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ABSTRACT

We make several contributions to understanding how the COVID-19 epidemic and policy responses have affected U.S. labor markets, benchmarked against two previous recessions. First, monthly Current Population Survey (CPS) data show greater declines in employment in March 2020 (relative to February) for Hispanics, workers aged 20 to 24, women, those with large families, and less-educated workers. Second, we show that job loss was larger in occupations that require more interpersonal contact and that cannot be performed remotely. Third, occupational sorting explains about half of the Hispanic/non-Hispanic gap in employment outcomes, but less than a quarter of the employment gaps between other groups. Finally, the labor market effects of the epidemic are widespread across the country and do not appear to be stronger in states that were hit early, nor in states that were earlier in limiting social and economic activity. We also address measurement issues known to have affected the March CPS. In particular, non-response increased dramatically, especially among the incoming rotation groups. Some of the increase appears non-random, but is not likely to be driving our conclusions. We also demonstrate the importance of tracking workers who report having a job but being absent, in addition to tracking employed vs. unemployed workers. Our work shows trends in employment disparities that arise in the very early days of the epidemic and its policy responses. Data from future months will improve the accuracy of our estimates and provide further evidence on the labor market disparities that have already emerged.

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1 Introduction

The COVID-19 epidemic and the social distancing responses to it have already had profound effects in the United States. Between February and March 2020, the US witnessed a drastic reduction in the size and scope of economic activity. Large sectors – transportation, hospitality, and tourism – have essentially shut down their normal operations, while others have made changes either to mitigate health risks or cope with higher or lower demand for certain goods and services. State governments have issued a series of mandates designed to reduce physical mobility and interaction, including non-essential business closures, and shelter-in-place orders.

This paper is among the early attempts to document demographic heterogeneity in the early labor market impacts of the COVID-19 epidemic. We investigate broad patterns of job losses in the starting weeks of the epidemic and compare these changes with the Great Recession and the 2001 recession. We examine evidence surrounding several hypotheses that link labor market outcomes with the basic biology of SARS-COV-2, the virus that causes COVID-19. The virus spreads mainly through droplet transmission that occurs when people are in close physical proximity. Aggregate demand fell dramatically due to economic uncertainty and state closure policies. But the nature of the transmission mechanism also implies large reductions in demand for labor in sectors that involve face-to-face contact while increasing labor demand in some sectors, including essential jobs, and less impact on jobs based on online interactions, where remote work is possible. On the supply side, the transmission mechanism also raises the health risks of work tasks that require face-to-face contact with customers or co-workers that cannot be conducted online. Moreover, mortality risks from COVID-19 vary across individuals, most notably increasing with age. We expect that high-risk workers may supply less labor, especially in high-exposure jobs. As argued by Guerrieri et al. (2020), theory suggests that individuals will reduce labor supply to contain contagion. But labor supply might decrease through other channels as well. Disruptions associated with the epidemic also stem from reductions in the availability of child care and schooling, as discussed in Dingel et al. (2020), and from COVID-19 related care for oneself or family members.

We present four broad analyses to investigate heterogeneity in labor market impacts. First, we use data from the monthly Current Population Survey (CPS) to document how labor market outcomes (current employment, recent unemployment, and absence from work) have changed in subpopulations defined by age, gender, race/ethnicity, education, parental status, presence of children, occupation, and industry.[1] We find large declines in employment and increases in recent unem-

[1] We consider the labor force category of employees absent from work because some employers released workers intending to rehire them (Bogage 2020; Borden 2020). Moreover, some workers may have requested leave from their schedule to provide dependent care, or due to the illness of a household member. Finally, paying particular attention to the absent-from-work category is necessary due to a misclassification problem during the data collection of the March

ployment among younger workers, non-whites, Hispanics, and parents of large families. There is also an education gradient; there were fewer job losses among workers with a college degree.

Second, we explore heterogeneity in employment outcomes by job characteristics: extent of in-person interactions involved in the work, and whether the work is considered an "essential activity". We use the O*NET database to develop indices of the extent to which each occupation involves job tasks compatible with remote work, require face-to-face interaction, and require work outside the home. Previous studies have recognized the importance of analyzing the impact of COVID-19 on employment outcomes accounting for how various socio-demographic groups sort in occupations with different levels and types of interactions (Leibovici et al. 2020; Mongey and Weinberg 2020; Dingel and Neiman 2020). We show larger declines in employment in March 2020 for occupations that rely more heavily on face-to-face activities. Jobs that can be performed remotely actually experienced an increase in employment. We classify jobs as essential based on the "Guidance on the essential critical infrastructure workforce" of The Department of Homeland Security (2020) and found that such jobs experience somewhat better labor market outcomes. In particular, workers in jobs deemed essential are less likely to report that they have been absent from work. Because changes in employment may reflect demand or supply shocks, we seek to tease out the extent of supply changes by examining employment among workers in high-exposure industries. We expect these industries might retain more low-risk workers and fewer high-risk workers, in relative terms. We classify workers' risk levels based on evidence demonstrating that older people, and older men in particular, have higher risk of death from SARS-COV-2 infections than younger people and women.[2] We find very little evidence of a relative reduction of high-risk workers' presence in high-exposure industries. This suggests that the overwhelming majority of employment changes are driven by aggregate demand and not by labor supply. Of course, this may change in later stages of the epidemic as risks are better understood and as other policies such as paid sick leave and enhanced unemployment benefits becomes available. To assess the importance of dependent care as a factor in labor supply, we estimate changes in employment for families with many children, and for women in particular. These estimates show that families with four or more children experience greater employment declines.

As our third contribution, we decompose the gross differences in job losses across key demographic and social groups using an Oaxaca-Blinder decomposition. The Oaxaca decomposition decomposes the difference in employment losses between two demographic groups into parts due to their sorting into certain occupations (such as work that cannot be done at home) as well as hu-

2020 CPS. We detail these issues in Section 3.

[2]We expect that changes of this nature may not entirely reflect labor supply– high-exposure employers may also, out of concern over workers' welfare, substitute low-risk for high-risk workers. If so, this approach will attribute some employer-driven behavior to be labor supply responses.

man capital characteristics. Unsurprisingly, a significant share of differences in employment loss across groups is explained by differences in (pre-epidemic) sorting across occupations. However, in almost all cases, a much larger share cannot be explained by either occupation sorting or other observable traits.

Fourth, we assess the extent to which job losses are shaped by state level measures of the severity of the epidemic and whether the state elected to close elementary and high schools early in the epidemic. These models shed light on the extent to which the COVID-19 recession is shaped by national vs regional information and events.

In addition to these substantive contributions, we provide two technical insights. We first show that it is important to account for people who are employed but absent from work in quantifying the labor market effects of COVID-19 and its policy responses. Second, we analyze the spike in non-response in the CPS in March 2020. We provide evidence that at least some of the increase is non-random with respect to demographics and likely with respect to employment status.

2 Related Research

The literature on labor market impacts of COVID-19 is evolving rapidly. There is mounting evidence that layoff statistics may severely underestimate the extent of labor market adjustments (Coibion et al. 2020). Using data from a survey of households conducted in early April, the authors estimate that unemployment greatly exceeds that indicated by UI claims data. Mongey et al. (2020) use March 2020 CPS to show that workers who have the ability to work remotely experienced a protective effect. There are still many unanswered questions on how the epidemic is affecting different types of workers and families in the United States. Lozano-Rojas et al. (2020) study initial unemployment claims during the first several weeks of the epidemic, finding 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. Their work suggests that most of the disruption to date stems from the public health shock itself rather than from the unintended consequences of policy actions to mitigate the spread of the virus. Similarly, Kahn et al. (2020) show a large drop in job vacancy postings (an indicator of labor demand) in the second half of March, so that by early April, there were 30% fewer job postings than at the beginning of the year. Looking across states, the authors find that the large declines in postings happened across the board, regardless of the state policies or local extent of the epidemic.

Gupta et al. (2020) use cell phone data on mobility and interaction patterns to study the effects of state and local policies on measures of time spent at home. They document a massive, nation-wide decline in multiple measures of mobility outside the home (for work or non-work reasons). Even states that have not adopted restrictive policies experienced large reductions in mobility. However, Gupta et al. (2020) also find evidence that early and information-focused state policies did lead to larger reductions in mobility. These reductions in time outside the house 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.

There is a sparse but growing literature using O*NET occupational characteristics to capture the type of work conducted by each occupation and further investigate the employment variation attributed to three occupational traits. Both Dingel and Neiman (2020) and Mongey and Weinberg (2020) use measures in O*NET to define high work-from-home occupations and Leibovici et al. (2020) take a similar approach to measure occupations with high interpersonal contact.

Studies have investigated the pandemic's heterogeneous shock on different demographic groups as well. Alon et al. (2020) find that the social-distancing policies have a larger effect on women than men, unlike in a "regular" recession, as social-distancing measures have large impacts on sectors with high female employment shares. They point out this crisis's impact on working mothers could be persistent. Studies using data outside the U.S., including both developed and developing countries, also have investigated employment inequality among socio-demographics groups in the pandemic era (Adams-Prassl et al. 2020; Dasgupta and Murali 2020).

3 Data

3.1 Current Population Survey

Our main analysis uses the Basic Monthly CPS collected during the first quarter of 2020. In the survey, respondents are asked about their labor market activities during a reference week that includes the 12th of the month (U.S. Census Bureau 2019). This means that the reference week for the March 2020 CPS was quite early in terms of the COVID-19 epidemic and associated policy responses. To focus on job losses related to the epidemic, we use a measure of recent unemployment. We define a worker to be recently unemployed if he/she is coded as being unemployed in March 2020 and reports having been unemployed for at most 4 weeks. When analyzing this variable, we exclude individuals who are out of the labor force from the denominator. In Section 5 we show how this measure of recent unemployment compares favorably to the more conventional month-over-month change in the employment rates calculated by comparing between February and March 2020.

U.S. Bureau of Labor Statistics (2020) warns of several data quality issues in the March 2020 survey that arose from the epidemic. The BLS largely halted field operations, but respondents may also have been more difficult to reach for other reasons. Together, these factors led to a historic decline in the response rate, by around ten percentage points. We conduct a basic assessment of the effects of non-response on our analysis in Appendix A.

As another measure of recent job loss, we study workers who report being employed, but absent from work. The CPS defines "all those 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) as "absent from job." There was a large increase in March of reporting employed but absent from work. BLS had 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 (2020) explain that surveyors appeared to code at least some of them in the employed-but-absent category. Therefore, for a more comprehensive measure of recent job loss, in some analyses we combine the recently laid off with the employed-but-absent-from-work.

In addition to the CPS data from the first quarter of 2020, we also used CPS monthly data from earlier years to examine peak-to-trough employment changes in the 2001 recession and the Great Recession. To determine the peak and the trough months, we use business cycles periods following reference dates set by the National Bureau of Economic Research (2012). The NBER considers the 2001 recession to run from March 2001 to November 2001. The Great Recession runs from December 2007 to June 2009. When focusing on the COVID-19 crisis, we only compare February to March 2020 for now. We compare the employment rate over there three events in Figure 1.

3.2 O*Net

The Occupational Information Network (O*Net) Work Context module is a database that reports summary measures of the tasks involved in 968 occupations (SOC 2010).[3] The data are gathered through surveys asking workers how often they perform particular tasks or the importance of different activities in their job. Some of the questions relate to the need for personal interaction, or how easily work could be done remotely. 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.

To measure the extent to which an occupation involves tasks that are affected by the COVID-19 epidemic, or that might protect against job disruption during the epidemic, we developed indices for: (1) Face-to-Face interactions, (2) the potential for Remote Work, and (3) the extent to which

[3] See O*NET National Center for O*NET Development (2020). The survey is updated yearly and we are using the 2019 update in this paper.

work occurs Outside the Home. Table B.1 presents the specific O*Net questions used in the construction of the indices. The value of each index for an occupation is a simple average O*Net questions listed in the table.

3.3 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.[4] The DHS guidance outlines 14 employment categories that are defined as essential critical infrastructure workers. We use the DHS guidance to classify occupation codes as DHS Essential vs DHS Non-essential. Out of 765 occupations, 234 are defined as "essential" occupations.

3.4 COVID-19 Exposure and Early Policy Actions

We link CPS data to information on a state's COVID-19 exposure (cases and deaths) and to early state policies related to school closures and to Emergency Declarations to explore heterogeneity in employment outcomes across states. We detail our estimation in Section 6. We retrieve information on COVID-19 cases and deaths from The New York Times (2020), calculating per capita measures using state level Census population estimates.

We classify information regarding state Emergency Declarations and school closures following Gupta et al. (2020) who build on data gathered by Raifman and Raifman (2020) and Fullman and Wilkerson (2020). We group states based on whether policy occurred by the reference week of the CPS. School closures varied substantially at the sub-state level prior to state closures, such that approximately 15 percent of US K-12 students were affected by school closures at the district level prior to governor's state level shutdowns. Using information from Education Week, we compiled enrollment-weighted data on the share of school-weeks lost among the students in each state during the second week of March.[5]

3.5 COVID-19 Mortality Risk

We constructed a COVID-19 mortality risk index by age and gender using data on case-mortality rates released by CDC China and based on deaths in Mainland China as of February 11, 2020 (Surveillances 2020). We applied the case-fatality rates to the U.S. workers in our sample by normalizing the product of age fatality rate and the gender fatality rates. Our goal is to measure

[4] The list of critical infrastructure occupations is available at: `https://www.cisa.gov/publication/guidance-essential-critical-infrastructure-workforce`.

[5] These data are available at: Education Week - Map: Coronavirus and School Closures.

expectations (as of the second week of March) about COVID-19 mortality rates. While mortality rates likely differ between the U.S. and China, these data are the best available at this time and likely a primary factor in forming expectations.

4 Employment Disruptions in Three Recessions

Figure 1 shows the path of seasonally-adjusted non-farm employment between March 2000 and March 2020. The shaded areas indicate the 2001 Recession (March 2001 to November 2001), the Great Recession (December 2007 to June 2009), and the COVID-19 Recession (which covers just the two month period from February to March 2020 and does not yet include many of the most recent job losses.) We augment the CPS employment series by subtracting new unemployment insurance claims from the second half of March from the BLS March employment estimate. This extrapolation is shown as the dashed line in the figure and it suggests that after only one month, the COVID-19 has generated an employment decline almost as large as the entire employment loss from peak-to-trough of the Great Recession.

Figure 1 provides a sense of the overall magnitude and timing of employment changes during the recessions and how they compare with the COVID-19 epidemic to date. However, the gross change in employment masks substantial heterogeneity in employment changes across different groups of workers. To understand the distribution of employment disruptions, we computed peak-to-trough changes in employment for several sub-populations of workers in the 2001 Recession and the Great Recession. We compared these changes with the one-month change in employment from February 2020 to March 2020. We defined employed individuals as people who were employed and currently at work or employed but absent from work; we computed employment rates using the CPS sampling weights.

Figure 2 shows total employment losses from peak-to-trough across demographic groups for the three events. The left panel shows changes in employment by gender, race, Hispanic ethnicity, and age group. The right panel shows employment changes by education and family size. We examine four education groups: less than high school, high school graduates, some college, and college graduates, and seven family type categories: parents with any children up to 13 years old, parents with any children who are at least 14 years old, childless adults, and parents with one, two, three or at least four kids.

The changes in employment are negative for each of the subgroups and across all three events. No group is spared from employment loss during recessions. The decline in employment in the very first month of the COVID-19 epidemic is, in most cases, at least half as large as the one workers experienced from peak-to-trough in the 2001 Recession and the Great Recession, which instead span nine and nineteen months respectively. The labor market shock in the 2001 recession disproportionately hit non-whites, Hispanics, middle-aged workers, high school degree holders, and workers with children. The Great Recession lead to a dramatic decrease in employment among Hispanics, middle-aged workers, families with children (especially if young) and, above all, holders of undergraduate or graduate degrees. Focusing on COVID-19, the bar graph shows that between February and March employment rates fell slightly more among women than men. Similarly, African Americans and the "Other Race" group face somewhat larger declines in employment than whites, and the same holds for workers with a middle level education, compared to undergraduate or graduate degree holders and workers with less than a high school degree. Importantly, in the first month of COVID-19, workers aged 20 to 24 and parents of at least four children have already experienced a more substantial decrease in employment than they did during the entire duration of the previous two recessions.

The employment of parents of at least four children decreased by almost 5 percentage points in this period. Because we find a large decrease even for parents of three children, we conclude that the negative finding on employment applies to large families overall.

Young workers' employment declined by more than 5 percentage points, and for Hispanics the change was of almost 4 percentage points. Our conjecture is that these two groups disproportionately work in industries that are particularly hit by social distancing measures, including food service and construction. There are, overall, two main takeaways from Figure 2. First, given the much shorter time frame over which we compute the COVID-19 change in employment versus the other shocks, the comparison with previous recessions makes the COVID-19 numbers extremely dramatic. Second, although the employment of all socio-demographic groups decreases in each of the recessions considered, there is considerable variation in terms of the impact on subgroups during these three shocks. Next, we will attempt to explain the differences in the employment outcomes across socio-demographic groups that arise during the COVID-19 recession.

5 Job Tasks and Recent Unemployment

The COVID-19 epidemic has increased the health risks of interpersonal interactions. Thus, it seems likely that jobs involving higher levels of face-to-face contact and more work performed outside of the home have been disproportionately disrupted, while jobs that can be done remotely should be more secure. Recall that we study the incidence of recent unemployment, as measured in the March CPS. Recently unemployed workers are those who report being unemployed and have an unemployment duration of four weeks or less. Figure 3 shows that the incidence of recent unemployment across demographic groups is very similar to month-over-month changes from February to March in the employment-to-population ratio. The left panel of Figure 3 shows the average change in employment rates from February 2020 to March 2020 by demographic sub-population. The right panel shows the fraction of labor force participants who became unemployed recently as of the March CPS reference week. The figure shows that changes in employment and recent unemployment rates are both substantially higher for Hispanic workers than non-Hispanic workers; for black workers than for white workers; for workers without a college degree than those with; and for younger workers. Given the similarity between the two measures, we focus our analysis on recent unemployment.[6]

We explore the extent to which these patters are due to workers being employed in jobs with different exposure to epidemic-sensitive job tasks. To do so, we standardized the job task indices so that they have a mean of zero and a standard deviation of 1. Figure 4 shows the mean of the standardized Face-to-Face Index and Remote Working Index by sub-populations in the February 2020 CPS. The Remote Work Index measures how much a particular job involves tasks that can be performed remotely, such as email, written letters or memos, and telephone conversations. The right panel of Figure 4 shows that Hispanics, workers between 20 and 24 years old, and less educated workers (i.e. less than high school and high school degree) have jobs with below average scores on the Remote Work Index. In contrast, college educated workers work in jobs with higher than average scores on the Remote Work Index. The Face-to-Face Index measures the extent to which the occupation involves in-person conversations with individuals or teams, or work that must be performed in close physical proximity to other people. The left panel of Figure 4 shows that younger workers and women tend to work in jobs that require more face-to-face interaction. Less educated workers tend to be in jobs with lower scores on the Face-to-Face index.

Figure 5 displays the association between the different index scores in an occupation and the rate of recent unemployment in that occupation in the March CPS. The scatterplot, then, is preliminary evidence on the role that occupation characteristics have in determining job losses during COVID-19. The bubbles are sized in proportion to the number of workers in that occupation. There are a total of 346 occupations[7] in our sample and the occupation-specific recent unemployment rates range from 0% to 5%. To make the graph readable, we exclude 33 observations with recent unemployment rates of more than 4.34%, which is the 90th percentile of the distribution. The left panel in figure 5 shows that the March recent unemployment rate tends to be lower in occupations with higher scores on the Remote Work Index, suggesting that the ability to work from home has helped protect employment during the early months of the epidemic. The right panel

[6]Doing so allows us to study employment loss at the individual level without the need to link the CPS across months.

[7]Specifically, Census 2010 occupation codes.

shows that recent unemployment rates are higher in occupations that involve more face-to-face tasks. In other words, the more heavily the occupation relies on face-to-face activities, the more likely its workers are to become unemployed as a result of the COVID-19 epidemic and/or the policy responses to it.

Job tasks are not the only factors that may explain recent job losses. It is possible that school closures and reduced access to child care have disrupted employment in households with children. Heterogeneity in worker mortality risk from COVID-19 may have played a role as well in reducing labor supply among certain groups. To examine these possibilities in more detail, we fit OLS regressions of recent unemployment and also recent work absences on a collection of worker and job characteristics:

$$\begin{aligned} y_{ij} = {} & Face_j\beta_1 + Remote_j\beta_2 + Out_j\beta_3 + Essential_j\beta_4 \\ & + Mortality_i\beta_5 + Female_i\beta_6 + Child_i\beta_7 + (Child_i \times Female_i)\beta_8 \\ & + X_i\delta + \epsilon_{ij} \end{aligned} \tag{1}$$

In the model, y_{ij} is an indicator set to 1 if person i from occupation j is recently unemployed.[8] The variables $Face_j$, $Remote_j$, and Out_j are the Face-to-Face, Remote Work Index, and Outside the Home Work indices. The variable $Essential_j$ is a dummy variable equal to one if the occupation is considered essential by DHS. We define an index of a person's COVID-19 mortality risk, denoted $Mortality_i$.[9] $Female_i$ indicates that the person is female, $Child_i$ is an indicator set to 1 if person i has a child under age 13 in the household, and X_i is a vector of covariates, including a quadratic in age, indicators for race/ethnicity, and indicators for levels of education. In some specifications, we include interaction terms between mortality risk and job task indices, state fixed effects, and occupation code fixed effects.

The estimated coefficients on the job task indices and mortality risk variables are in Table I. The coefficients on the demographic and education variables are in Table I (Cont.). In both tables, the left panel presents the coefficients from models of recent unemployment, and the right panel presents coefficients from models of recent work absence. Column 1 shows estimates from models that do not adjust for mortality risk but do adjust for occupation and individual characteristics. Column 2 includes the mortality risk variable, and column 3 includes the interaction between mortality risk and job task indices. Column 4 replaces the job task indices with occupation fixed

[8] We also fit models where the dependent variable indicates the worker reports being employed, but absent from work during the CPS reference week.

[9] As indicated, we define mortality risk as the COVID-19 case fatality rate for the person's age and gender reported by CDC China.

effects to account for any additional time-invariant characteristics of the jobs and state fixed effects to control for local conditions fixed over time. In the appendix, we also include the estimated coefficients for the models using the combined recent unemployment and work absence as well as for employment rate as outcomes (Table B.2).

Focusing on the job task indices, the models suggest that, even after adjusting for other covariates, people working in jobs with more potential for remote work were less likely to become unemployed in the four weeks leading up to the March 2020 CPS. The estimated coefficients on the remote work index are quite stable across specifications and they imply that working in a job that scores one standard deviation above the mean on the remote work index reduces the risk of recent job loss by about 0.0085 percentage points. The overall average job loss rate was 3.9 percent in March, implying that a one standard deviation increase in the remote work score is associated with a decrease in job loss of 21 percent. When looking at the socio-demographic characteristics, we find that the likelihood of becoming unemployed during the four weeks before the March CPS interview is significantly higher for racial and ethnic minorities. Moreover, our results on age imply that older workers are far less likely to become recently unemployed, and, since the squared term is positive, this is particularly true at very young ages. The insights obtained from the raw data on employment change in Figure 2 persist in this analysis of the recently unemployed workers, even when controlling for other demographic characteristics and occupation tasks.

Table I suggests the importance of focusing on those who are employed but absent from work In fact, the trends indicated by the estimates of the model with "Employed - Absent" as outcome do not necessarily arise from the analysis on recent unemployment. First, the likelihood of being absent from work is stronger for women and for people with higher education. Second, workers in jobs that heavily rely on face-to-face tasks are more likely to be absent from work during the first month of COVID-19. Instead, there seems to be a negative relationship between the probability of becoming unemployed in the four weeks before the survey and the job's intensity of outdoor activities. Third, Workers in occupations declared essential are less likely to be recorded as employed but absent from work. Overall, working remotely, outdoor, or in essential jobs appear to represent shields against negative labor market outcomes during the epidemic. To understand the deeper meaning of these results, it is crucial to unveil the fate of those workers who in March were classified as employed but absent. In the following months, data will reveal whether they returned to work or were laid off shortly after.

The analysis on mortality risk shown in Table I is helpful to infer trends regarding the labor supply response to COVID-19. We find that COVID-19 mortality risk does not seem related to job loss during March, unless interacted with specific occupation characteristics. The same holds when we consider the other employment outcomes.

Our null findings on the relationship between COVID-19 mortality risk and employment outcomes can have several possible explanations. It is possible that our index is an imperfect measure of exposure to risk in an occupation, as it is merely based on the age and sex of COVID-19 related casualties in China. Another possibility is that our large standard errors are due to a present, but delayed effect of mortality risk exposure on supply of labor, which will show up as later months increment our dataset. Alternatively, large standard errors could be explained by the collinearity present between the mortality risk index and two covariates we include, age and gender, which are used to build the index. Finally, it is possible that the epidemic is affecting the labor market mainly on its demand side, making the effects on supply too marginal to be detected.

6 Decomposing Group Differences in Recent Unemployment

In this section of the paper, we use regression models to decompose the variation in COVID-19 employment disruptions in two ways. First, we use a Oaxaca-Blinder decomposition to describe the way that gross differences in job losses across groups are explained by sorting across occupations and human capital endowments rather than unexplained differences in employment outcomes across groups. Second, we examine the way that the February to March change in employment patterns are explained by differences in the severity of the epidemic and the scope of early state mitigation policies.

6.1 Decomposing Group Differences in Employment Loss

We measure the extent to which disparities in employment loss across different demographic groups can be explained by differences in the kinds of jobs they held prior to the epidemic. To this end, we conduct Oaxaca-Blinder decompositions of the gap in recent unemployment for several groups of workers. The decomposition helps us identify what share of the raw gap in recent unemployment experienced between, say, Hispanic and non-Hispanic workers, can be explained by a set of observed variables (including occupation), and what part remains unexplained after controlling for those variables.

We have a few key findings. First, occupational sorting is a significant correlate of gaps in recent unemployment across all groups; especially sorting on remote work and across service and construction occupations. In spite of this, our second finding is that the bulk of the gaps in recent unemployment are due to factors not associated with demographics or occupational sorting. Occupation sorting can explain around half of the Hispanic-non-Hispanic gap and the college-high school gaps, but less than a quarter of other gaps.

Table II presents the results of our decomposition exercise. We only report results for demographic groups where we see an economically meaningful gap in recent unemployment, as described in Section 5. These include: Hispanic versus non-Hispanic (column 1); white versus black (column 2); younger versus older (column 3); high school graduates versus those with no high school diploma (column 4); and college graduates versus high school graduates (column 5). For each gap, we estimate two decomposition models. The first, denoted Model A, includes three indices describing occupational characteristics: the Face-to-Face, Remote Work, and Outside Home indices. The second, Model B, includes a full set of 324 occupation dummies.[10] Both models include basic demographic controls (i.e. age, gender, race, ethnicity, education, and the presence of young children in the home).

Focusing on non-Hispanic and Hispanic workers in column (1) of Table II, the raw gap of -0.007 is quite large relative to a baseline employment loss of around 0.02. In Model A, we find that 31.40 percent of this gap is explained by differences in the Remote Work Index on jobs held by Hispanic workers. A further 33.25 percent is explained by differences in other demographic characteristics associated with recent unemployment experience. Yet, a full 43.97 percent of the gap cannot be explained under the model.

The patterns are similar for the white-black gap in recent unemployment, though the magnitudes are different. In particular, 84 percent of the white-black gap cannot be explained by differences in demographic characteristics or occupational characteristics. Of the 16 percent of the gap that can be explained, about half is explained by differences in the Remote Work Index, and most of the rest by differences in other demographic traits.

For young relative to older workers, the results are very similar to the results for white relative to black workers: most of the gap is unexplained, and the explained part is split between the Remote Work index and demographic traits. When comparing high school graduates to those without a diploma, most of the gap is unexplained (86.69 percent), and of the explained portion, only differences in remote work potential are statistically significant or economically relevant.

Comparing those with a college degree to those without, more of the variation is explained by the model: 49.45 percent. Of that, we find that sorting on the basis on the Outside Home index predicts a smaller gap than we actually observe, accounting for -20.23 percent of the variation. Offsetting this, differences in the Remote Work Index explain 61.09 percent of variation.

One potential reason why our model does not explain more of the variation in the data is that

[10]For Model B, we report the share of variation explained by occupational sorting in five groups that correspond to top-level categories in the Census occupational classification system: "Management, Business, Science, and Arts", "Service", "Sales and Office", "Natural Resources, Construction, and Maintenance", "Production, Transportation, and Material Moving". A sixth category, "Military Specific Operations", is not included in our data, presumably because the CPS is a survey of the civilian non-institutional population.

the three occupation indices do not fully capture shifts in labor demand for specific occupations. Model B addresses this possibility by including a full set of occupation dummies. Interestingly, while the richer model has greater explanatory power, these improvements are largest for the non-Hispanic/Hispanic model and the college/high school models, which already performed relatively well under the more restrictive Model A. For the white/black, older/younger, and high school/no high school gaps, Model B still explains no more than 25 percent of the gap. Nevertheless, the richer model allows us to look into which occupations contribute the most to gaps in recent unemployment. Across the board, differential sorting into service and construction occupations are most relevant in explaining gaps in recent unemployment. This finding echoes the recent study, Athreya et al. (2020), in which the authors find the service sectors are most vulnerable to the social-distancing shock. Although we find that occupations, especially in the service and construction industries, are indeed important to explain the differences in outcomes, there is a large share of such differences that remains unexplained. Next, we investigate the role of public policies in determining the variation in employment outcomes across subgroups during the pandemic.

6.2 Analysis of Changes over Time

From our analysis of the March CPS, it is not clear how much recent unemployment increased relative to the period prior to the epidemic. In this section, we compare outcomes across the February and March CPS. We are also interested in whether, and to what extent, recent job loss is stronger in areas that were affected by the epidemic earlier. We estimate panel data regressions of recent unemployment that include unrestricted state and occupation effects, along with demographic controls. We also add occupation task indices, and indicators for which states had early school closures, emergency declarations, or COVID-19 cases.[11] We are interested in the differential effect in March for states with early policies or COVID-10 cases, as well as the differential effects for jobs with particular tasks, and for various demographic groups.

Table III presents the results in two columns. In the first column, only interactions of the indicator for observations in March 2020 and the state group variables are included. In the second column, the add interactions of time with job tasks and individual characteristics. Our first result from this analysis is quite similar to (Lozano-Rojas et al. 2020), and shows that employment outcomes were affected by a nation-wide shock. During March, the probability of becoming

[11] States with early school closures, and the share of students affected by March 13 were: Tennessee (23%), Washington (16%), Nebraska (22%), Texas (14%) and Georgia (5.4%). States with early emergency declaration were: Washington (29 Feb), California (4 Mar), Hawaii (4), Maryland (5 Mar), Indiana (6 Mar), Utah (6 Mar), Kentucky (6 Mar), Pennsylvania (6 Mar), New York (Mar 7) and Oregon (Mar 8). For states with early COVID-19 cases the indicator variables are set to 1 for the top 5 states: Washington, New York, Massachusetts, Nebraska, and the District of Columbia.

recently unemployed rose significantly. Our estimates suggest that the probability of becoming unemployed in the last four weeks is significantly positive, and depending on the specification the increase ranges between 0.5 and 4.6 percentage points. The model with more interactions presumably estimates the effect of the outbreak on recent unemployment more accurately. It is this more specified model, in column (2), that yields a much larger magnitude for the positive effect of the outbreak on recent unemployment. Considering that the baseline recent unemployment in February was 2.55%, and using the smaller coefficient, we calculate that the lower bound for the increase in recent unemployment is 21.6% at minimum. In contrast, policy actions as well as differential COVID-19 exposure had little effect on early labor outcomes as captured by the coefficients on the interactions between time and state groups. An F-test fails to find evidence that rejects the null hypothesis that the state policy-by-March interactions are all zero. By contrast, we estimate that the March-specific differences across occupation tasks and socio-demographic characteristics are jointly significant. Finally, we find that black, Hispanic, and younger workers were more likely to become recently unemployed during March relative to February. Regarding the occupational indices, workers with job tasks performed outside had a lower chance of being recently unemployed relative to February. In both cases, the panel results confirm that the recent increases in job loss, and their distribution across groups, were unique to March, and presumably are driven by the economic consequences of the COVID-19 epidemic.

7 Conclusion

Although the March CPS was conducted relatively early with respect to the spread of COVID-19 and policies expected to affect labor markets, the data show remarkably large employment declines. These declines are comparable in magnitude to previous recessions and emergencies, albeit over a much shorter time period. Moreover, they do not appear to be concentrated in areas with greater early exposure to COVID-19, nor with early policy actions. This calls into question how much, or little, official lock-downs and shelter-in-place policies have done, or can do, in exacerbating or mitigating the labor market effects of the epidemic.

While the labor market impacts of the epidemic have been widespread, both geographically and across sectors, we observe rather large variation in employment loss across different demographic groups. Furthermore, using data on occupation-specific tasks, we find that workers in occupations involving more tasks that can be performed remotely, face-to-face contact, and work outside the home have experienced greater employment losses. Unsurprisingly, a significant share of differences in employment loss across groups is explained by differences in (pre-epidemic) sorting across occupations. However, in almost all cases, a much larger share cannot be explained by either occupation sorting or other observable traits. There are three possible sources for the unexplained share. First, workers may have different labor supply responses to the epidemic. Second, variation in exposure to labor demand shocks may not be fully reflected in occupational or demographics differences. Finally, workers may face disparate treatment when their employers are deciding whom to lay off. The available data do not allow us to distinguish between these three channels, and we cannot reject that more than one factor is in play.

The early labor market evidence from the CPS suggests that many workers are being separated from their employers, with the potential for long-term scarring effects known to befall workers displaced during recessions. Finding and forming productive employment matches is costly. Furthermore, workers receive health care and other benefits through employers. Assuming economic conditions could return to their pre-epidemic state, policymakers are right to help workers maintain jobs and preserve links to their employers. On the other hand, if economic conditions do not return to normal rapidly, then the reallocation of workers into different types of jobs may also be desirable. Our analysis suggests the costs of job loss are more concentrated among particular groups of workers that might need extra protection from policy makers during this unprecedented time. Whether these trends have continued, or been mitigated by subsequent policy actions will be a topic of ongoing research.

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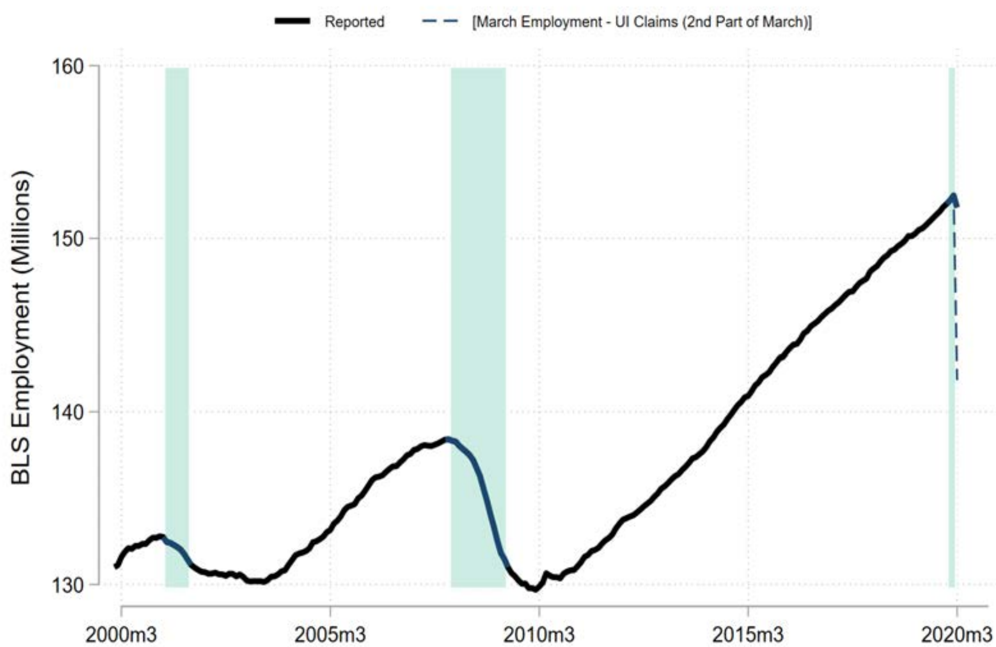
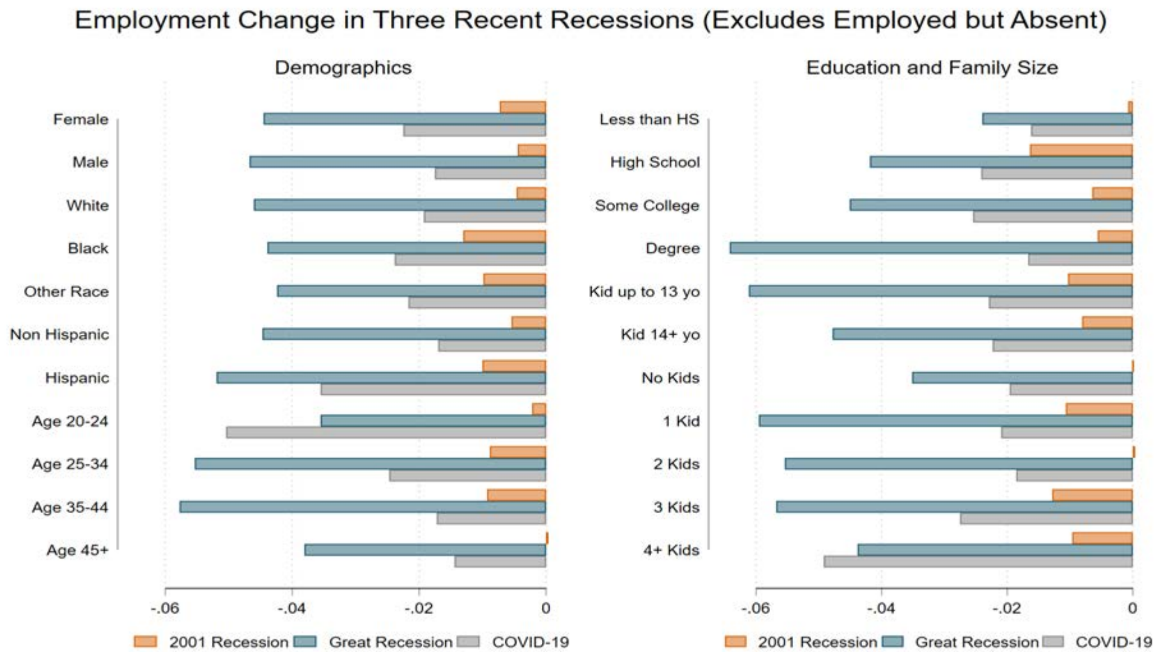
Tables and Figures

Figure 1: BLS Employment Series (Seasonally Adjusted)



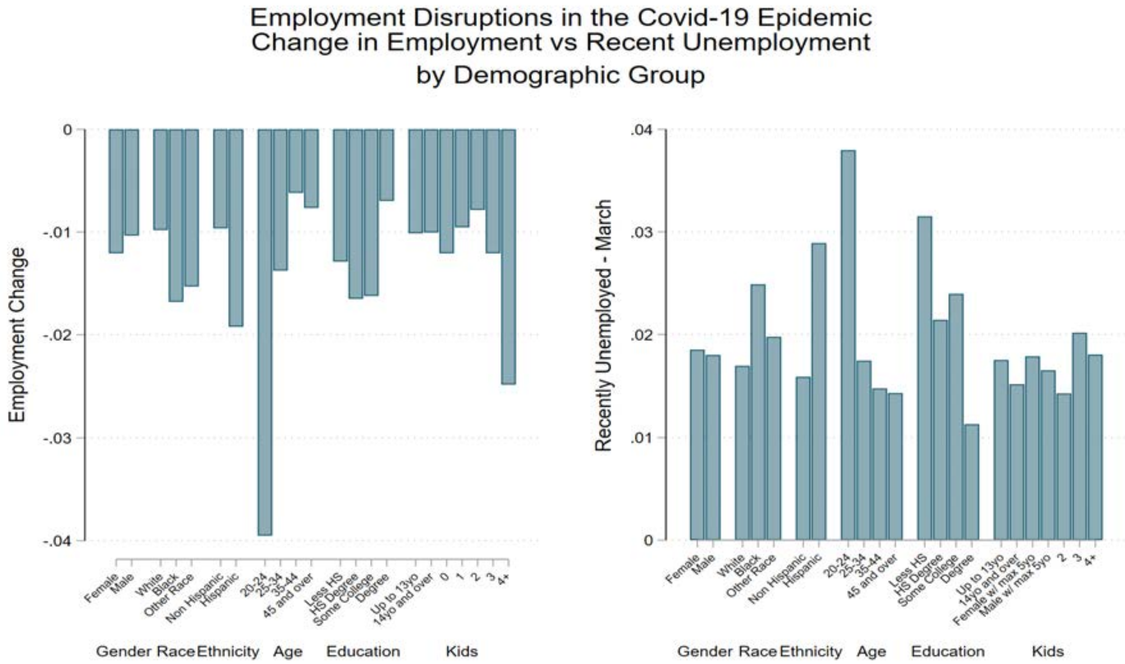
Note: The Figure presents the seasonally adjusted series for All Employees in non-farm jobs (millions).The shaded areas represent recessions; see Section 4. To obtain the last point in the series, we subtract national Unemployment Insurance (UI) claims filed in the second part of March assuming they fully represent jobs lost in that period. The figure implies that jobs lost during March exceed jobs lost in either of the two previous recessions.

Figure 2



Notes: We computed the change in employment rates by demographic group over the three recent recessions National Bureau of Economic Research (2012). Change in employment, in this chart, was computed excluding individuals who are absent from work. The estimates were weighted using the CPS composited final weights.

Figure 3



<u>Note:</u> Employment Change is computed as the February employment rate minus the March rate. Recently Unemployed is reported only from the March CPS. The change in employment is computed including workers who are employed but absent from work.

Figure 4

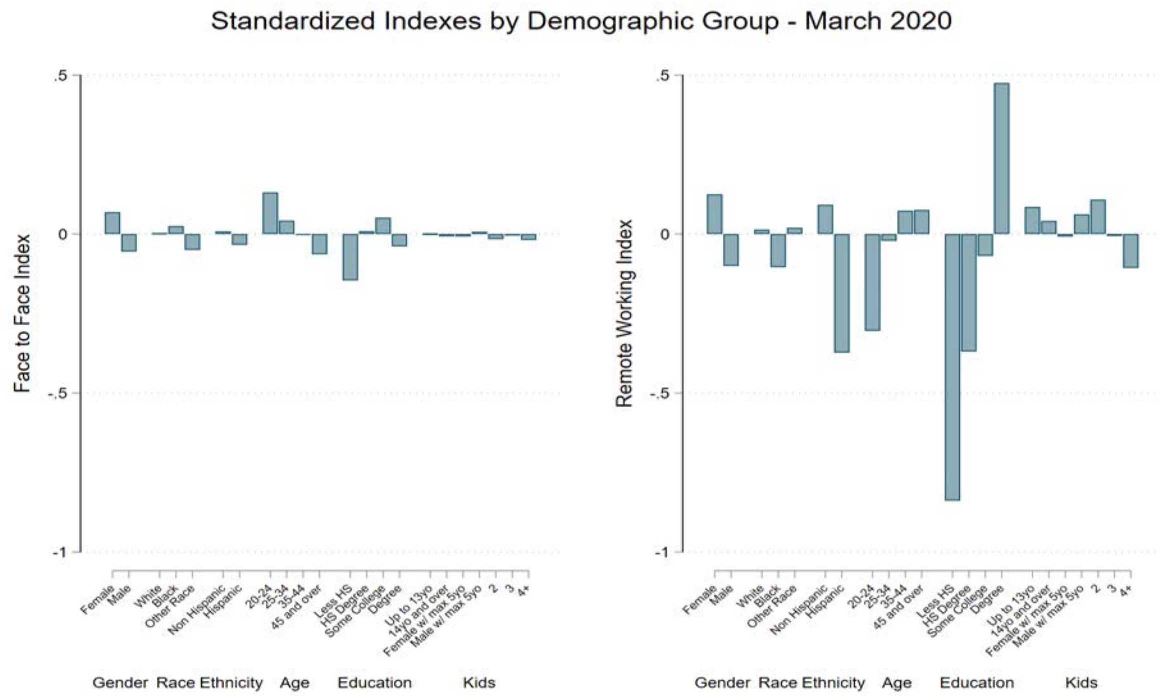
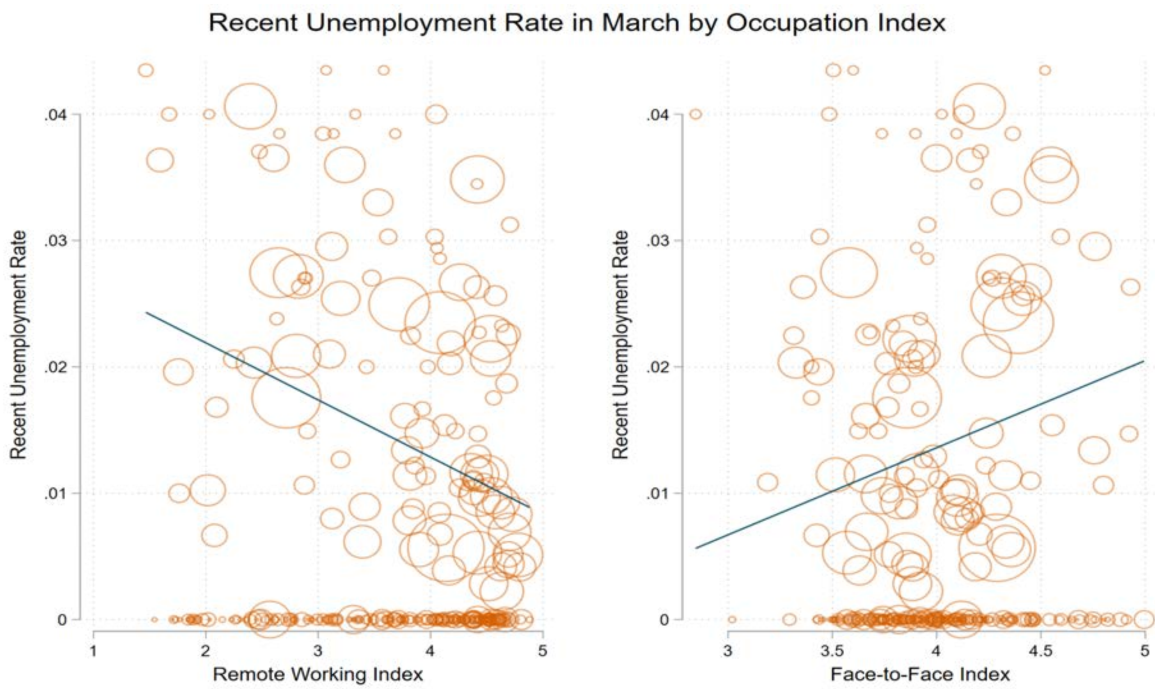

Standardized Indexes by Demographic Group - March 2020
Face to Face Index
Remote Working Index
.5
0
-.5
-1
Female
Male
White
Black
Other Race
Non Hispanic
Hispanic
20-24
25-34
35-44
45 and over
Less HS
HS Degree
Some College
Degree
Up to 13yo
14yo and over
Female w/ max 5yo
Male w/ max 5yo
2
3
4+
Gender
Race
Ethnicity
Age
Education
Kids

Figure 5



Recent Unemployment Rate in March by Occupation Index
Recent Unemployment Rate
.04
.03
.02
.01
0
1
2
3
4
5
Remote Working Index
Recent Unemployment Rate
.04
.03
.02
.01
0
3
3.5
4
4.5
5
Face-to-Face Index

Table I: Cross-Sectional Models: Recently Unemployed and Employed but Absent – Occupation Characteristics and COVID-19 Mortality Risk

	Recently Unemployed				**Employed - Absent**			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Face-to-Face	0.00130	0.00130	0.00116		0.00800***	0.00800***	0.00805***	
	(0.00134)	(0.00134)	(0.00133)		(0.00209)	(0.00209)	(0.00209)	
Remote Work	-0.00845***	-0.00844***	-0.00848***		-0.00626***	-0.00629***	-0.00627***	
	(0.00201)	(0.00201)	(0.00195)		(0.00197)	(0.00197)	(0.00196)	
Outside	-0.00430**	-0.00429**	-0.00426**		0.00244	0.00241	0.00254	
	(0.00178)	(0.00178)	(0.00174)		(0.00203)	(0.00204)	(0.00203)	
Essential	0.000993	0.000984	0.000921		-0.00357**	-0.00355**	-0.00352**	
	(0.00154)	(0.00154)	(0.00150)		(0.00163)	(0.00163)	(0.00162)	
Risk Index		-0.00163	-0.00227			0.00289	0.00338	
		(0.00256)	(0.00275)			(0.00331)	(0.00347)	
Risk x Face-to-Face			-0.00217**				0.000962	
			(0.000948)				(0.00177)	
Risk x Remote Work			0.00151				0.00196	
			(0.00142)				(0.00161)	
Risk x Outside			0.000371				-0.000623	
			(0.00110)				(0.00155)	
Risk x Essential			-0.00228**				0.00186	
			(0.00114)				(0.00137)	
N	33,175	33,175	33,175	36,479	33,175	33,175	33,175	36,479
R2 Adj.	0.00816	0.00816	0.00869	0.0202	0.00611	0.00612	0.00617	0.0168

Notes: Coefficients for Equation 1 using March 2020 CPS Data. Dependent variables: 1) Recent Unemployment status and 2) Employed but absent from work. Column (1) includes socio-demographic and occupation characteristics. Model (2) includes COVID-19 mortality factor (Risk). Column (3) interacts the risk factor with occupation characteristics. Column (4) includes states and occupation fixed effects and socio-demographic variables. Standard errors clustered at the occupation level in parentheses. Statistical significance level: * p<0.1; ** p<0.05; *** p<0.01

Table I: Cross-Sectional Models: Recently Unemployed and Employed but Absent (*Cont.*) – Socio-Demographic characteristics

	Recently Unemployed				**Employed - Absent**			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Fem x Child-U13	0.00383	0.00427	0.00416	0.00271	0.00731	0.00654	0.00683	0.00424
	(0.00413)	(0.00414)	(0.00418)	(0.00357)	(0.00608)	(0.00604)	(0.00612)	(0.00585)
Child under 13	-0.00275	-0.00270	-0.00267	-0.00154	-0.00207	-0.00216	-0.00239	-0.00233
	(0.00250)	(0.00249)	(0.00248)	(0.00243)	(0.00356)	(0.00356)	(0.00359)	(0.00355)
Female	0.000412	-0.000203	-0.000178	-0.00114	0.0186***	0.0197***	0.0200***	0.0127***
	(0.00276)	(0.00268)	(0.00268)	(0.00252)	(0.00369)	(0.00363)	(0.00361)	(0.00357)
Afro-American	0.00912**	0.00914**	0.00921**	0.00916**	-0.00471	-0.00475	-0.00477	-0.0000589
	(0.00390)	(0.00390)	(0.00390)	(0.00375)	(0.00390)	(0.00390)	(0.00390)	(0.00372)
Hispanic	0.00989***	0.00989***	0.00977***	0.00777***	0.00456	0.00457	0.00447	0.000224
	(0.00289)	(0.00289)	(0.00288)	(0.00297)	(0.00350)	(0.00350)	(0.00350)	(0.00364)
Age	-0.00199***	-0.00232***	-0.00230***	-0.00171***	-0.000669	-0.0000858	-0.000000962	-0.000699
	(0.000561)	(0.000739)	(0.000756)	(0.000493)	(0.000614)	(0.000820)	(0.000835)	(0.000575)
Age Squared	0.0000195***	0.0000240***	0.0000242***	0.0000172***	0.0000116*	0.00000349	0.00000233	0.0000119*
	(0.00000574)	(0.00000878)	(0.00000910)	(0.00000511)	(0.00000679)	(0.0000104)	(0.0000107)	(0.00000633)
Less-than HS	0.00597	0.00602	0.00620	0.00410	-0.00231	-0.00240	-0.00232	-0.00447
	(0.00408)	(0.00407)	(0.00406)	(0.00403)	(0.00514)	(0.00513)	(0.00511)	(0.00473)
Some College	0.00514	0.00514	0.00504	0.00509	0.00371	0.00372	0.00371	0.00323
	(0.00362)	(0.00362)	(0.00360)	(0.00349)	(0.00331)	(0.00331)	(0.00331)	(0.00311)
BA/AD Degree	-0.00183	-0.00177	-0.00169	-0.00123	0.00947**	0.00935**	0.00938**	0.00835***
	(0.00284)	(0.00282)	(0.00282)	(0.00319)	(0.00426)	(0.00427)	(0.00427)	(0.00322)
Posgraduate Degree	-0.00159	-0.00148	-0.00168	-0.00120	0.00737	0.00717	0.00710	0.000621
	(0.00333)	(0.00331)	(0.00329)	(0.00469)	(0.00463)	(0.00464)	(0.00464)	(0.00417)
Constant	0.0607***	0.0657***	0.0647***	0.0534***	0.0295**	0.0207	0.0194	0.0338***
	(0.0122)	(0.0144)	(0.0145)	(0.0104)	(0.0133)	(0.0151)	(0.0151)	(0.0123)
N	33,175	33,175	33,175	36,479	33,175	33,175	33,175	36,479
R2 Adj.	0.00816	0.00816	0.00869	0.0202	0.00611	0.00612	0.00617	0.0168

Notes: Coefficients for Equation 1 using March 2020 CPS Data. Dependent variables: 1) Recent Unemployment status and 2) Employed but absent from work. Column (1) includes socio-demographic and occupation characteristics. Model (2) includes COVID-19 mortality factor (Risk). Column (3) interacts the risk factor with occupation characteristics. Column (4) includes states and occupation fixed effects and socio-demographic variables. Standard errors clustered at the occupation level in parentheses. Statistical significance level: * p<0.1; ** p<0.05; *** p<0.01

Table II: Decomposition: Recently Unemployed

	Non-hispanic/Hispanic		White/Black		Older/Younger		HS/non-HS		Coll/non-Coll	
	Estimate	Share	Estimate	Share	Estimate	Share	Estimate	Share	Estimate	Share
Raw Gap	-0.0077	100.00%	-0.0100	100.00%	-0.0152	100.00%	-0.0131	100.00%	-0.0062	100.00%
Model A										
Explained	-0.0043	56.03%	-0.0016	16.08%	-0.0025	16.56%	-0.0017	13.31%	-0.0031	49.45%
demographic	**-0.0026**	**33.25%**	**-0.0007**	**7.06%**	-0.0010	6.66%	0.0000	-0.20%	**-0.0005**	**7.53%**
FacetoFace	0.0000	0.00%	0.0000	0.15%	0.0000	0.09%	0.0001	-0.68%	**-0.0001**	**1.05%**
Remote Work	**-0.0024**	**31.40%**	**-0.0008**	**7.92%**	**-0.0015**	**9.55%**	**-0.0024**	**18.11%**	**-0.0038**	**61.09%**
Outside Home	0.0006	-8.06%	**-0.0001**	**0.95%**	0.0000	0.25%	0.0005	-3.92%	**0.0013**	**-20.23%**
Unexplained	-0.0034	43.97%	-0.0084	84.00%	-0.0127	83.44%	-0.0114	86.69%	-0.0031	50.55%
Model B										
Explained	-0.0056	72.77%	-0.0022	22.34%	-0.0028	18.61%	-0.0033	25.18%	-0.0048	78.29%
demographic	**-0.0018**	**23.15%**	**-0.0005**	**4.75%**	-0.0001	0.95%	0.0007	-4.98%	-0.0004	5.91%
Mgmt/Tech/Arts	0.0002	-3.09%	0.0000	-0.04%	**0.0013**	**-8.29%**	0.0001	-0.62%	0.0007	-10.82%
Service	**-0.0015**	**19.95%**	**-0.0012**	**12.38%**	**-0.0029**	**18.88%**	-0.0007	5.57%	**-0.0021**	**33.80%**
Sales/Office	0.0000	-0.35%	**-0.0003**	**3.26%**	**-0.0014**	**9.41%**	-0.0003	2.28%	**-0.0005**	**7.89%**
Constr/Nat. Res.	**-0.0018**	**23.91%**	**0.0005**	**-4.63%**	0.0003	-1.99%	**-0.0025**	**18.94%**	**-0.0012**	**18.65%**
Prod./Trans.	**-0.0007**	**9.30%**	**-0.0007**	**7.19%**	0.0001	-0.36%	-0.0005	4.00%	**-0.0014**	**22.86%**
Unexplained	-0.0021	27.12%	-0.0077	77.73%	-0.0124	81.39%	-0.0098	74.82%	-0.0013	21.71%

Notes: This table show Oaxaca decomposition of gap in the proportion of workers recently laid off. Entries in bold are statistically significant at the 5% level. The upper and lower panels are decomposition results from two models. Model A includes three indexes describing occupational characteristics: the Face-to-Face, Remote Working, and Outside Job indexes. Model B includes a full set of 324 occupation dummies. Both models include basic demographic controls, including age, gender, race, ethnicity, education, and the presence of young children in the home.

Table III: Changes Over Time and Across States: Recently Unemployed

	(1) Recently unemp.	(2) Recently unemp.
March	0.00552***	0.0458***
	(0.00169)	(0.0117)
School Closures (Top 5 Sts.) x March	-0.00217	-0.00371
	(0.00272)	(0.00295)
Emergency Declaration Sts. x March	0.00409	0.00334
	(0.00249)	(0.00274)
COVID-19 Cases (Top 5 Sts.) x March	0.00208	0.00305
	(0.00324)	(0.00355)
Face-to-Face x March		0.00178
		(0.00157)
Remote Work x March		-0.00317
		(0.00227)
Outside x March		-0.00355*
		(0.00183)
Essential x March		0.000579
		(0.00163)
Fem x Child-U13 x March		0.00327
		(0.00409)
Children-U13 x March		-0.00208
		(0.00256)
Female x March		-0.0000302
		(0.00273)
Black x March		0.00907**
		(0.00403)
Hispanic x March		0.00837***
		(0.00287)
Age x March		-0.00190***
		(0.000543)
Age Sq. x March		0.0000188***
		(0.00000558)
Less-than HS x March		0.00383
		(0.00407)
Some College x March		0.00592
		(0.00366)
BA/AD Degree x March		-0.000225
		(0.00295)
Posgr. Degree x March		0.000817
		(0.00374)
Controls	Yes	Yes
State and Occupation F.E.	Yes	Yes
Observations	78,130	71,101
R^2	0.018	0.018
Adjusted R^2	0.013	0.012
F-test ($StateGroups = 0$)	1.582	1.496
D.F. restriction	3	3
D.F. model	346	322
p_value	0.193	0.216
F-test ($Job\,Task\,Indices = Socio\,Demo. = 0$)		2.367
D.F. restriction		15
D.F. model		322
p_value		0.00303

Note: We test the joint significance of the variables related to COVID-19 exposure and early policy actions F-test ($State\,Groups = 0$) in both models. In model (2) we also test the joint significance of occupation and individual characteristics F-test ($Job\,Tasks = Socio\,Demo. = 0$). Standard errors clustered at the occupation level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

A CPS Data Quality

It is possible that survey response rates may have have varied across the first three months of 2020, and especially in March 2020, given the widespread disruption associated with the epidemic. Figure A.1 shows the mean monthly response rates to the basic monthly CPS over the past five years to give a sense of how the epidemic has affected the availability and quality of data on labor market outcomes in the United States. We see that, while the response rates were already dropping over time, they plummet in March 2020, from about 0.86 to less than 0.80. Such drop is unprecedented considering the last years of data.

Figure A.2 shows which of the 8 CPS rotation groups responded the least in March 2020, when the COVID-19 and its social distancing policies came about. For comparison purposes, we also report the average nonresponse rates for the previous period, comprised of January and February 2020. The bar chart reports the non-response rates by each rotation group on the three months and facilitates the identification of changes in non-response rates between the pre- and post- COVID-19 outbreak. In order to control for drops in response rates across rotation groups that regularly happen regardless of the epidemic, we include non-response rates by rotation group in January 2020. Changes in non-response rates between January and February of 2020 can be considered as patterns that happen regularly over the rotation groups, and so, in case we observe similar trends between February and March, such trends cannot be attributed to the epidemic.

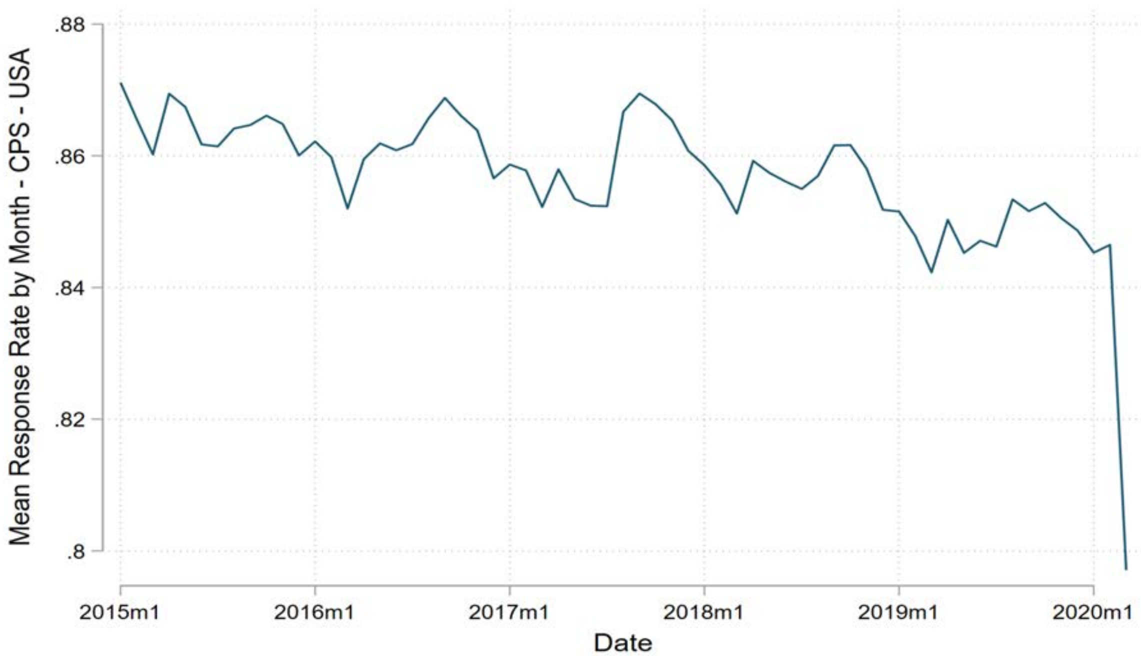
Figure A.2 exhibits a sharp increase in non-response rates between either January and February 2020, and the outbreak month, March 2020. Non-response rates increase between the pre- and post-outbreak months disproportionately among the first rotation group, the one that is first entering the CPS monthly survey. Thus, while there seems to be increased non-response across the board, the responses to the surveys dropped the most for respondents who were about to start their rotations.

However, the increase in non-response rates could be derived from two different sources. On the one hand, it is possible that Census Bureau Interviewers are less able to carry out interviews, especially those in person. This was indeed the case for March 2020, as the Census Bureau U.S. Bureau of Labor Statistics (2020) explains. In fact, households in their first or fifth CPS rotation are usually interviewed via a personal visit. For safety reasons, in person interviews were suspended five days in the interviewing process, and replaced by telephone interviews. Telephone interviews, rather than in person meetings, might have contributed to the sharp decrease in response rates of the first rotation. On the other hand, it is possible that the COVID-19 outbreak made it harder for respondents in their first rotation to complete the survey. This could be due to the general disruption and re-organization occurring during the interview period and caused by the outbreak and its containment measures.

Understanding the reasons behind the CPS response rate drop is crucial in order to draw conclusions on the data quality. In fact, should the non-response be driven by non-random factors that are correlated to the changes in employment outcomes in March 2020, we could interpret our findings as conservative or as upper bounds of the true effects, depending on the direction of the sample bias.

In order to assess that, we use demographic information from respondents in February 2020 and impute them for the same individuals in March, provided that they did not respond to the

Figure A.1: CPS Response Rates over Time

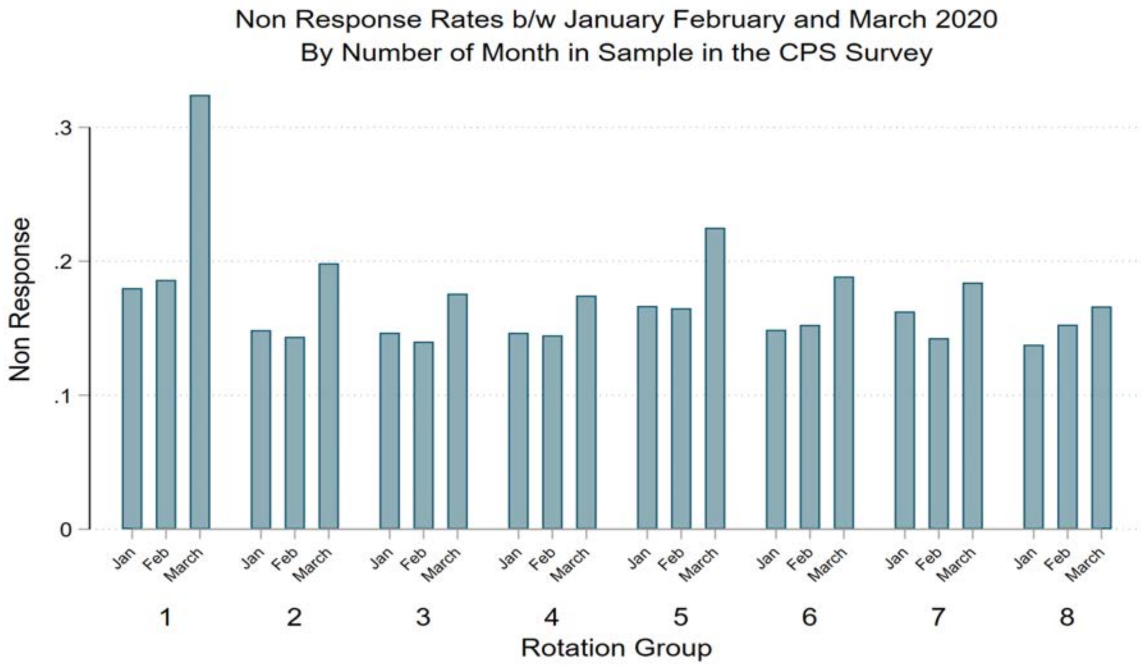


March CPS. In order to do that, we use information on the rotation groups to infer whether the same individual responding in February is expected to belong to the March CPS as well. We dropped fourth and either months-in-sample in February, and the first and fifth months in sample in March. As a result, we obtain a sample where all the respondents in the March CPS are expected to participate to the February CPS, and vice-versa. We match these individuals according to the appropriate CPS person identifiers, namely HRHHID1, HRHHID2 and PULINENO, as suggested on Census (2004). Finally, we impute basic quasi-immutable socio-demographics information into the sample of March non-respondents only for those individuals that did respond in February. In other words, for the individuals that did not respond to the survey in March, we go back to February to see if they responded then and, if so, we impute their socio-demographics in March.

Table A.1 shows the number of individuals that we expected to find in the March CPS (N), those that actually responded, the number of non-respondents and, in the last column, the number of observations for which we manged to impute information. For example, for the second month-in-sample, if there was a full response, we should have had 16,290 individuals in our sample. However, only 13,056 responded, while the remaining 3,234 are missing from the March sample. Out of these 3,234, we were able to retrieve information from February for 2,183 of them. We could not impute any information on the first and fifth months-in-sample as these respondents were not part of the survey in February.

We then investigated whether the socio-demographics of the imputed sample differed from those of the respondents. Table A.2 reports the results from a balancing analysis that shows the mean and its standard error of some socio-demographics for the sample of respondents and the sample of non-respondents that we managed to rescue through our imputation process. Although

Figure A.2: Nonresponse Rates by CPS Rotation Group



the imputed sample and the sample of respondents are similar across several dimensions, there are some important differences. The imputed sample is on average younger, more racially diverse, more Hispanic, and less educated.

This analysis gives us reasons to think that, while the increase in the March non-response is partly due to changes in the collection methods, it is possible that the non-response is also moderately driven by non random factors. In fact, the imputed sample is disproportionately composed of the subgroups whose employment outcomes were particularly hit by the outbreak. Overall, we should interpret the findings of analysis that use the March CPS with caution. Moreover, further analysis is needed to understand more precisely the source of the sample bias, and how to control for it when using CPS data collected during the COVID-19 outbreak.

Table A.1: Counts on Non-Respondents and Imputed Observations

March 2020 CPS

	Total			
Month-In-Sample	N	Responded	Non-Respondent	Imputed
1	14,923	10,084	4,839	
2	16,290	13,056	3,234	2,183
3	16,690	13,532	2,935	1,827
4	16,391	13,532	2,859	1,905
5	16,445	12,744	3,701	
6	16,892	13,705	3,187	1,755
7	16,717	13,638	3,079	1,845
8	17,230	14,364	2,866	1,611
Total	131,578	104,655	26,700	11,126

The number of imputed observations is a share of the number of non-respondents.

Table A.2: Summary Statistics: Response to CPS

	Did not Respond in March			Responded in March		
	N	Mean	SE	N	Mean	SE
Age	11,126	35.553	0.205	104,878	41.044	0.072
White	11,126	0.763	0.004	104,878	0.803	0.001
African American	11,126	0.132	0.003	104,878	0.102	0.001
Other Race	11,126	0.132	0.003	104,878	0.102	0.001
Female	11,126	0.516	0.005	104,878	0.514	0.002
Hispanic	11,126	0.216	0.004	104,878	0.14	0.001
Less than High School	11,126	0.328	0.004	104,878	0.284	0.001
High School Degree	11,126	0.255	0.004	104,878	0.222	0.001
Some College	11,126	0.132	0.003	104,878	0.137	0.001
Degree	11,126	0.253	0.004	104,878	0.32	0.001
Young Child	11,126	0.097	0.003	104,878	0.083	0.001
Child at least 14 yo	11,126	0.114	0.003	104,878	0.108	0.001
Presence of Children	11,126	0.211	0.004	104,878	0.191	0.001
Presence of 1 Child	11,126	0.094	0.003	104,878	0.08	0.001
Presence of 2 Children	11,126	0.074	0.002	104,878	0.072	0.001
Presence of 3 Children	11,126	0.03	0.002	104,878	0.027	0.001
Presence of 4+ Children	11,126	0.013	0.001	104,878	0.012	0

Weights for the nonresponse sample use imputed weights from February, 2020.

The computation of the descriptive statistics applies weights. SE is the standard error of the mean.

B Additional Tables and Figures

Table B.1: O*Net Index related Questions

Index	O*Net Items
Face To Face	How often do you have face-to-face discussions with individuals or teams in this job?
	To what extent does this job require the worker to perform job tasks in close physical proximity to other people?
Remote Work	How often do you use electronic mail in this job?
	How often does the job require written letters and memos?
	How often do you have telephone conversations in this job?
Outside Home	How often does this job require working exposed to contaminants (such as pollutants, gases, dust or odors)?
	How often does this job require exposure to disease/infections?
	How often does this job require exposure to hazardous conditions?
	How often does this job require exposure to hazardous equipment?
	How often does this job require exposure to high places?
	How often does this job require exposure to minor burns, cuts, bites, or stings?
	How often does this job require exposure to radiation?
	How often does this job require exposure to whole body vibration (e.g., operate a jackhammer)?
	How often does this job require working outdoors, exposed to all weather conditions?
	How often does this job require working outdoors, under cover (e.g., structure with roof but no walls)?
	How often does this job require working in very hot (above 90 F degrees) or very cold (below 32 F degrees) temperatures?
	How much does this job require wearing common protective or safety equipment such as safety shoes, glasses, gloves, hard hats or life jackets?
	How much does this job require wearing specialized protective or safety equipment such as breathing apparatus, safety harness, full protection suits, or radiation protection?

Note: The O*Net "Work Context" module (2019 version: available https://www.onetcenter.org/dictionary/24.2/excel/work_context.html) reports summary measures from worker surveys of the tasks involved in 968 occupations using the Standard Occupation Code, 2010 version). The questions use a 1-5 scale, where 1 indicates rare/not important. We developed three indices: (1) Face-to-Face interactions, (2) the potential for Remote Work, and (3) the extent to which work occurs Outside the Home using these variables. The value of each index for an occupation is a simple average O*Net questions listed in the table.

Table B.2: Combined (Recent Unemployed and Absent) and Employed Cross-Section – Occupation Characteristics and COVID-19 Mortality Risk

	Combined (Recent Unemployed + Absent)				**Employed**			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Face-to-Face	0.00930***	0.00930***	0.00921***		-0.00857***	-0.00857***	-0.00847***	
	(0.00293)	(0.00293)	(0.00293)		(0.00284)	(0.00284)	(0.00286)	
Remote Work	-0.0147***	-0.0147***	-0.0147***		0.0243***	0.0244***	0.0244***	
	(0.00343)	(0.00343)	(0.00339)		(0.00388)	(0.00388)	(0.00383)	
Outside	-0.00187	-0.00188	-0.00172		0.00143	0.00144	0.00121	
	(0.00322)	(0.00322)	(0.00319)		(0.00393)	(0.00393)	(0.00387)	
Essential	-0.00257	-0.00257	-0.00260		0.00326	0.00326	0.00329	
	(0.00264)	(0.00264)	(0.00262)		(0.00339)	(0.00339)	(0.00336)	
Risk Index		0.00126	0.00111			-0.000259	-0.0000403	
		(0.00462)	(0.00486)			(0.00510)	(0.00536)	
Risk x Face-to-Face			-0.00120				0.00111	
			(0.00190)				(0.00218)	
Risk x Remote Work			0.00346*				-0.00501**	
			(0.00198)				(0.00210)	
Risk x Outside			-0.000252				0.000103	
			(0.00187)				(0.00219)	
Risk x Essential			-0.000418				0.000500	
			(0.00166)				(0.00193)	
N	33,175	33,175	33,175	36,479	33,175	33,175	33,175	36,479
R2 Adj.	0.00813	0.00810	0.00828	0.0225	0.0133	0.0132	0.0135	0.0299

Notes: Coefficients for Equation 1 using March 2020 CPS Data. Dependent variables: 1) Combined status of Recent Unemployment or Employed but Absent from work and 2) Status Employed. Column (1) includes socio-demographic and occupation characteristics. Model (2) includes COVID-19 mortality factor (Risk). Column (3) interacts the risk factor with occupation characteristics. Column (4) includes states and occupation fixed effects and socio-demographic variables. Standard errors clustered at the occupation level in parentheses. Statistical significance level: * $p<0.1$; ** $p<0.05$; *** $p<0.01$

Table B.2: Combined (Recent Unemployed and Absent) and Employed Cross-Section (*Cont.*) – Socio-demographic characteristics

	Combined (Recent Unemployed + Absent)				Employed			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Fem x Child-U13	0.0111	0.0108	0.0110	0.00695	-0.0219***	-0.0218***	-0.0220***	-0.0163**
	(0.00767)	(0.00760)	(0.00774)	(0.00691)	(0.00837)	(0.00828)	(0.00845)	(0.00771)
Child under 13	-0.00482	-0.00486	-0.00507	-0.00387	0.0127***	0.0127***	0.0130***	0.0106**
	(0.00447)	(0.00446)	(0.00452)	(0.00444)	(0.00473)	(0.00472)	(0.00480)	(0.00471)
Female	0.0190***	0.0195***	0.0198***	0.0116***	-0.0142***	-0.0143***	-0.0146***	-0.00975**
	(0.00454)	(0.00435)	(0.00432)	(0.00398)	(0.00528)	(0.00519)	(0.00515)	(0.00478)
Afro-American	0.00441	0.00439	0.00444	0.00910*	-0.0210***	-0.0210***	-0.0210***	-0.0251***
	(0.00488)	(0.00489)	(0.00489)	(0.00463)	(0.00619)	(0.00621)	(0.00620)	(0.00618)
Hispanic	0.0145***	0.0145***	0.0142***	0.00799*	-0.0105	-0.0105	-0.0102	-0.000143
	(0.00466)	(0.00466)	(0.00466)	(0.00474)	(0.00643)	(0.00643)	(0.00642)	(0.00649)
Age	-0.00266***	-0.00240*	-0.00230*	-0.00241***	0.00347***	0.00342**	0.00329**	0.00286***
	(0.000860)	(0.00125)	(0.00128)	(0.000761)	(0.00101)	(0.00153)	(0.00155)	(0.000893)
Age Squared	0.0000310***	0.0000275*	0.0000265*	0.0000292***	-0.0000368***	-0.0000361*	-0.0000348*	-0.0000319***
	(0.00000905)	(0.0000155)	(0.0000160)	(0.00000809)	(0.0000108)	(0.0000187)	(0.0000191)	(0.00000960)
Less-than HS	0.00366	0.00362	0.00387	-0.000373	-0.0294***	-0.0294***	-0.0298***	-0.0216**
	(0.00729)	(0.00726)	(0.00722)	(0.00656)	(0.0102)	(0.0101)	(0.0101)	(0.00941)
Some College	0.00886*	0.00886*	0.00875*	0.00832**	-0.00581	-0.00581	-0.00567	-0.00566
	(0.00457)	(0.00457)	(0.00454)	(0.00422)	(0.00519)	(0.00519)	(0.00516)	(0.00510)
BA/AD Degree	0.00763*	0.00758*	0.00769*	0.00711**	0.000845	0.000856	0.000699	-0.00214
	(0.00433)	(0.00434)	(0.00435)	(0.00355)	(0.00503)	(0.00503)	(0.00504)	(0.00437)
Posgraduate Degree	0.00578	0.00569	0.00541	-0.000579	-0.0000169	0.000000520	0.000363	0.00304
	(0.00490)	(0.00491)	(0.00494)	(0.00695)	(0.00569)	(0.00567)	(0.00569)	(0.00766)
Constant	0.0902***	0.0864***	0.0841***	0.0872***	0.857***	0.858***	0.861***	0.873***
	(0.0190)	(0.0234)	(0.0235)	(0.0164)	(0.0223)	(0.0291)	(0.0292)	(0.0194)
N	33,175	33,175	33,175	36,479	33,175	33,175	33,175	36,479
R2 Adj.	0.00813	0.00810	0.00828	0.0225	0.0133	0.0132	0.0135	0.0299

Notes: Coefficients for Equation 1 using March 2020 CPS Data. Dependent variables: 1) Combined status of Recent Unemployment or Employed but Absent from work and 2) Status Employed. Column (1) includes socio-demographic and occupation characteristics. Model (2) includes COVID-19 mortality factor (Risk). Column (3) interacts the risk factor with occupation characteristics. Column (4) includes states and occupation fixed effects and socio-demographic variables. Standard errors clustered at the occupation level in parentheses. Statistical significance level: * p<0.1; ** p<0.05; *** p<0.01