre-event trends in the outcome that are associated with a reopening and β_{Pb} traces out differential post-event trends in the outcome that occur after a state announces reopening.

4.2 Monthly CPS Analysis

We use the January 2015 to May 2020 waves of the monthly basic CPS data to estimate the effects of the state reopening and shutdown policies using a generalized version of a difference-in-difference model. Specifically, let S_s be the date when state s imposed a stay-at-home mandate, and let R_s be the date when the state implemented it's initial reopening. We define S_s^{end} to be the date when the state announced its date of the reopening, which is 4 days prior to the actual reopening for the median state.

Let $t^* =$ May 12, 2020 be the focal date of the May CPS. Then $SAH_s = S_s^{end} - S_s$ is the number of days that the stay-at-home policy had been in place by the May CPS. Likewise, $Reopen_s = t^* - R_s$ is the number of days that the state's reopening plan had been in place in a state as of the May CPS focal date. Finally, let May_{mt} be an indicator variable equal to 1 if the observation is from the May 2020 CPS and set to 0 otherwise. We use a generalized difference-in-difference model to study the effects of the policies on labor market outcomes. We fit a base model that examines only the reopenings:

$$y_{ismt} = \delta_1(Reopen_s \times May_{mt}) + X_{ismt}\beta + \theta_s + \gamma_{mt} + \epsilon_{ismt}.$$

The main effects of the $Reopen_s$ and May_{mt} are absorbed in the state fixed effects and $month \times year$ fixed effects. δ_1 measures the extent to which the May 2020 labor market changes were larger among states that had been "open" for an additional day. In addition to the main specification, we also fit a model that adjusts for reopening and for the length of the original shutdown using:

$$y_{ismt} = \delta_1(Reopen_s \times May_{mt}) + \delta_2(SAH_s \times +May_{mt}) + X_{ismt}\beta + \theta_s + \gamma_{mt} + \epsilon_{ismt}.$$

In this model, δ_2 measures the differential change in labor market outcomes in May among states with an extra day of stay-at-home orders. Finally, we estimate a model that allows the effect of the reopening the vary with the length of the shutdown:

$$\begin{aligned} y_{ismt} &= \delta_1(Reopen_s \times May_{mt}) + \delta_2(SAH_s \times May_{mt}) + \delta_3(Reopen_s \times SAH_s \times May_{mt}) \\ &+ X_{ismt}\beta + \theta_s + \gamma_{mt} + \epsilon_{ismt} \end{aligned}$$

In this specification, δ_3 measures the extent to which the effect of an additional day of reopening increases for each additional day that a state operated under a stay-at-home order. In each of these regressions, the models were estimated using CPS sampling weights and standard errors allowed for clustering at the state level.

4.3 Longitudinal CPS Analysis of Employment Transitions

Using the longitudinally linked CPS sample, we study factors related to an individual's likelihood of reemployment in May 2020 focusing on individuals who were not working in the April 2020. This includes people whose employment status is coded as "unemployed-on layoff" and "unemployed-looking". We estimate separate models for people coded as "employed-absent" because this group has grown substantially during the epidemic due to changes in CPS coding and perhaps genuine increases in temporary absences from otherwise stable jobs. Within a sample of people who have CPS records in both April and May 2020 and who were not employed in April 2020, we let y_{is} be a binary indicator of whether individual i in state s is reemployed in May. d_{is} represents duration of the person's unemployment spell in weeks as reported in May. J_{is} contains features of individual i's previous job, including whether it involved work in an essential industry, the amount of face-to-face contact, and availability of remote work. [8] We also control for two-digit NAICS industry fixed effects and two-digit SOC occupation fixed effects. X_{is} is a vector of individual demographic and education characteristics. θ_s is a state fixed effect. The regression is:

$$y_{is} = d_{is}\alpha + J_{is}\rho + X_{is}\beta + \theta_s + \epsilon_{is}$$

In the model, α measures the extent to which transition to employment rates depend on the length of a person's unemployment spell. The ρ coefficients measure how transitions out of unemployment differ across people working in jobs with more remote work capacity, jobs that require more face-to-face interaction, and jobs in essential industries.

In order to compare the probability of reemployment for people in different employment

[8] See Montenovo et al. (2020) for a discussion of our measures of essential industries, face-to-face contact, and remote work capacity.

states in April, we pooled the sample of unemployed individuals (coded as either unemployed-on layoff or unemployed-looking) and employed-but-absent individuals. Let E_{is} be a set of dummy variables representing i's April employment status. We fit the following model to the pooled sample:

$$y_{is} = E_{is}\lambda + d_{is}\alpha + J_{is}\rho + X_{is}\beta + \theta_s + \epsilon_{is}$$

One concern with this longitudinal job transition framework is that it does not adjust for the kinds of job transition patterns that might always occur between April and May. To adjust for seasonality in job flows, we also constructed a longitudinal sample for April-May 2019. Combining the 2019 and 2020 April-May samples, we let $t = 2019, 2020$ index the two years of April-May data, and we let $Y20_{ist} = 1(t = 2020)$ be a dummy variable indicating that the person is observed in the 2020 sample rather than the 2019 sample. We pool the data and fit a model that allows the effect of employment status, unemployment duration, and job type attributes to differ in 2019 and 2020:

$$\begin{aligned} y_{ist} =& E_{ist}\lambda_1 + d_{ist}\alpha_1 + J_{ist}\rho_1 \\ &+ (Y20_{ist} \times E_{ist})\lambda_2 + (Y20_{ist} \times d_{ist})\alpha_2 + (Y20_{ist} \times J_{ist})\rho_2 \\ &+ X_{ist}\beta + \theta_s + \delta_t + \epsilon_{ist}, t = 2019, 2020 \end{aligned}$$

We also investigate factors influencing individual's earnings and hours worked conditional on being employed in May of 2020. We can thus compare earnings and hours worked for people who have been employed in both April and May and people who transition from out-working in April to working in May.

5 Results

5.1 Work-Related Mobility Patterns

We begin with an analysis of our high-frequency data series on work related mobility with an event study analysis. Figure 2 plots the event study coefficients estimating the change in workplace mobility following the announcement of initial state reopenings and after actual reopenings. The left panel shows estimates of an increase in 'mobility in work locations' from Google Mobility data. The right panel shows estimates for changes in 'Fraction of devices at work' locations from SafeGraph data. The study window runs from April 15, 2020 to June 5, 2020. The vertical gray line denotes the day before initial re-opening in the state.

The Google mobility data show that, prior to initial reopenings and prioir to actual openings, the pre-trends are fairly flat in work-related mobility and then show a steady increase after the changes (left panel). SafeGraph data do not show any clear signs of increases in the fraction at work, with fairly flat trends before and after, in both policy measures.

5.2 Google Search Trends for Unemployment Related Terms

We next turn to another high-frequency measure of job-market-related behavior: Google search trends for unemployment-related search terms[9]. This measure serves as further data we examine to understand whether there were changes in unemployment-related searches around reopenings. Choi and Varian (2012) show that Google searches for unemployment-related-terms queries are predictive of downstream unemployment insurance claims and Aaronson et al. (2020) apply the idea to the COVID-19 epidemic.

Figure 3 reports event study results of the change in number of searches pre and post initial reopenings announcements. Our estimates are all statistically insignificant and appear like a decline that started even before policy actions, although it could be declining faster after the policy announcement.

5.3 Flow of Unemployment Insurance Claims

This section investigates initial and continuing unemployment insurance (UI) claims. While many researchers have studied initial claims, continuing claims have received considerably less attention. Figure 4 graphs the weekly rates of initial and continuing unemployment insurance claims calculated as the number of initial/continuing claims divided by the size of the labor force. The thick black line shows the "smoothed" 7 day moving average of the national estimates, while the grey lines show the individual state estimates. The grey line turns red after each state's initial opening date. The initial claims rate peaks in early April and then declines steadily. This is well before any state's initial reopening date. Continuing claims peak around mid-May and then decline slightly. This peak appears to come right around the first group of state initial reopenings.

We seek to use these series to estimate gross flows off unemployment insurance, which requires us to address delays in unemployment insurance benefits and also the denial of claims. There has been extensive media attention paid to delays in processing unemployment insurance benefits. The delay represents the time between the date the claim is filed and the

[9] These search terms include unemployment, unemployment benefit, stimulus, assistance, CARES act, department of labor, and insurance claims.

date the payment is mailed/deposited. Figure 5 reports the estimated percentage of total first payments that are subject to a delay by the length of the delay. Between 40% and 50% are delayed by about 1 week, while 30% to 40% are delayed by 2 to 3 weeks. Very few claims are delayed for 4 or more weeks. There is a distinct reduction in the share of claims paid in 1 week in April, almost entirely offset by claims that take 2 to 3 weeks.[10] While there is some increase in claims delayed 8 to 8 weeks, which can have a tremendous personal cost, this increase is relatively small.

Figure 6 plots the average number of weeks first payments are delayed. The estimates indicate that the length of delays increased in April relative to March and January (but not February) and that there is substantial heterogeneity across states, but that in most states, the average delay remains less than 2 weeks. Based on these findings, when trying to align the initial and continuing claims in Figure 4 we can assume that the majority of these claims are paid quickly and do not not make adjustments for delays.[11]

Figure 7 plots national gross and net unemployment insurance claims flows as well as smoothed series. The lines depicting gross flows show the number of initial UI claims in thousands over time from the first week of March to the last week of May 2020. These flows assume a 20% denial rate of initial claims.[12] Gross flows onto UI after accounting for denials increased from a low level in early March to an unprecedented level of roughly 5 million in the first week of April. Gross flows then fell substantially and steadily until the series ends, but remain quite elevated.

The line depicting net flows shows the number of initial claims minus the number of ended claims in a given week.[13] Positive net flows indicate that more people are entering than leaving UI. Negative net flows indicate more people are exiting than entering the program. Net flows peak quite early - at the beginning of April. They display a substantial, steady downward trend throughout April. In May the raw data shows volatility in the measure of net flows, but the smoothed estimates show the trend turning negative by early May. The April and May trends indicate a substantial and increasing mobility off of UI.

The difference between gross and net flows provides an estimate of outflows from unem-

[10]The increase in the number of claims paid quickly in March may well be an artifact of data reporting. Given that the surge in claims occurred later in March, only those claims that were processed quickly would have been paid in March.

[11]An adjustment process would be noisy because we know about the delay based on when the claim was paid, not when it was filed.

[12]To estimate this denial rate, we estimate the number of monetary and separation (i.e. the person quit or was fired for cause instead of let go) determinations in a given quarter. We then estimate the number of these determinations that ended in denial.

[13]Given the recency of most claims and the expansions of benefits, ending claims are dominated by people who are reemployed.

ployment insurance. While small relative to the gross flows onto unemployment insurance, gross flows off of unemployment insurance are not negligible even in March. They grow considerably during April to roughly 1 Million people per week and end the period at well over 2 Million people per week. Taken together these estimates indicate tremendous churn in the labor market with considerable and consistently growing numbers of people returning to work even as many others are losing jobs. These outflows begin long before the reopening period and suggest that the increase in reemployment was not solely driven by reopenings.

5.4 Burning Glass Job Postings

Given an uptick in employment that is likely related to reopenings, we turn to data from Burning Glass Technologies (BGT) to assess the extent to which the increase in employment was associated with an increase in job postings, as an indicator of the formation of new employment relationships as opposed to the resumption of previous employment matches. Figure 8 plots the national weekly online job postings by US employers overall and in seven major industry sectors including Healthcare, Retails, Education, Accommodation & Food Services, Manufacturing, and Construction between June 22, 2019 and June 10, 2020. After a precipitous decline in job postings in March 2020, there is noticeable increase in postings in early May 2020. We observe the lowest number of job postings in May 2 - May 9 during this time period (approximately 330,000 vs. 644,000 in March 7 - March 13). Similarly, the number of job postings in healthcare sectors declines by 80% between March 7 and May 2. The total job postings recover nationally in recent weeks (539,000 in June 6 - June 10). This uptick appears across most sectors.

We next turn to an event study design to assess how the timing of postings in each state relates to reopenings. Figure 9 presents the results from an event study analysis of the effects of initial reopening using state-by-week-level data on online job vacancy between April 11 and June 10, 2020. After controlling for national trends, the data shows some suggestive evidence on the increases in the number of job postings following reopenings. Within sectors, accommodation and Food shows a downward pretrend, which appears to reverse after reopenings. Few of the other sectors show any increase (in levels or trends) in job postings around reopenings.

Overall, these results, suggest that there may be a slight increase in jobs search after reopenings. However, the change appears to be relatively limited. When viewed in conjunction with the earlier results suggesting some increase in people returning to work, this small increase in job postings suggest that the initial increase in employment likely came from people returning to previous employers. New job postings, may be targeted toward the next tranche of employment. If so, it may well entail a slower process of reemployment because of the time associated with job search and matching as well as firm-specific human capital accumulation.

5.5 Monthly CPS DID Analysis

Table 1 reports results on the effect of reopening policies on six labor outcomes - (i) employment; (ii) absent but employed; (iii) earnings among the employed; (iv) earnings in the full sample, including people with zero reported earnings; (v) hours worked among the employed; and (vi) and hours worked in the full sample, including people with zero hours of work. The earnings analysis is limited to people in the outgoing rotation groups of the CPS sample because only these groups are asked questions about earnings. All regressions are weighted using the appropriate CPS sampling weights.[14].

Panel A presents from our baselines specification coefficients for the interaction of days since reopening (until mid May), Panel B additionally controls for the interaction of length of stay at home orders (SAH) and May and Panel C considers the interaction between the two. In panel A, an additional day since reopening increases the probability of being employed by 0.2% and reduces the probability of being employed but absent group by 0.07 percentage points. Meanwhile, an additional day is associated with 4% higher hours worked last week overall (i.e. including zeros), but a reduction in hours worked last week among the employed by 0.03 hours (0.1% increase). The earnings estimates are not significant. Controlling for the length of SAH orders interacted with May (in Panel B) yields qualitatively similar results for days since reopening to our baseline specification (Panel A), although the estimates in Panel A are somewhat larger and substantially more precise.

The additional interaction between days since reopening and length of SAH in May (Panel C), yields estimates that are substantially similar to those in Panel A. In this specification, reopenings impact the earnings of the employed. Every additional day of reopening significantly reduces weekly earnings by 1.5% and every additional day of SAH significantly reduces earnings of employed by 0.23%. Moreover, after reopening every additional day of reopening after every additional day of SAH *increases* earnings by 0.04%, implying that reopening after longer SAH incrementally increases weekly earnings of the employed. Looking at our employment estimates, in Panel C, employment was 2.6% higher in May as compared to April. Depending on the specification, that gap can be generated by a reopening roughly 10 days earlier.

[14]We use the earnings study weights for analysis based on the earnings outcome, and the final CPS sampling weight for all other analyses.

5.6 Longitudinal CPS Analysis

The panel of graphs in figure 10 shows the distribution of employment status in a recent month by sub-populations defined by employment status in the previous month. The first row of graphs compares employment status shares in May 2020 by employment status in April 2020. For comparison, the second and third rows show similar plots for March-April 2020, and April-May 2019. Looking at the first row of graphs, which compare May employment status patterns across groups with each employment status in April, the first column shows that people who were employed and at work in April 2020 were disproportionately employed and at work in May of 2020. This is probably not surprising given that employment increased between the two months. The second column reports estimates for people who were employed, but absent from work in April 2020. This category, which is supposed to include people who are, for instance, on vacation, has received considerable attention in technical discussions that have spilled over into the public discourse because many people who were unemployed on layoff are believed to have been misclassified into this category. The third column reports people who were listed as unemployed on layoff. One would typically expect these two categories to differ substantially in terms of subsequent labor market status, with the employed absent very likely to return to work, as in 2019. Instead these two columns are strikingly similar in ways that suggest that there likely was some meaningful amount of misclassification. For instance, both of these groups have somewhat under a 40% probability of being employed in May of 2020. Moreover, while the employed absent in April are more likely to be listed as employed absent than unemployed on layoff in May and those unemployed on layoff in April were more likely to be listed as unemployed on layoff in May than employed absent, the sum of employed absent and unemployed on layoff in May of roughly 50% is implausibly similar for the employed absent and unemployed on layoff in April. Thus, while there appears to be persistence in misclassification between these two categories, it seems highly likely that there is important misclassification into these two groups. The balance of the employment statuses is quite similar for these categories.

The remaining columns show considerable persistence. Roughly half of the April unemployed looking remaining in that category in May and only 15% are employed. This low return rate among the unemployed looking compared to the substantially higher rates among the employed absent and unemployed on layoff is strong suggestive evidence that the return to work between April and May was a product of people who had retained a relationship with their original employers returning to work rather than people finding new jobs. Not surprisingly, virtually all of the April retired and disabled remain in those categories in May. Roughly 70% of people not in the labor force in April remain out of the labor force in May.

Taken as a whole, these estimates show that there was strong retention in work among those already employed and resumption of work between April and May, among people who had retained relationships with their prior employers. The resumption of work is far weaker among the other groups.

We next turn to people who are newly reemployed in May 2020 and compare them to the newly reemployed in May 2019. An individual is defined as newly reemployed if in April they were classified as unemployed on layoff, unemployed and looking, or employed and absent from work then in May were classified as employed and at work. Figure 11 breaks down the composition of April employment status for this group in 2019 and 2020 for comparison. In May 2019, roughly 70% of the newly reemployed had been employed but absent in April 2019. Just under 10% had been on layoff and roughly 20% had been looking in April of 2019. By contrast, in May 2020, roughly half of the newly reemployed had been employed but absent in April 2020 while roughly 40% were coming off layoff and less than 10% had been looking in April 2020. Intuitively, far fewer people who were being reemployed in May of 2020 were newly hired (had been looking) than in May of 2019 and far more had an employment relationship in April of 2020 than in April of 2019 (below we use data on industry and occupation changes to assess the likelihood that they were returning to the same job as opposed to taking a new job). Presumably, the reemployment of people who had been on layoff increases relative to that of people who had been employed but absent between 2019 and 2020 because more of the employed absent in April 2020 were effectively on layoff in 2020 than in 2019, making for a smaller return probability and the number of people on layoff was much higher in April 2020 than in April 2019.

Figure 12 reports the probability that people who were unemployed (including on layoff and looking for a job) in April are employed in May by the duration of their unemployment in April. The top panel reports results for April and May 2020; the bottom panel reports results for April and May 2019. The left panel shows the number of people unemployed for different lengths of time in April of both years. In April 2020, the number of people unemployed for 7-8 weeks or more is low and the counts decline at higher duration of unemployment. The number of people unemployed is markedly higher for duration of 0-2 weeks, 5-6 weeks, and especially 3-4 weeks (which corresponds to the weeks of March 15 and 22). Not surprisingly, the data for 2019 are an order of magnitude lower than the peak. Moreover, they are considerably more flat. The right panel reports estimates for the probability that people remain unemployed versus being reemployed in May. In 2020, there is a large monotonic decline with the duration of unemployment in the reemployment probability. The 2019 show a broadly similar, but considerably less regular pattern. While this cut through the data is different from the previous one, it tells a remarkably consistent story - reemployment between April and May 2020 was substantially higher among people who had (recent) connections to their employers.

Next we rerun the analysis breaking down by various demographic groups in 2020 only. Figure 13 reports results by age group. It is clear that reemployment probabilities are greatest for people who are in their prime working years, peaking between ages 41 and 50 and decreasing monotonically for younger and older workers. This pattern follows unemployment by age (Panel A), which is lowest for the 41-50 group and increases for both younger and older workers. Age groups most protected against unemployment are also most likely to become reemployed. Meanwhile, Figure 14 reports results by gender. While more women were unemployed overall, the probability of reemployment is the same for both genders.

Figure 15 reports results by race and ethnicity. Unsurprisingly, non-Hispanic whites are the largest group of unemployed but have the lowest unemployment rate. There are moderate differences in the probability of reemployment across the various racial and ethnic groups, with non-Hispanic whites having the highest reemployment probability. Out of all racial and ethnic groups, the Asian group had the lowest reemployment probability.

Figure 16 reports results on probability of reemployment by level of educational attainment. Panel A shows the number employed and unemployed by education subgroup. Not surprisingly, it shows that unemployment declining in education. However, Panel B and Panel C, show that there are only very small differences in reemployment probabilities across education levels. These findings indicate that while education is protective against unemployment, conditional on unemployment, it does not associated with a higher reemployment probability. This finding contrast with the previous figures which generally showed that those with lower unemployment rates also had the highest probability of becoming reemployed.

Figure 17 reports similar results by 22 occupation groups. Panel C, shows that conditional on being unemployed in April the healthcare practitioner, production, community and social services, legal, and healthcare support occupations were more likely to regain employment in May than people in other occupations. Computer and mathematical occupations had the lowest probability of reemployment, although that was the occupation group with the lowest unemployment rate in April. The group of Food preparation and serving occupations is particularly noteworthy given its very high 42.4% unemployment rate in April. This group had the 8th lowest reemployment rate of the 22 occupation groups, as both Panel B and C illustrate.

Figure 18 reports results by 20 industry groups. Construction, agriculture, and manufacturing industries had the highest probabilities of reemployment. Management of companies and information industries had the lowest probability of reemployment although they both had relatively small April unemployment rates of 4.5% and 7.8%. Health care and social assistance is the industry with the largest fraction in the labor force and of particular interest during a pandemic. It had an April unemployment rate of 9.5% and fared fourth best in reemployment probability. Arts, entertainment, and recreation as well as accommodation and food services had the highest April unemployment rates at 38.4% and 37.4% respectively. They also had the 6th and 7th lowest reemployment probability.

These figures show that most demographic and occupational groups with lower unemployment in April also have a higher chance of reemployment in May. However, this pattern does not hold for educational attainment. Conditional on job loss, education did not play a role in May reemployment. This is an interesting pattern that suggests other aspects of jobs besides skill level are driving reemployment. Below, we provide evidence that during the pandemic, other aspects of a jobs such as essential work designation, face-to-face interaction, and ability to work remotely are important determinants of reemployment.

Unfortunately, the CPS does not indicate whether people who are reemployed are returning to a previous employer or have found a new job. Lacking that information, we use changes in industry and occupation as proxies for employer switches. These measures are at best proxies because people who switch employers may not switch industries and/or occupations and people who do not switch employers may switch industries and/or occupations. Both of these may be more common if employers move people between establishments or across jobs in response to COVID-19. Moreover, even if workers do not change industries or occupations there is reporting / coding noise in these classifications. With those caveats, Figure 19 reports the fraction of workers within different employment status categories that switched industries (Panel A) or occupations (Panel B). These results are reported for 2019 (left) and 2020 (right) for comparison. For workers who are recorded as unemployed (whether on temporary layoff or looking) in April, the industry and occupation switches are those that occurred between April and May in case they regain employment during these two months. We see that very few people who are employed (whether at work or absent) switch either industries (top panel) or occupations (bottom panel) between April and May of either 2019 (left panel) or 2020 (right panel). The low and relatively constant rate of switching among the formerly employed but absent appears to contrast somewhat with many of our previous results, which suggested that in April 2020, the workers employed but absent were more similar to those on layoff than in the past. At the same time, this tendency toward a higher switch rate ought to be offset somewhat because fewer people on layoff are switching industries or occupations in 2020 than in 2019. Indeed, the next columns show that fewer people who are unemployed on layoff switch industries and occupations when they are reemployed in 2020 than in 2019. The same pattern can also be seen for the those unemployed and looking, in April, and employed in May. Taken together these results suggest that more people may be being rehired by their previous employers. It is also possible that new employers are only hiring people who are very well suited to their positions in the sense of having immediately relevant previous experience.

Table 2 reports the effect of various worker and demographic characteristics on reemployment probabilities. These effects are broken down by previous employment status and reported for both 2019 and 2020. Columns (1) and (3) report the effects for those who were unemployed in April, show that the length of time people are unemployed is strongly associated with a lower reemployment probability. In 2020, an additional week of unemployment duration is associated with a 0.32 percentage point decrease in the probability of reemployment. This effect is .11 percentage points stronger than in 2019.

We also explore characteristics of the jobs that people hold - whether they are essential, require more face-to-face interactions, and allow for remote work. Being an essential worker or being a worker in an occupation that requires more face-to-face contact does not significantly impact reemployment probabilities for this group in either year. However, those in occupations that allow for more remote work see a significant increase in reemployment probabilities in 2020. None of these worker characteristics had significant effects on reemployment probabilities for the unemployed in 2019.

Columns (2) and (4) report results for those who were employed and absent from work in April 2020. These columns show that, for this group of individuals, job characteristics have a significant effect on reemployment probabilities. Essential workers in this group are almost ten percentage points more likely to be reemployed than their non-essential counterparts in 2020. Workers in occupations that require more face-to-face contact are less likely to be reemployed, while those in occupations allowing for remote work are more likely to be reemployed in 2020. None of these characteristics had significant effects in 2019. Thus, being in an essential job, having greater ability to work remotely, and less face-to-face interaction while working all are associated with higher reemployment rates. While they are not always significant, the demographic variables show similar patterns to those in the figures. Mothers of young children (below 6 years old) who were employed but absent in April are less likely to be reemployed in May than males, and this relationship is weaker in 2020 than in 2019. Overall, there is evidence that the pandemic changed what aspects of a job and worker affect the probability of reemployment.

Table 3 reports regression results for the pooled sample of people who are unemployed and who are employed but absent in April of 2020 and 2019. Column (1) contains 2020 results while Column (2) contains 2019 results. Both years show a positive effect of employed but absent and unemployed on layoff in April on probability of employment in May when compared to the reference category of those unemployed and looking for a job. However, the magnitudes of the estimates indicate that employed but absent workers are less likely to go back to work in 2020 compared to 2019. Meanwhile, unemployment duration shows a negative effect in both years. However, people with longer length of unemployment are even less likely to be reemployed in 2020 than 2019. Importantly, the job characteristics coefficients show major changes between 2019 and 2020. Being in essential industries and in jobs with remote working were non-significant in 2019 but became significant in 2020. Being an essential worker increased probability of reemployment by 6.18 percentage points, and the ability to do work remotely increased probability of reemployment by 4.23 percentage points. This table reinforces that the characteristics of a job that were previously unrelated to reemployment have become important during the COVID-19 epidemic.

Table 4 reports the probability of reemployment among matched April-May groups in the CPS in 2019 and 2020. Here, we include a dummy variable between employment or work characteristics and year 2020 to estimate the differential association with reemployment in 2020 compared to 2019. Being employed and absent and employed and on layoff were both associated with higher reemployment probabilities relative to unemployed and looking, the reference group. However, the gap between the employed-but-absent and unemployed on layoff and unemployed looking is smaller in 2020. Meanwhile, increased unemployment duration is associated with a reduced reemployment probability and relationship is more negative in 2020 than in 2019.

Among the job characteristics, only face-to-face interactions were significantly related to reemployment probabilities in 2019. In 2020 face-to-face interactions are more negatively related to reemployment. In 2020, workers in essential jobs have a 9 percentage point higher probability of reemployment. Tables 2 - 4 support similar conclusions.

Table 5 takes weekly earnings and weekly hours worked for those who are employed in May as outcomes. Among employed workers in May, those who were also employed in April have significantly higher earnings and hours worked than people with other employment statuses in April. Those who were employed in April had 18% higher earnings in May compared to those who were unemployed and looking in April. In terms of hours worked in the previous week, those who were employed in April work four hours more in reference week in May. The other demographic variables are significant and have the expected signs. Thus, the reemployed face a wage and hours worked penalty when compared to those who kept their jobs.

6 Conclusion

The COVID-19 epidemic led to a massive and sudden reduction in economic activity in the United States and other countries. Although unemployment rates remain at very high levels, employment rates did begin to rise somewhat in May. This paper provides an early window into the relationship between state reopening policies and the return to work using multiple high frequency data sources as well as more conventional data based on the monthly CPS.

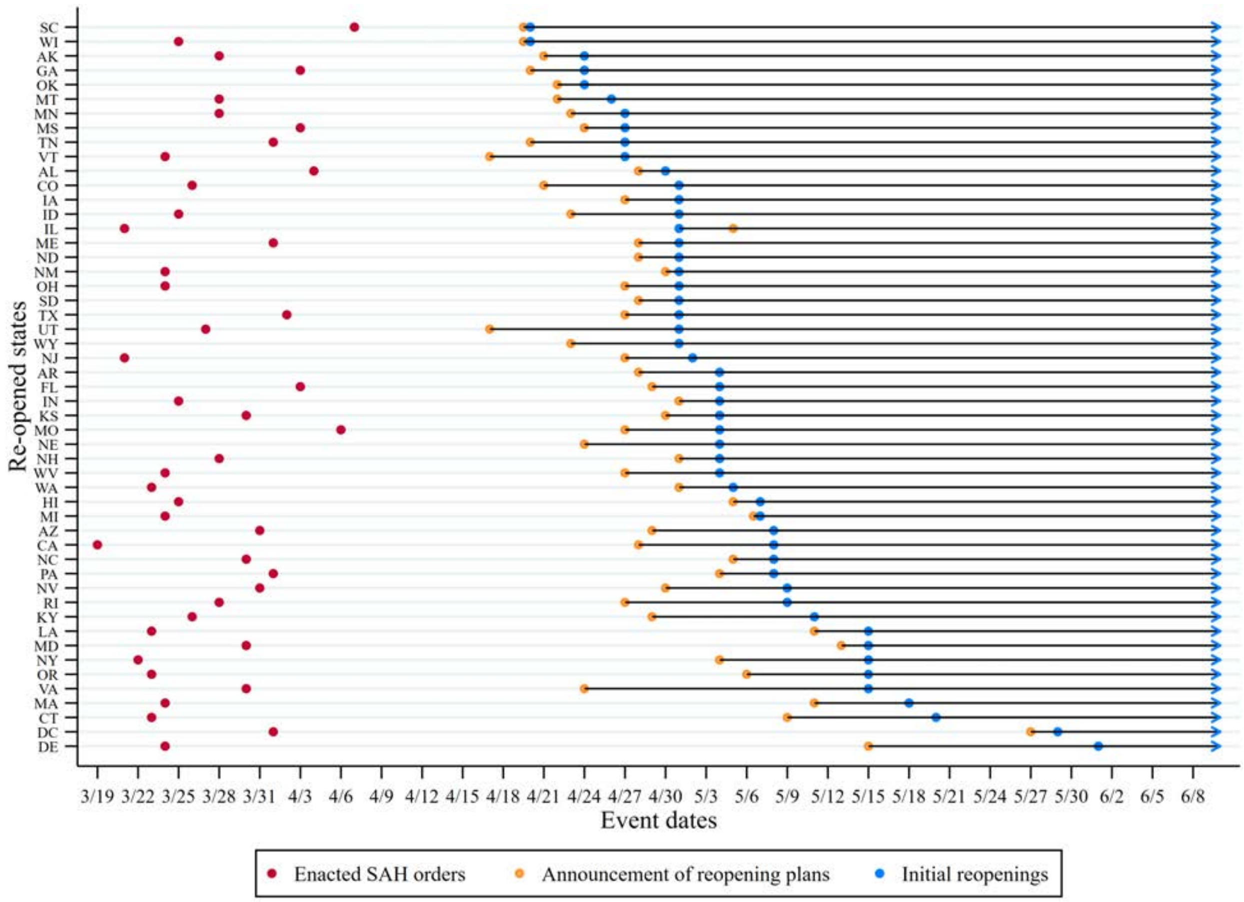
Estimates from event studies and difference-in-difference regressions suggest that some of the recent increases in employment activity, as measured by cellphone data on work-related mobility, internet searches related to employment, and new and continuing unemployment insurance claims, were likely related to state reopening policies. However, labor market activity began to pick up somewhat in advance of the actual state reopening date.

Evidence from longitudinal CPS data and from internet job posting data suggests that most of the increase in employment in May came from people resuming work at their prior job. About one third of workers who were unemployed-on-layoff or employed-but-absent in April transitioned to employment in May. Of these, we estimate that 92% were re-employed in their same industry and occupation, among those employed-but-absent, but only about half were re-employed in the same industry and occupation among those unemployed-on-layoff. In both cases, the remainder started jobs within new industries or occupations.

These estimates suggest that employment relationships prove durable in the short run, but raise concerns that employment gains requiring new employment matches may not be as rapid. Additionally, our analysis is partial equilibrium in the sense that we can not estimate the effect of reopening on future COVID-19 cases and subsequent employment.

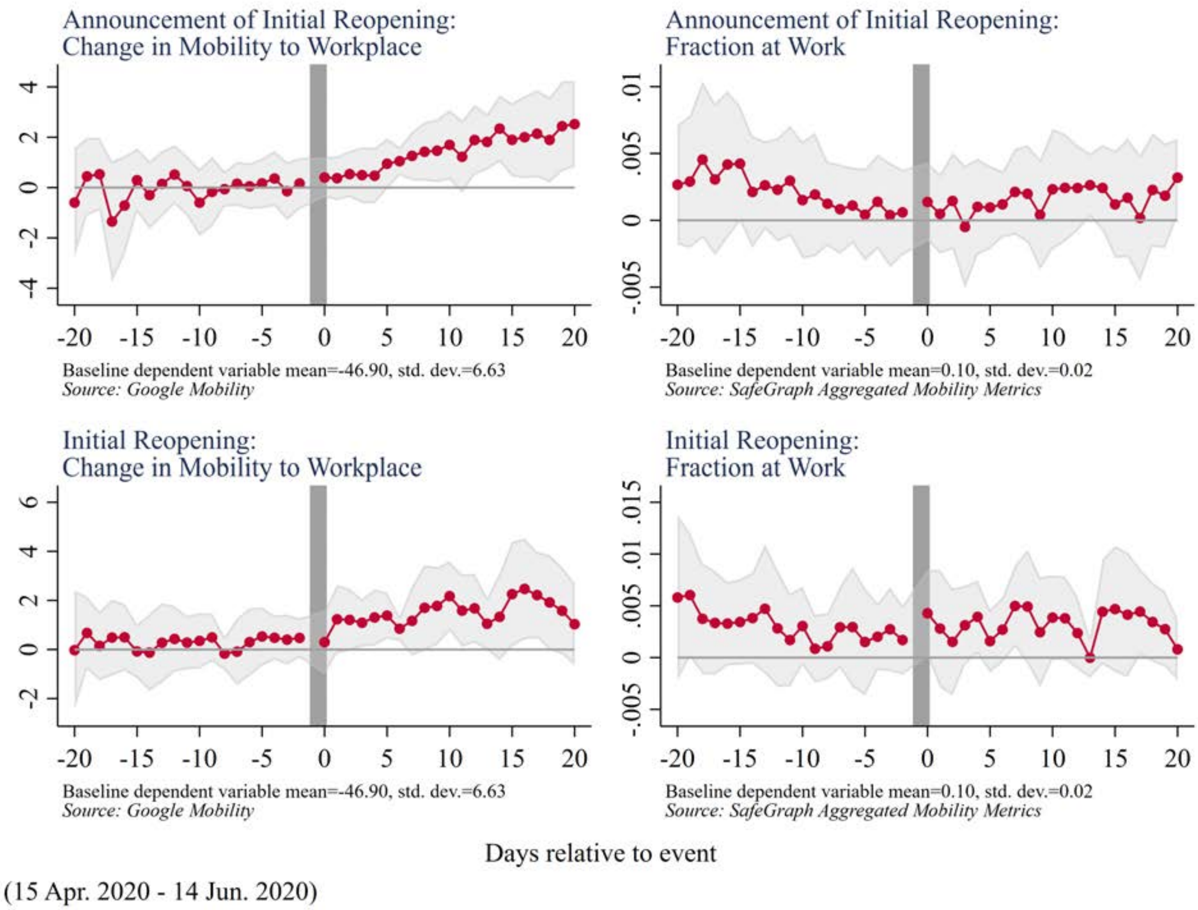
Tables and Figures

Figure 1: States' Reopening Timelines



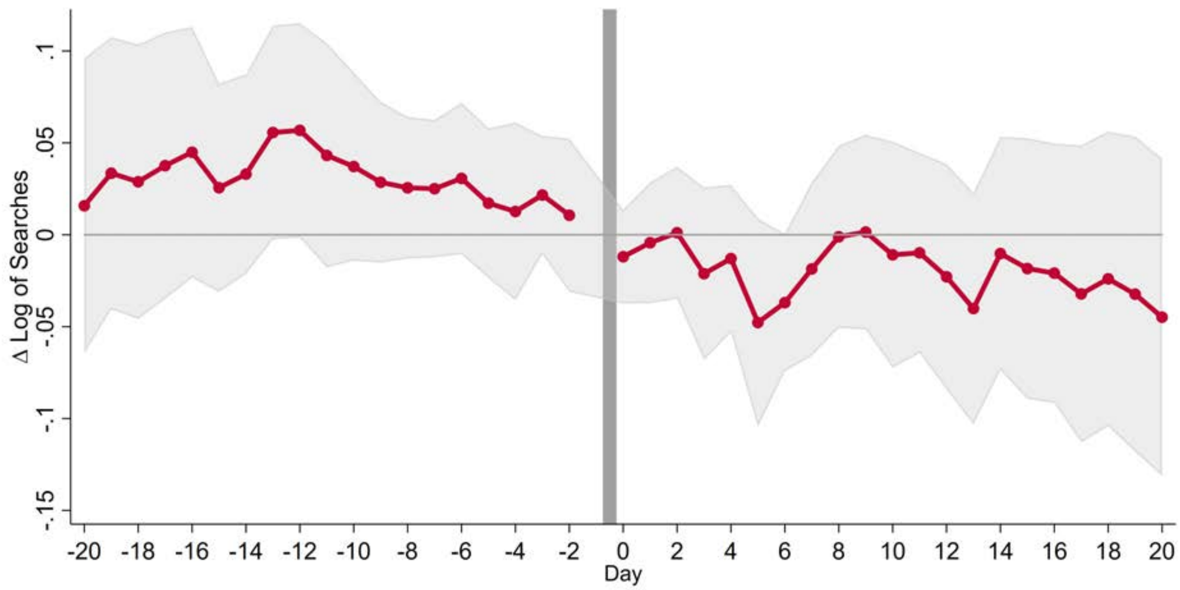
Notes: Figure shows for each state, the timeline of their SAH orders (red), official announcement of reopening plans (orange), and initial reopening (blue). The Illinois governor released a phased plan of reopenings on May 5, several days after their initial reopening on certain outdoor activities (according to the timeline of the New York Times). The timeline is updated as of June 15.

Figure 2: Effect of state re-openings on work related mobility. Regression Results (Coefficients and 95% Confidence Intervals) (April 15 - June 5th 2020)



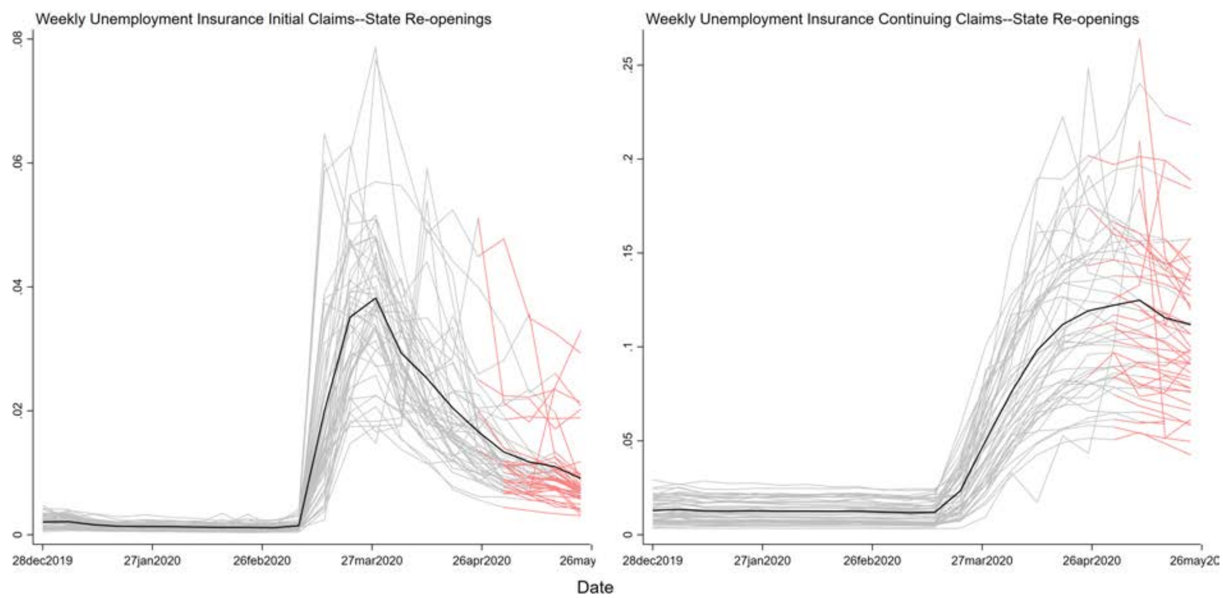
Notes: Author's calculation based on cellular device movement data from Google Mobility and SafeGraph Aggregated Mobility Metrics. Each panel is a separate regression. Vertical gray line denotes day before initial re-opening in the state. The regression controls for state fixed effects and date fixed effects. Estimation sample window is 15 April 2020 - 05 June 2020. Reported baseline dependent variables as of 15 April 2020.

Figure 3: Effect of state announcements of re-openings on Google Trends unemployment-related Searches



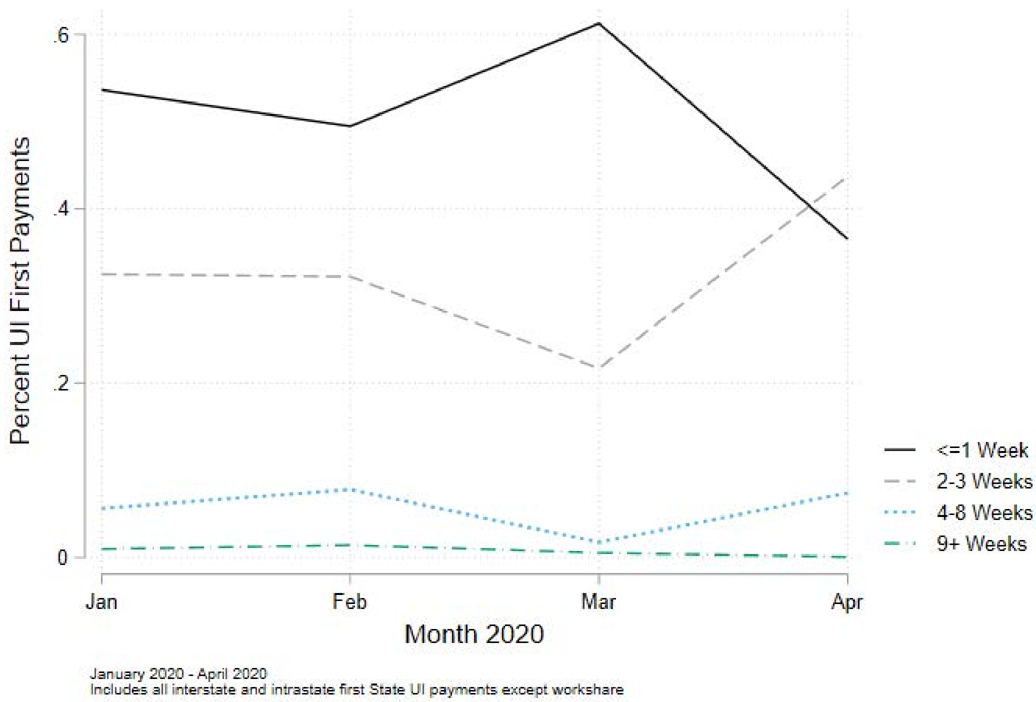
Notes: Author's calculation based on Google Trends search data. The outcome variable is log of number of searches on unemployment-related terms, including unemployment, unemployment benefit, stimulus, assistance, CARES act, department of labor, insurance claims. Vertical gray line represents the day before truncated announcement date. The regression controls for state fixed effects and date fixed effects. The estimation window is 1 April 2020 - 12 June 2020.

Figure 4: Trends in initial and continuing unemployment insurance claims.



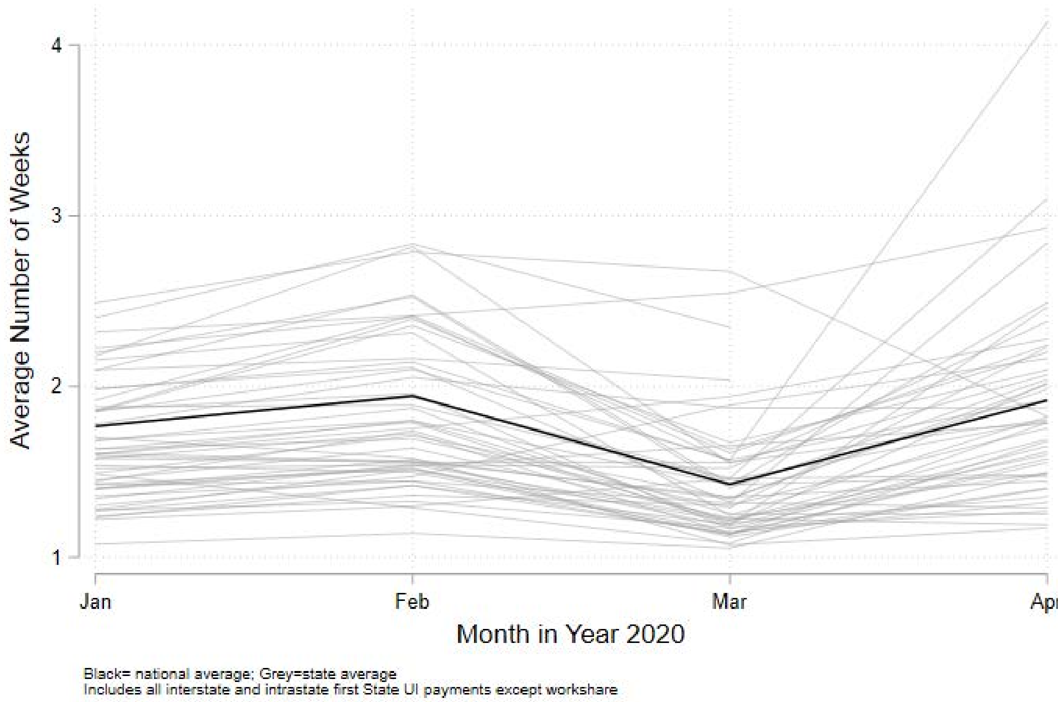
Notes: The panels present the authors' estimates of the weekly rates of initial and continuing unemployment insurance claims calculated as the number of initial/continuing claims divided by the labor force, as estimated by the Bureau of Labor Statistics. Each line represents a state. The black segments are for the period before the state reopened; the red segments represent periods after reopening. The thick black line represents a "smoothed" 7 day moving average of the states.

Figure 5: Monthly Percentage of State UI Payments Delayed by Number of Weeks Delayed



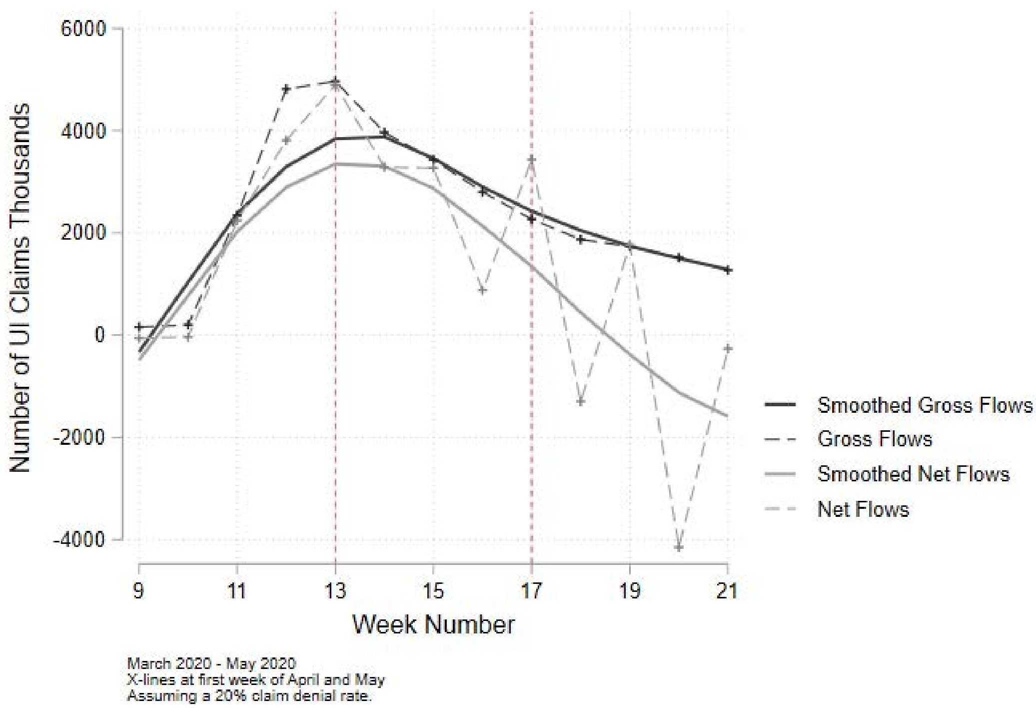
Notes: This figure presents the authors' estimates of the monthly percentage of first payments delayed by number of weeks delayed. This combines the monthly first payment activity data (ETA 5159) and the monthly payment lapse data (ETA 9050). These averages include all State UI (full and partial) interstate and intrastate first payments. Workshare payments are excluded.

Figure 6: Monthly Average Number of Weeks First UI Payments Delayed



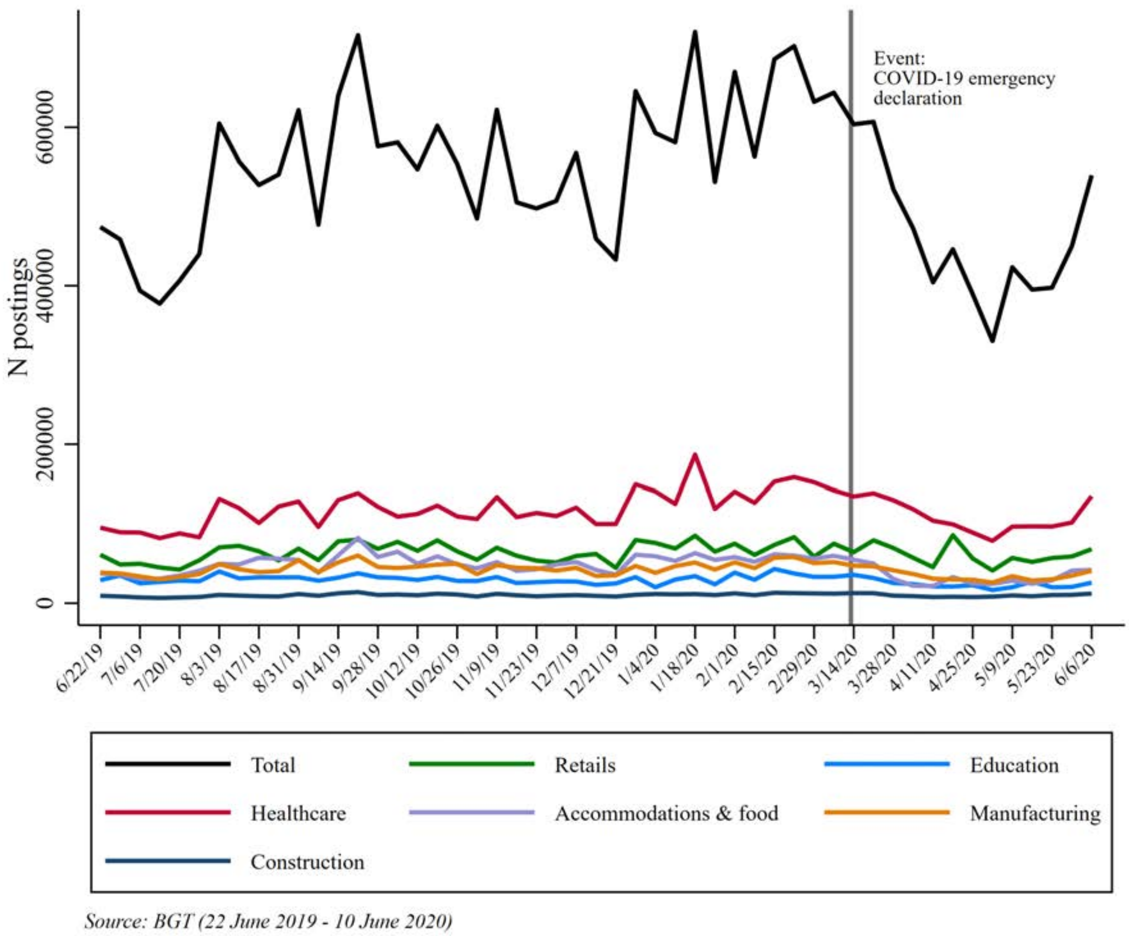
Notes: This figure presents the authors' estimates of the monthly average number of weeks UI first payments are delayed. This combines the monthly first payment activity data (ETA 5159) and the monthly payment lapse data (ETA 9050). These averages include all State UI (full and partial) interstate and intrastate first payments. Workshare payments are excluded.

Figure 7: Gross and Net Unemployment Insurance Flows



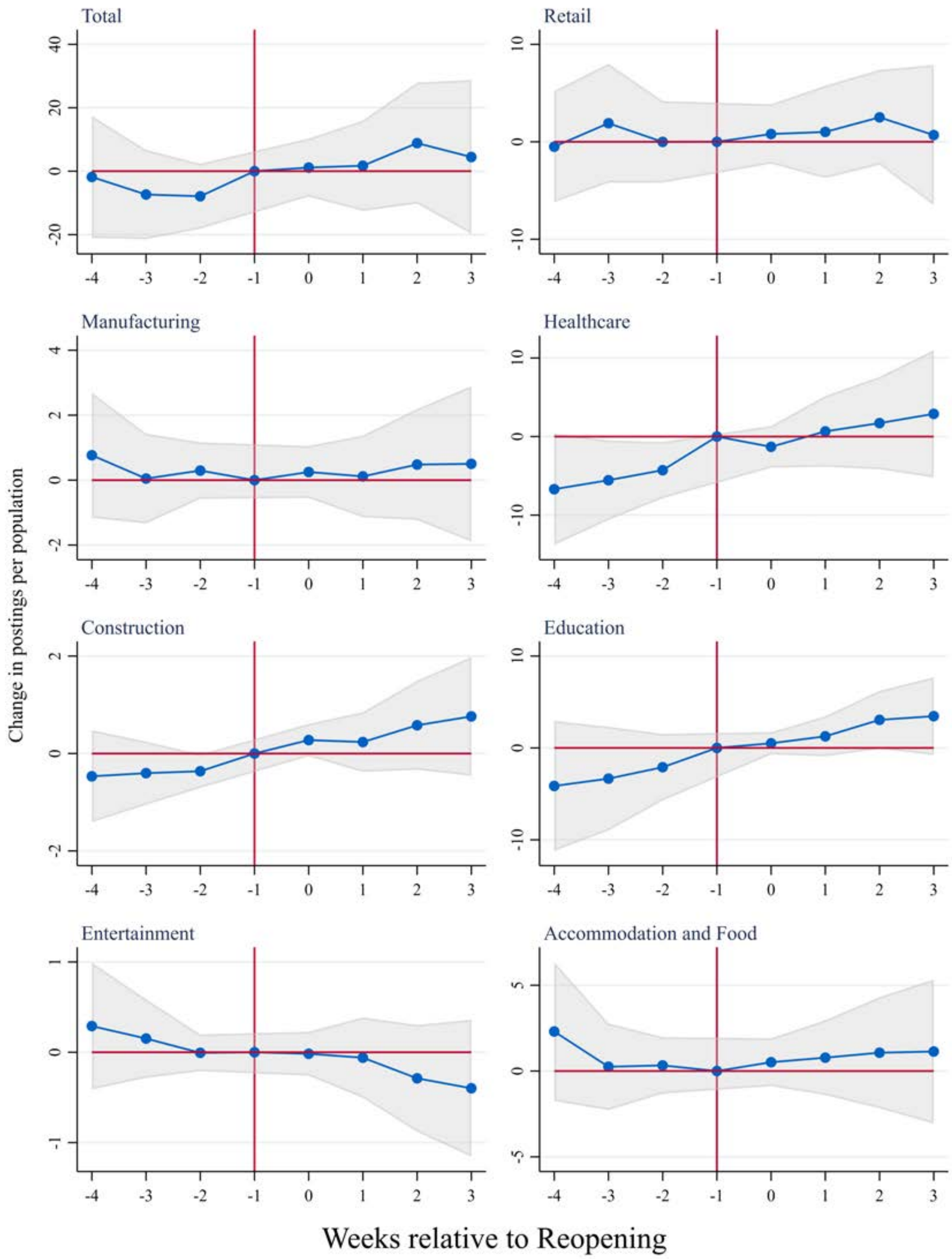
Notes: The figure presents the authors' estimates of national weekly gross flows (incoming cases) and net flows onto UI (incoming UI claims less ending UI claims) based on initial and continuing claims data each week. These estimates assume a 20% denial rate on initial claims. The difference between the two series gives the gross outflows from UI. Both raw data and smoothed series are included. Smoothing done with cross validated bandwidths.

Figure 8: Trends of job postings in total and by industry



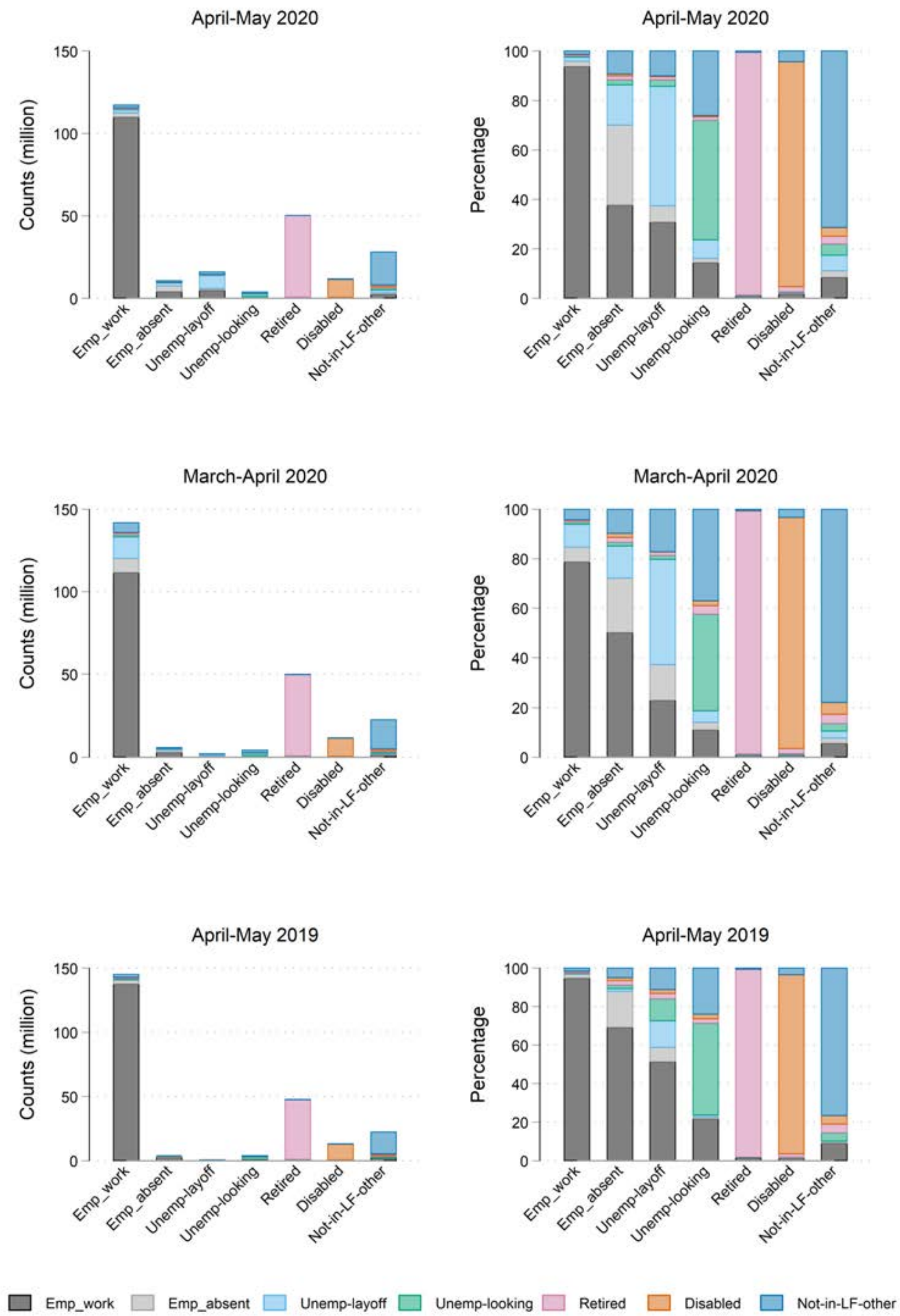
Notes: We are grateful to Burning Glass Technology (BGT) for access to job postings data. The black line shows the trends of total job postings by week. Other lines show the trends in job posting of seven major industry sectors.

Figure 9: Event study regression coefficients and 95 percent confidence interval: effect of reopenings on job postings



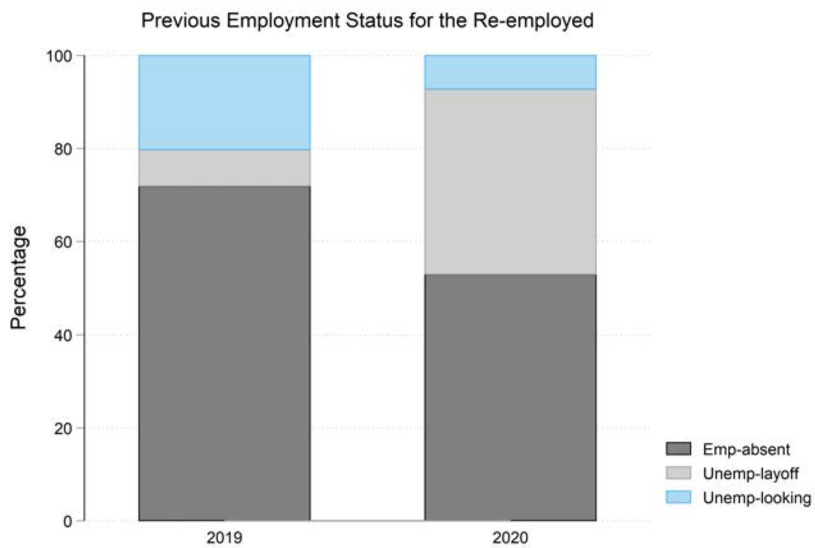
Notes: Authors' calculations based on BGT job postings data. Each panel is based on a separate regression. The outcome is the weekly number of job postings per 100,000 state population. Sample window is April 11, 2020 - June 10, 2020. Vertical red line depicts the week before the state's re-opening. All models include state fixed effects and date fixed effects. Standard errors clustered at state level.

Figure 10: Transition of Employment Status



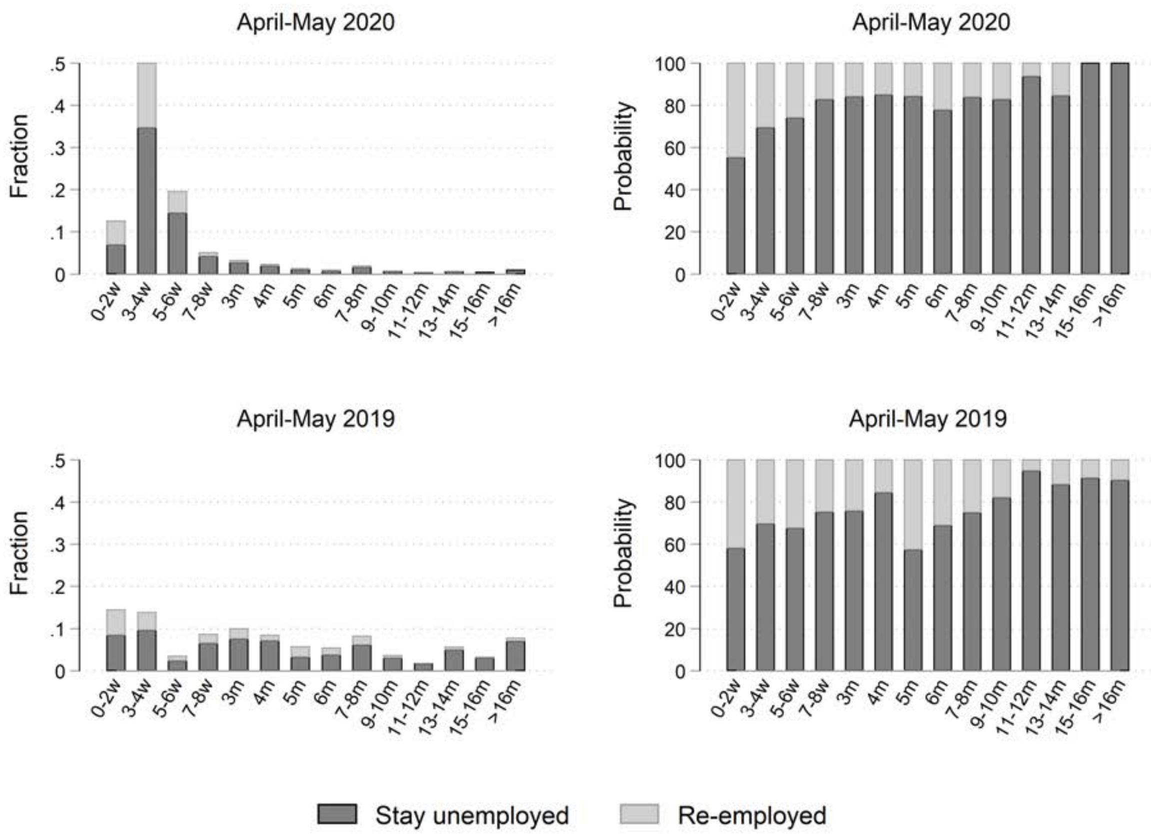
Notes: Each graph shows the transition of matched CPS individuals from the previous month to the focal month. x axis represents employment status in the previous month and color of the bar represents employment status in the focal month. The focal months for the top, middle and bottom panels are May 2020, April 2020, and May 2019 respectively. The left panel shows counts weighted using longitudinal weights and the percentages from the panel to the right.

Figure 11: Composition of the Re-employed



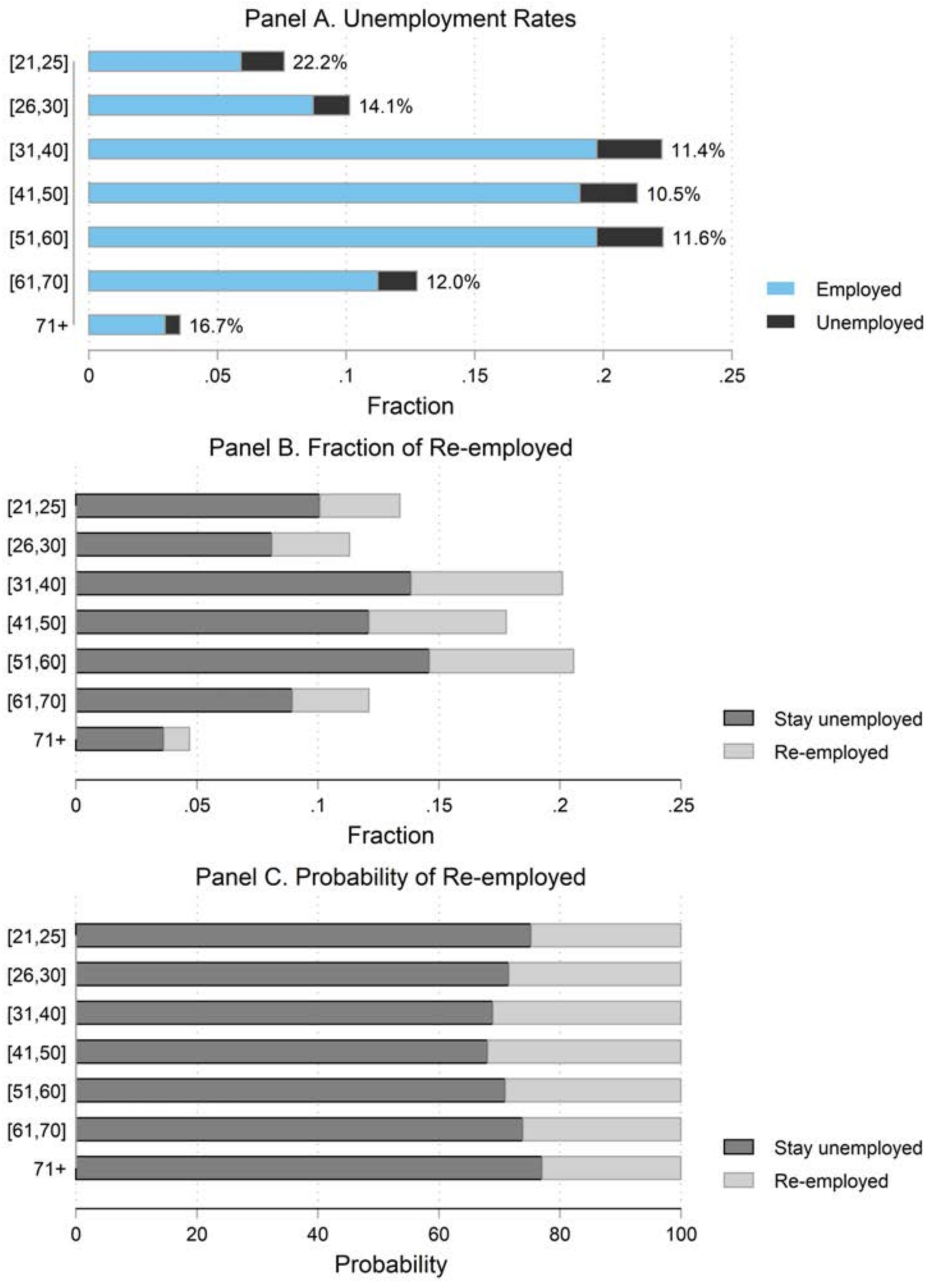
Notes: The sample includes people who transition from not working (both the employed but absent and the unemployed) to working, from April to May, in 2019 and in 2020. The colors represent, among people who are reemployed in May, the percentage who were employed but absent, unemployed-on layoff and unemployed-looking in April.

Figure 12: Duration of Unemployment and Probability of Re-employment



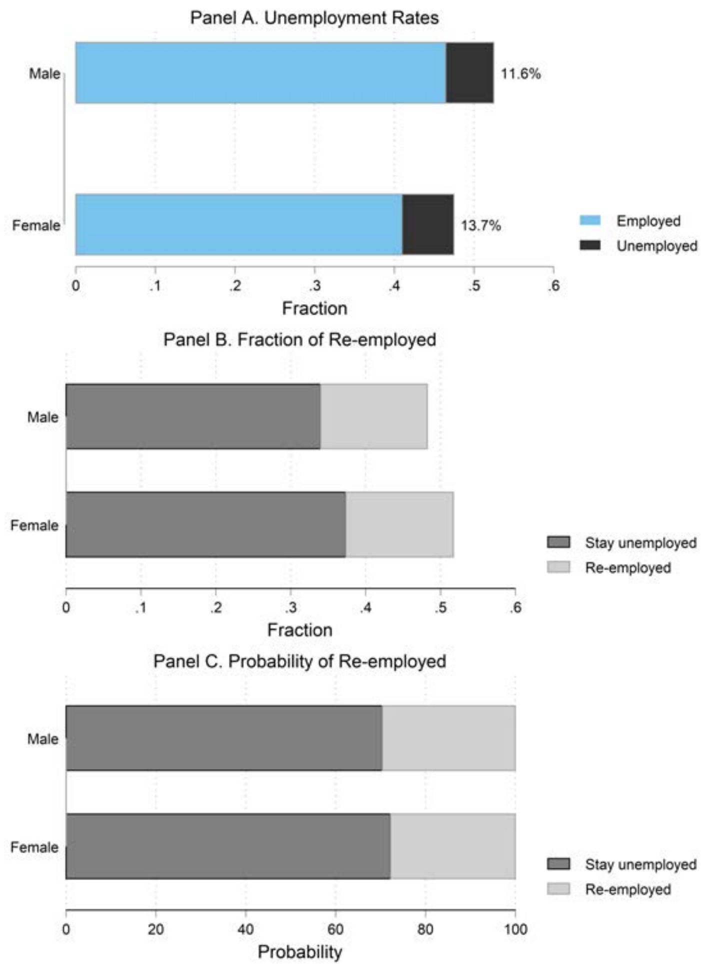
Notes: Left panel depicts the distribution of unemployment duration in April and right panel shows the probability of reemployment in May given each length of unemployment. The unemployed includes both unemployed-on-layoff and unemployed-looking in April. Top panel represents 2020 and bottom panel represents 2019.

Figure 13: Age and Probability of Re-employment



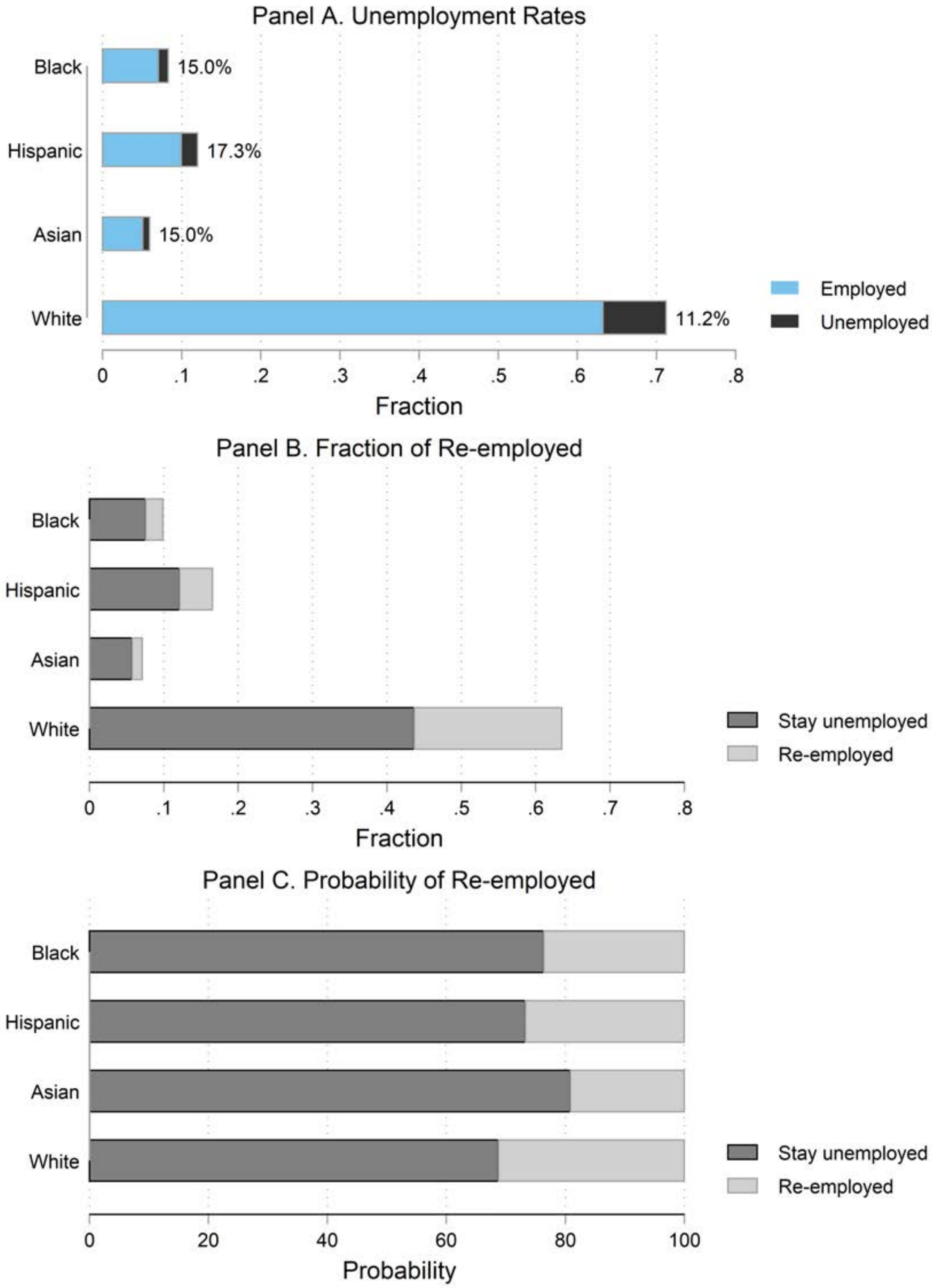
Notes: Panel A shows the percentage of labor force workers in each age group and the colors represent whether they are unemployed in April. The numbers next to the bars indicate the unemployment rate in each age group. Panel B depicts fraction of unemployed workers in each age group in April and the colors represent whether they are re-employed in May. Panel C shows the probability of re-employment for each age group.

Figure 14: Gender and Probability of Re-employment



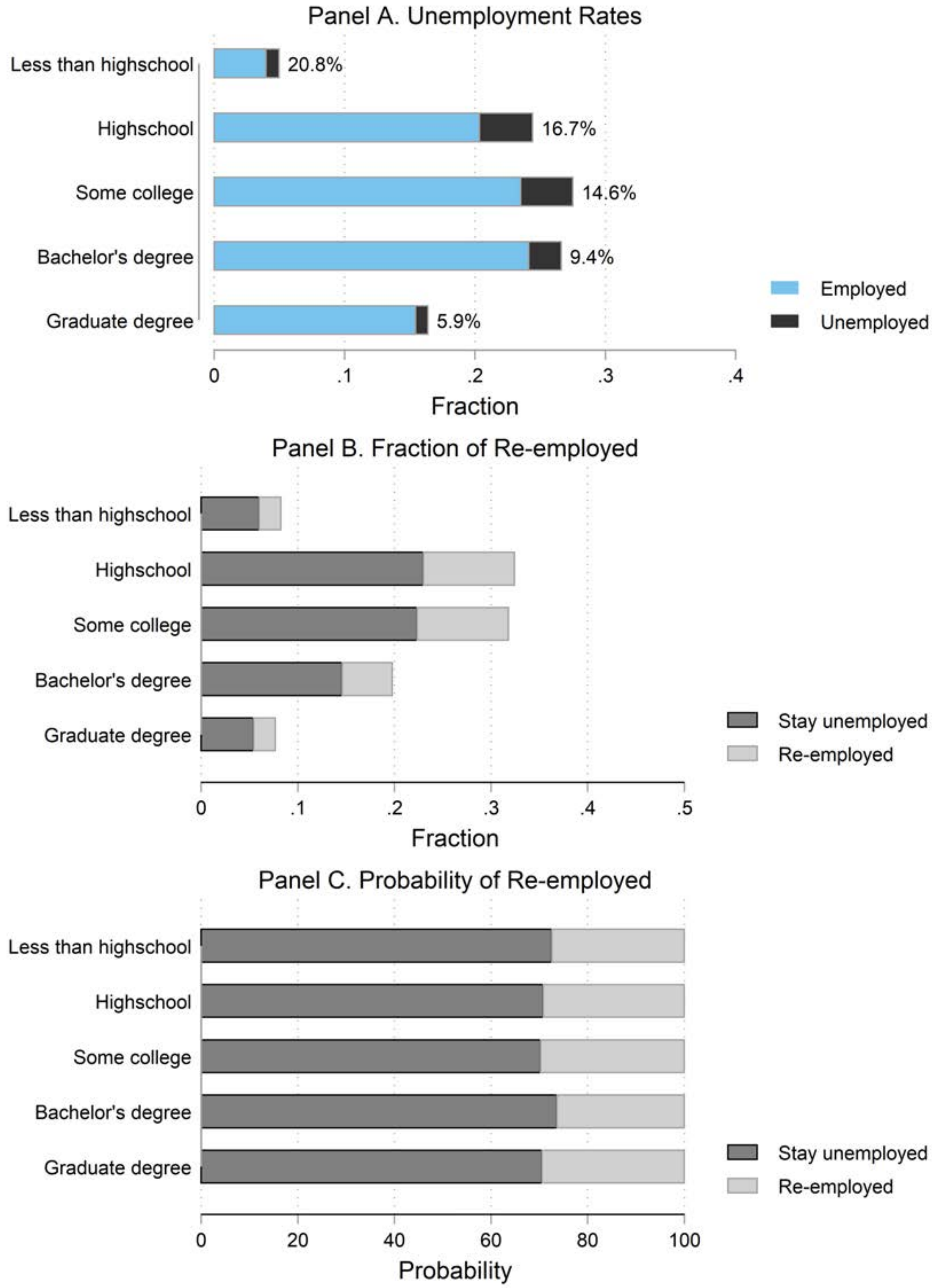
Notes: Panel A shows the percentage of female and male labor force workers and the colors represent whether they are unemployed in April. The numbers next to the bars indicate the unemployment rate in each gender group. Panel B depicts fraction of unemployed workers in each gender group in April and the colors represent whether they are re-employed in May. Panel C shows the probability of re-employment for each gender group.

Figure 15: Race and Probability of Re-employment



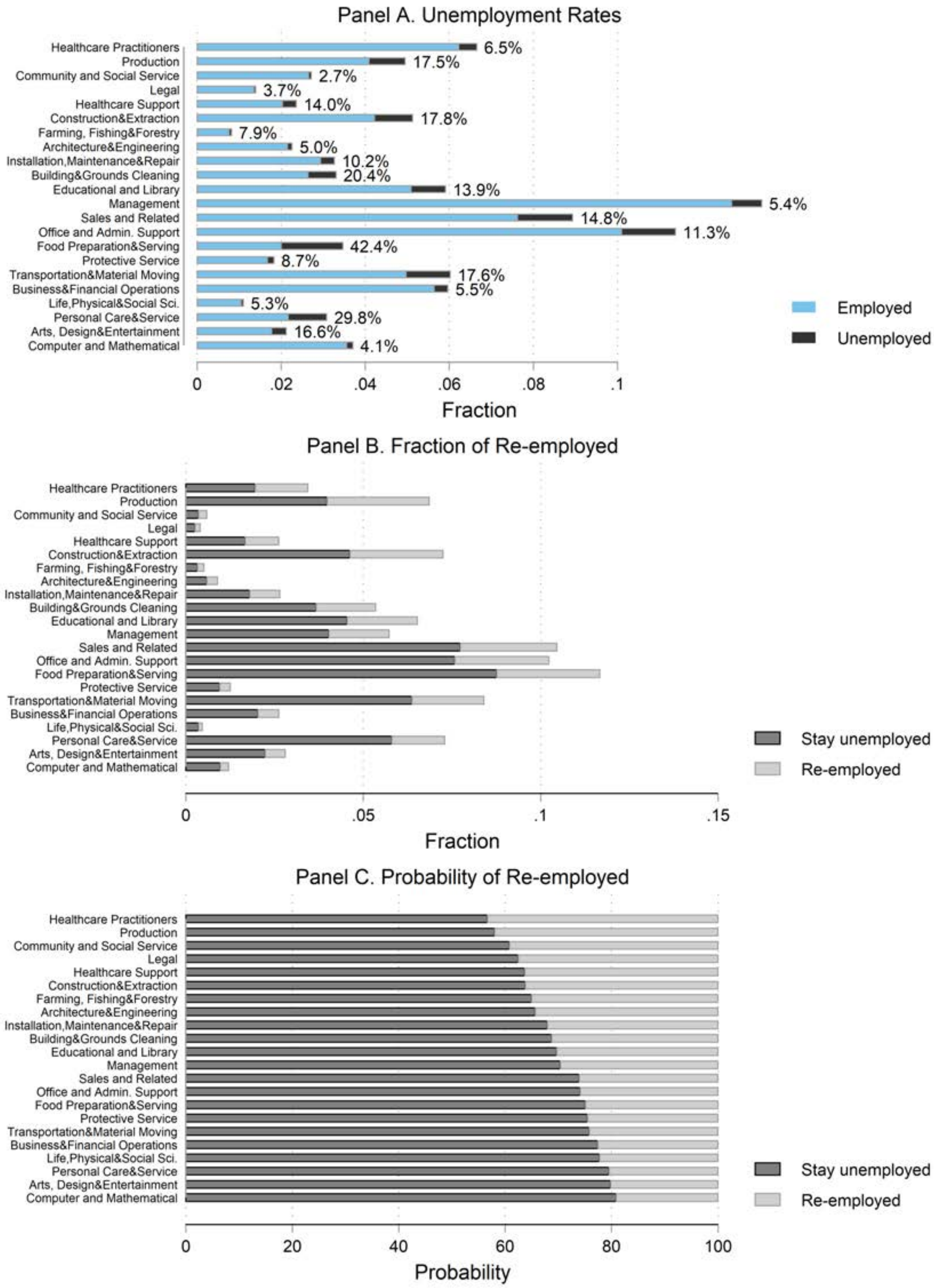
Notes: Panel A shows the percentage of labor force workers in each race group and the colors represent whether they are unemployed in April. The numbers next to the bars indicate the unemployment rate in each race group. Panel B depicts fraction of unemployed workers in each race group in April and the colors represent whether they are re-employed in May. Panel C shows the probability of re-employment for each race group.

Figure 16: Education and Probability of Re-employment



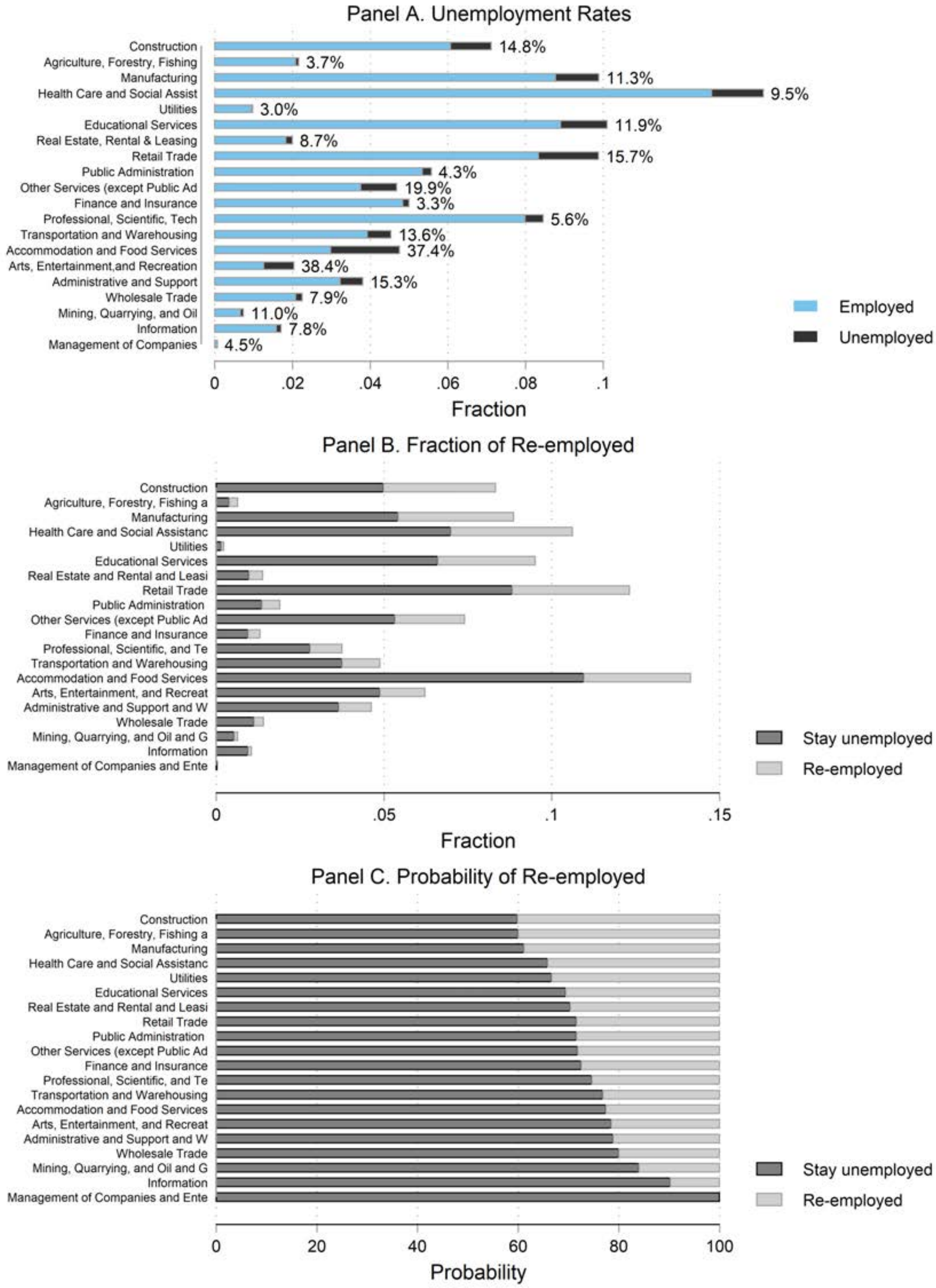
Notes: Panel A shows the percentage of workers in the laor force by education category and the colors represent whether they are unemployed in April. The numbers next to the bars indicate the unemployment rate in each education category. Panel B depicts fraction of unemployed workers in each education group in April and the color represents whether they are re-employed in May. Panel C shows the probability of re-employment for each education group.

Figure 17: Occupation and Probability of Re-employment



Notes: In Panel A, the bars represent fraction of workers in each occupation in April. The colors represent their employment status in April. 'Unemployed' means both unemployed-layoff and unemployed-looking, following the CPS classification. The numbers right next to the bars indicate the unemployment rate in each occupation in April. Panel B shows the fraction of unemployed workers in each occupation in April, and the colors represent whether they are re-employed in May. Panel C shows probability of re-employment between April and May in each occupation.

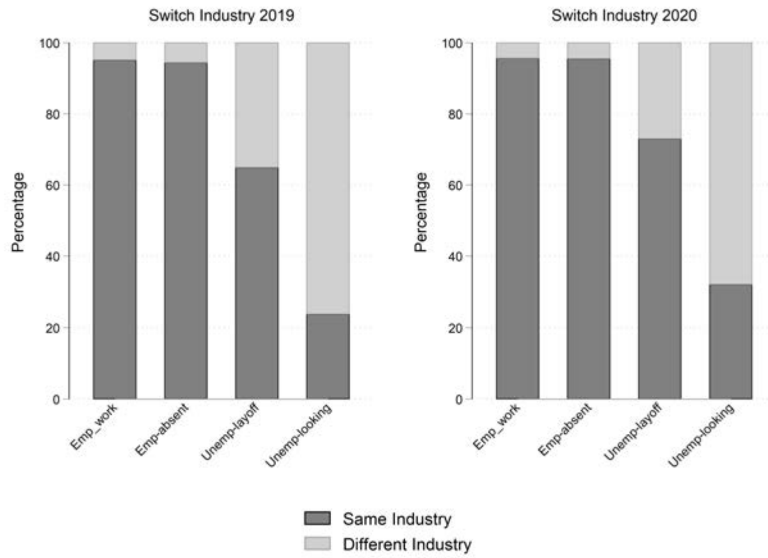
Figure 18: Industry and Probability of Re-employment



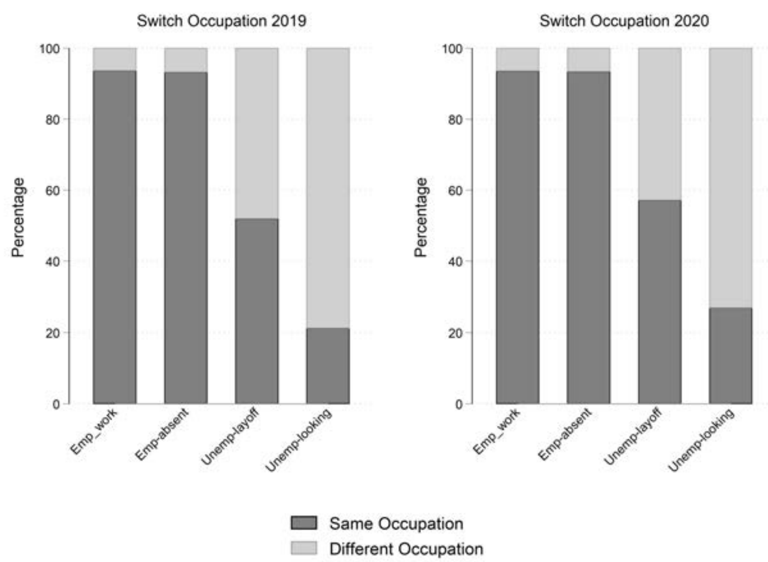
Notes: In Panel A, the bars represent fraction of labor force in each NAICS 2 digit industry in April. The colors represent their employment status in April. 'Unemployed' means both unemployed-layoff and unemployed-looking, following the CPS classification. The numbers right next to the bars indicate the unemployment rate in each industry in April. Panel B shows the fraction of unemployed workers in each industry, and the colors represent whether they are re-employed in May. Panel C shows probability of re-employment in each industry.

Figure 19: Industry and Occupation Switches

(a) Industry



(b) Occupation



Notes: This figure depicts whether individuals switch industries or occupations in May conditional on they are at work in May. Different bars represent different groups of people by their employment status in April. Panel (a) shows industry switches and Panel (b) shows occupation switches. The figure on the left of each panel represents 2019, and the right one represents 2020. An individual who has a different non-missing census occupation code in May from that in April is considered to have switched occupation. Industry switchers are defined similarly using census industry codes.

Table 1: Effects of Reopening Policies and Stay at Home Orders Duration on Labor Market Outcomes

	(1) Empl.	(2) Empl. - Absent	(3) Earn - Empl.	(4) Earn - Overall	(5) Hrs Last Wk - Empl.	(6) Hrs Last Wk - Overall
Panel A: Days Since Reopening						
Days since Reopening x May	0.0021**	-0.0007**	-0.0018	0.0094	-0.0323**	0.0422*
	(0.0006)	(0.0002)	(0.0020)	(0.0062)	(0.0154)	(0.0212)
Controls	X	X	X	X	X	X
R-squared	0.2621	0.0073	0.2311	0.3121	0.0731	0.2796
N	5,914,419	5,914,419	817,000	1,401,691	3,487,659	5,782,299
Panel B: Length of SAH						
Days since Reopening x May	0.0013	-0.0005	-0.0028	-0.0001	-0.0267	0.0230
	(0.0016)	(0.0004)	(0.0025)	(0.0132)	(0.0226)	(0.0589)
Length SAH x May	-0.0004	0.0001	-0.0006	-0.0047	0.0067	-0.0082
	(0.0009)	(0.0002)	(0.0014)	(0.0059)	(0.0099)	(0.0337)
Controls	X	X	X	X	X	X
R-squared	0.2615	0.0073	0.2321	0.3113	0.0727	0.2791
N	5,371,097	5,371,097	739,345	1,275,325	3,148,884	5,251,279
Panel C: Interaction						
Days since Reopening x May	0.0035*	-0.0005	-0.0147**	-0.0004	-0.0113	0.1121*
	(0.0018)	(0.0007)	(0.0059)	(0.0138)	(0.0233)	(0.0653)
Length SAH x May	-0.0001	0.0001	-0.0023**	-0.0047	0.0089	0.0045
	(0.0007)	(0.0002)	(0.0008)	(0.0055)	(0.0086)	(0.0270)
Length SAH x Days Reopening x May	-0.0001	-0.0000	0.0004**	0.0000	-0.0005	-0.0028
	(0.0000)	(0.0000)	(0.0002)	(0.0004)	(0.0007)	(0.0018)
Controls	X	X	X	X	X	X
R-squared	0.2615	0.0073	0.2321	0.3113	0.0727	0.2791
N	5,371,097	5,371,097	739,345	1,275,325	3,148,884	5,251,279
Mean of D.V. (May)	0.5157	0.0335	7.4984	3.8875	38.3383	20.4559
Mean of D.V. (April)	0.4897	0.0460	7.4823	3.7872	37.9826	19.4972
Mean of D.V. (Full)	0.5978	0.0221	7.3204	4.3457	39.3384	24.0484

Notes: A */** next to the coefficient indicates significance at the 10/5% level. Length of SAH orders is defined as number of days between SAH order enactment dates and expiration dates. For states where SAH orders were put in place, but no SAH expiration date is known or SAH expiration date is later than reopening date, we used the date of state reopening instead. Panel A regression only includes main effects for reopening. Panel B includes Length of SAH orders. Panel C includes the interaction between the reopening, SAH orders, and May. Control variables are: Female, Has a child under 6, Female x Has a child under 6, Black, Hispanic, Age (21-25), Age (26-30), Age (31-40), Age (51-60), Age (71+), Less than High School, Some College, Bachelor's degree, Graduate degree, and Metropolitan status. Standard errors are clustered at state level. The last three rows in the table show the mean values of the dependent variables for the full sample, 2020 April sample and 2020 May sample respectively.

Table 2: Probability of Re-employment (By Previous Employment Status)

	(1) Unemployed 2020	(2) Absent 2020	(3) Unemployed 2019	(4) Absent 2019
Unemployment Duration	-0.0032**		-0.0021**	
	(0.0003)		(0.0004)	
Essential	0.0296	0.0994**	-0.0078	-0.0466
	(0.0248)	(0.0375)	(0.0415)	(0.0824)
Face-to-Face	0.0094	-0.0290**	0.0216	0.0468
	(0.0137)	(0.0131)	(0.0244)	(0.0305)
Remote Work	0.0470**	0.0344**	0.0347	-0.0110
	(0.0142)	(0.0171)	(0.0241)	(0.0438)
Has Child Under 6 x Female	-0.0469	-0.2144**	-0.0537	-0.4079**
	(0.0425)	(0.0871)	(0.0920)	(0.0941)
Has Child Under 6	-0.0023	0.0798	0.0466	0.0360
	(0.0379)	(0.0679)	(0.0786)	(0.1039)
Female	-0.0007	-0.0359	0.0001	0.0029
	(0.0165)	(0.0312)	(0.0296)	(0.0412)
African-American	-0.0545	-0.0148	-0.0177	-0.1442*
	(0.0334)	(0.0376)	(0.0418)	(0.0789)
Hispanic	-0.0001	-0.0167	0.0097	0.1885**
	(0.0192)	(0.0328)	(0.0276)	(0.0479)
Age (21-25)	-0.0423	0.0721	-0.0397	-0.2663**
	(0.0279)	(0.0433)	(0.0338)	(0.0829)
Age (26-30)	-0.0089	0.0106	0.0104	-0.0628
	(0.0319)	(0.0288)	(0.0413)	(0.0643)
Age (31-40)	0.0161	0.0522	0.0346	-0.0610
	(0.0383)	(0.0339)	(0.0407)	(0.0556)
Age (51-60)	-0.0461**	0.0449	-0.0317	-0.0480
	(0.0208)	(0.0445)	(0.0252)	(0.0609)
Age (61-70)	-0.0835**	-0.0141	-0.0934**	-0.0639
	(0.0320)	(0.0466)	(0.0412)	(0.0601)
Age (71+)	-0.0616	0.0418	0.0253	-0.1200
	(0.0410)	(0.0395)	(0.0728)	(0.1276)
Less than High School	-0.0105	-0.0498	0.0389	-0.1746**
	(0.0377)	(0.0391)	(0.0524)	(0.0838)
Some College	0.0065	-0.0636**	0.0629**	0.0142
	(0.0174)	(0.0248)	(0.0312)	(0.0668)
Bachelors Degree	-0.0207	-0.0017	-0.0179	-0.0049
	(0.0238)	(0.0252)	(0.0347)	(0.0920)
Graduate Degree	0.0049	-0.0031	0.0117	0.0920
	(0.0291)	(0.0566)	(0.0431)	(0.0782)
Metropolitan	0.0160	0.0845**	-0.0446	-0.0228
	(0.0287)	(0.0364)	(0.0371)	(0.0566)
Constant	0.2570	0.4909**	0.0275	0.6540**
	(0.1589)	(0.1857)	(0.2043)	(0.1982)
R^2	0.0741	0.1154	0.1145	0.2634
N	4,477	2,084	1,442	734
Industry F.E.	Yes	Yes	Yes	Yes
Occupation F.E.	Yes	Yes	Yes	Yes

Notes: This table studies factors associated with probability of reemployment separately for those who were unemployed and those who were employed but absent. The first two columns use the matched CPS sample for April-May 2020 and the last two columns are for April-May 2019. Columns (1) and (3) represent individuals who are unemployed (both on layoff or looking for a job) in April, while Columns (2) and (4) represent individuals who are employed but absent in April. Longitudinal weights are incorporated in all regressions. Standard errors are clustered at state level. A */** next to the coefficient indicates significance at the 10/5% level.

Table 3: Probability of Re-employment

	2020	2019
Employed Absent (previous)	0.1721**	0.3893**
	(0.0262)	(0.0378)
Unemployed-Layoff (previous)	0.1375**	0.1950**
	(0.0285)	(0.0486)
Unemployment Duration	-0.0032**	-0.0019**
	(0.0005)	(0.0005)
Essential	0.0618**	-0.0276
	(0.0231)	(0.0352)
Face-to-Face	-0.0049	0.0231
	(0.0089)	(0.0163)
Remote Work	0.0423**	0.0185
	(0.0132)	(0.0271)
Has Child Under 6 x Female	-0.1017*	-0.2730**
	(0.0524)	(0.0624)
Has Child Under 6	0.0085	0.0236
	(0.0364)	(0.0943)
Female	-0.0256*	0.0251
	(0.0144)	(0.0319)
African-American	-0.0417*	-0.0545
	(0.0247)	(0.0412)
Hispanic	-0.0019	0.0473*
	(0.0188)	(0.0276)
Age (21-25)	0.0018	-0.0999**
	(0.0306)	(0.0439)
Age (26-30)	0.0034	-0.0142
	(0.0253)	(0.0416)
Age (31-40)	0.0361	-0.0289
	(0.0246)	(0.0403)
Age (51-60)	-0.0029	-0.0770
	(0.0223)	(0.0464)
Age (61-70)	-0.0602**	-0.1032**
	(0.0272)	(0.0495)
Age (71+)	-0.0372	-0.0644
	(0.0332)	(0.0798)
Less than High School	-0.0246	-0.0489
	(0.0312)	(0.0493)
Some College	-0.0229*	0.0436
	(0.0126)	(0.0385)
Bachelors Degree	-0.0059	-0.0185
	(0.0184)	(0.0515)
Graduate Degree	0.0137	0.0689
	(0.0405)	(0.0540)
Metropolitan	0.0511**	-0.0417
	(0.0229)	(0.0371)
Constant	0.3684**	0.1762
	(0.1247)	(0.1740)
R^2	0.0879	0.2973
N	5,920	1,480
Industry F.E.	Yes	Yes
Occupation F.E.	Yes	Yes

Notes: This table combines those who are unemployed and those who are employed but absent, in April, and studies factors associated with their probability of transitioning to being employed and working in May. Indicators for April's employment status are included in the regressions. The reference April employment status is 'Unemployed-looking'. Longitudinal weights are incorporated in all regressions. Standard errors are clustered at state level. A */** next to the coefficient indicates significance at the 10/5% level.

Table 4: Probability of Re-employment in May 2019 vs. May 2020

	(1) Incremental 2020 Effect
Employed-Absent	0.3972**
	(0.0367)
Employed-Absent x Year=2020	-0.2291**
	(0.0430)
Employed-On Layoff	0.2213**
	(0.0417)
Employed-On Layoff x Year=2020	-0.0881*
	(0.0465)
Unemployment Duration	-0.0017**
	(0.0005)
Unemployment Duration x Year=2020	-0.0015**
	(0.0006)
Essential	-0.0326
	(0.0348)
Essential x Year=2020	0.0930**
	(0.0413)
Face-to-Face	0.0273*
	(0.0160)
Face-to-Face x Year=2020	-0.0318*
	(0.0176)
Remote Work	0.0305
	(0.0265)
Remote Work x Year=2020	0.0103
	(0.0334)
N	7,400
R^2	0.1242

Notes: The sample consists of matched April-May CPS individuals (in 2019 and in 2020), whose employment status in April is either employed but absent, or unemployed. This table reports only some of the estimated coefficients due to space constraints. Other variables include demographic characteristics, education level, NAICS 2-digit industry dummies and their interaction with year of 2020, SOC 2-digit occupation dummies and their interaction with year of 2020. The reference April employment status is 'unemployed-looking'. Longitudinal weights are incorporated in all regressions. Standard errors are cluster at state level. A */** next to the coefficient indicates significance at the 10/5% level.

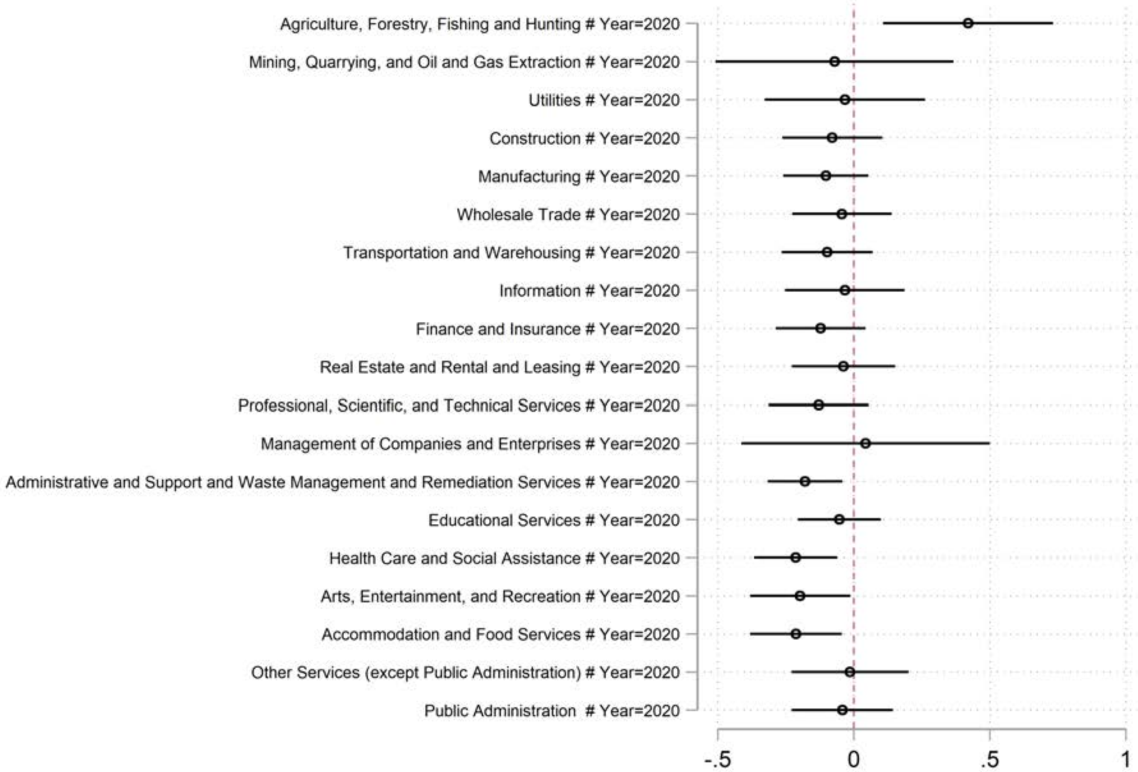
Table 5: Earnings and Hours Worked Conditional on (Re-)employment

	(1) Earnings	(2) Hours Last Week
Employed (previous)	0.1814**	3.9706**
	(0.0897)	(1.5347)
Employed Absent (previous)	0.0768	-2.2149
	(0.1074)	(1.3503)
Unemployed-Layoff (previous)	0.0352	-2.0239
	(0.0964)	(1.4254)
Has Child Under 6 x Female	0.0298	-1.6642**
	(0.0591)	(0.4928)
Has Child Under 6	0.0017	0.2549
	(0.0347)	(0.4755)
Female	-0.2141**	-2.6389**
	(0.0212)	(0.3151)
African-American	-0.1343**	0.4036
	(0.0304)	(0.2814)
Hispanic	-0.0694**	-0.2249
	(0.0193)	(0.3666)
Age (21-25)	-0.4300**	-2.5110**
	(0.0303)	(0.3075)
Age (26-30)	-0.2353**	-1.0495**
	(0.0256)	(0.3270)
Age (31-40)	-0.0919**	-0.1097
	(0.0288)	(0.2404)
Age (51-60)	0.0017	-0.5134*
	(0.0222)	(0.2972)
Age (61-70)	-0.1528**	-3.0288**
	(0.0307)	(0.3095)
Age (71+)	-0.4258**	-8.5026**
	(0.0783)	(0.6938)
Less than High School	-0.2152**	-1.0656**
	(0.0301)	(0.3402)
Some College	0.0181	0.2458
	(0.0213)	(0.2568)
Bachelors Degree	0.2801**	0.6453**
	(0.0202)	(0.3191)
Graduate Degree	0.4312**	1.7918**
	(0.0296)	(0.4300)
Metropolitan	-0.1013**	0.1942
	(0.0282)	(0.3196)
Constant	7.8825**	45.5890**
	(0.1308)	(2.0941)
R^2	0.3501	0.1198
N	8,610	25,024

Notes: Includes individuals who are employed and working in May, in the matched April-May 2020 sample. Column (1) represents earnings and Column (2) represents hours worked last week. The reference employment status is 'unemployed-looking'. Models include industry fixed effects, occupation fixed effects and state fixed effects. All regressions use longitudinal weights. Standard errors are clustered at the state level. A */** next to the coefficient indicates significance at the 10/5% level.

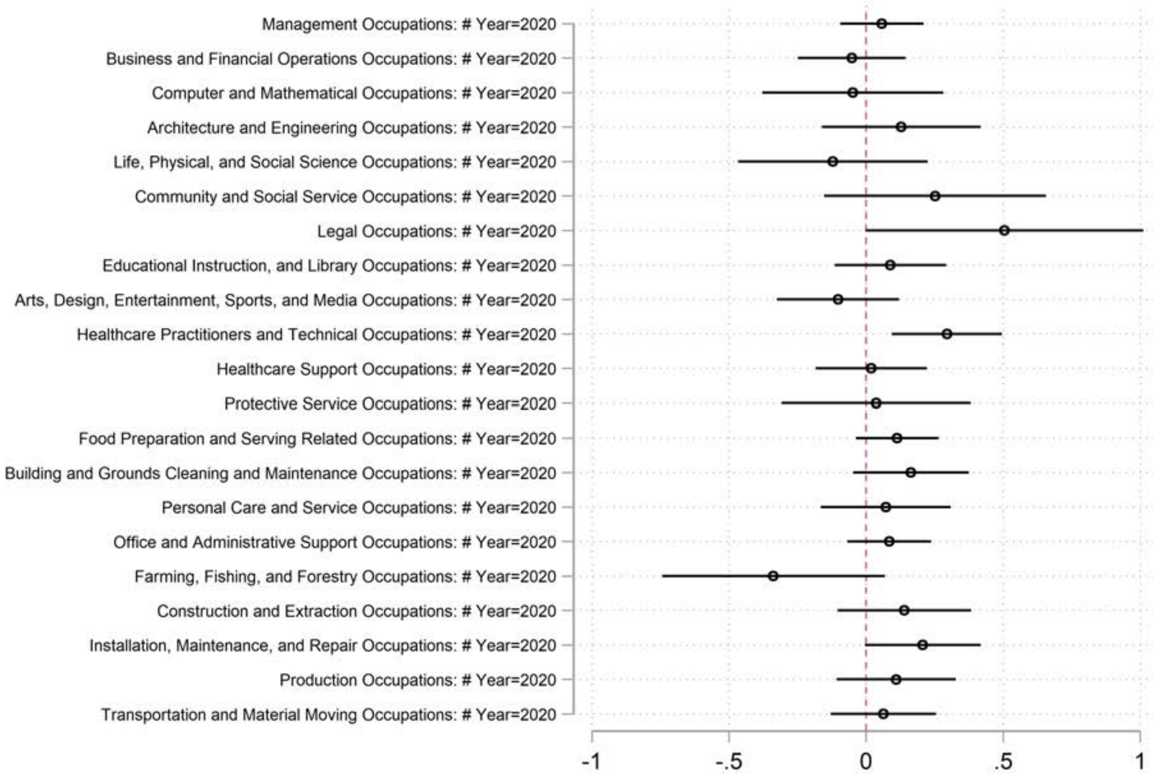
A Appendix

Figure 20: Estimated Coefficients for Industries



Notes: This figure plots 2020 differential effects for each industry (compared with 2019). The estimates are based on the regression in Table 4. In addition to the coefficients in front of industries interacted with year of 2020 terms (as plotted in the figure), the regression also has a full set of industry dummies which represents industry fixed effects in 2019. The reference industry is 'Retail Trade'.

Figure 21: Estimated Coefficients for Occupations



Notes: This figure plots 2020 differential effects for each occupation (compared with 2019). The estimates are based on the regression in Table 4. In addition to the coefficients in front of occupations interacted with year of 2020 terms (as plotted in the figure), the regression also has a full set of occupations dummies which represents occupation fixed effects in 2019. The reference occupation is 'Sales and Related Occupations'.

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