Determinants of Disparities in Covid-19 Job Losses
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NBER Working Paper No. 27132
May 2020, Revised in September 2020
JEL No. I1,J0,J08

ABSTRACT

We make several contributions to understanding the socio-demographic ramifications of the COVID-19 epidemic and policy responses on employment outcomes of subgroups in the U.S., benchmarked against two previous recessions. First, monthly Current Population Survey (CPS) data show greater declines in employment in April and May 2020 (relative to February) for Hispanics, younger workers, and those with high school degrees and some college. Between April and May, all the demographic subgroups considered regained some employment. While in most cases the re-employment in May was proportional to the employment drop occurred through April, we show that this was not the case for Blacks. Second, we show that job loss was larger in occupations that require more interpersonal contact and that cannot be performed remotely. Third, we see that consistent with theories of occupational segregation, the extent to which workers of certain demographic groups sort (pre-COVID-19) into occupations and industries can explain a sizeable portion of the gender, race, and ethnic gaps in recent unemployment. However, there remain substantial unexplained differences in employment losses across groups even in these detailed decompositions. We also demonstrate the importance of tracking workers who report having a job but are absent from work, in addition to tracking employed and unemployed workers. We conclude with a discussion of policy priorities and future research needs implied by the disparities in labor market losses from the COVID-19 crisis that we identify.

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September 9, 2020

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Keywords: Stratification, Economic Recession, Job Loss; Work Features; Decomposition; Discrimination
*JEL Codes: J6, J25, J15, J16, Z13

Montenovo: Indiana University;
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1 Introduction

The COVID-19 pandemic represented a large shock to the working and personal lives of millions of people around the world. The threat of contracting SARS-CoV-2 has made it risky to engage in a variety of economic, social, familial, and cultural activities that were commonplace only a few months ago. But the epidemic has had disparate impacts on different groups, frequently mediated by the kind of job a person holds, her household and family structure, geographic location, and various measures of socio-economic status.

The SARS-COV-2 virus spreads mainly through droplet transmission that occurs when people are in close physical proximity. It follows that employment losses may be larger in jobs that involve face-to-face contact and smaller in jobs that can be done remotely. At the same time, work continues in essential industries. Sub-populations of workers are differentially sorted in jobs that vary by these characteristics, and so their employment outcomes will differ accordingly. On the labor supply side, the transmission mechanism also raises the health risks of work tasks that require face-to-face contact with customers or co-workers. Moreover, the mortality risks of COVID-19 vary across individuals: mortality rates appear to be higher for men, older people, and people with underlying health conditions. We expect that high-risk workers may supply less labor, especially in high-exposure jobs (Guerrieri et al. 2020). Labor supply might decrease through other channels as well. For example, people might reduce their labor supply because the epidemic has compromised child care services, schooling options, and other types of home and family health care availability (Dingel et al. 2020).

In this paper, we focus on the labor market disruptions and job losses during the early months of the COVID-19 recession in the United States. We document substantial disparities in recent unemployment patterns across demographic sub-populations defined by age, gender, race/ethnicity, parental status, and education. We also show that job attributes are related to employment. Specifically, people working in jobs with more remote work capacity and less dependence on face-to-face interaction were more secure. Similarly, people working in essential industries were much less likely to become unemployed in the early months of the epidemic, patterns that seem likely to persist. In general, major demographic sub-populations are not evenly distributed across occupations and industries and this is one reason why some demographic groups have fared better than others. We use decomposition techniques to quantify the share of employment disparities that is rooted in pre-epidemic sorting across occupations and industries. Occupation and industry sorting explains a substantial share of many of the disparities in employment outcomes in recent months. And the job and industry factors that protected jobs during the early months of the epidemic are often also associated with higher income and job security in normal times. This suggests that the epidemic has often aggravated the existing inequalities and social divides in society.

Our work falls into a line focused on the determinants of socioeconomic inequality and mobility, and the mechanisms that contribute to their persistence over time. Research on social stratification takes on the role of "understanding and investigating the sources" of social inequality (Sakamoto and Daniel 2003) through the study of population composition affects. Our paper examines the distribution of job losses during the early epidemic in a social stratification framework that exploits population subgroups sorting across different jobs. We use information on how subgroups allocate themselves in different occupations and industries to explain the labor market shocks they experience during COVID-19, and the changes in inequality dynamics they will experience as a consequence.

We present four broad analyses to investigate disparate impacts in labor market impacts. First, we use data from the monthly Current Population Survey (CPS) to document and compare disparities across groups in a range of labor market outcomes (current employment, absence from work, and especially recent unemployment). We find large declines in employment and increases in recent unemployment among women, Hispanics, and younger workers. There is also polarization by education, with fewer job losses among college graduates (and above), who can often work remotely, and also high school dropouts, who are often in essential jobs. This finding is significant in that it suggests that although both groups are somewhat shielded from job loss, highly educated workers are also insulated from risk of infection, while less educated workers likely face greater risk of COVID-19 exposure. In this way, stratification operates differently in terms of health and employment risk. We contrast these changes with the employment losses experienced during the Great Recession and the 2001 Recession.

Second, we explore disparities in COVID-19 job losses across occupations and industries. We use O*NET data to develop indices of the extent to which each occupation allows remote work and requires face-to-face interaction. Both Dingel and Neiman (2020) and Mongey and Weinberg (2020) use measures in O*NET to define high work-from-home occupations. Leibovici et al. (2020) takes a similar approach to measure occupations with high interpersonal contact. We show larger declines in employment in April and in May 2020 in occupations requiring more face-to-face interactions. Workers in jobs that could be performed remotely were less likely to experience recent unemployment, although the relationship is weaker in May relative to April. We further classify jobs as essential based on the "Guidance on the essential critical infrastructure workforce" issued by The Department of Homeland Security (2020) using the interpretation in Blau et al. (2020). We show that workers in essential jobs are less likely to lose a job between February and April and are also less likely to have been absent from work; both these phenomena are present in May, but to a lower degree. We provide evidence that socio-demographic groups sort themselves in occupations that vary widely in their reliance on remote work and face-to-face activities. Then, we show how much of the differences in labor market outcomes can be explained by such sorting of sub-populations.

Third, exploiting the differences in COVID-19 mortality rates by gender and age groups, we provide some preliminary evidence about the labor supply effects during the epidemic. In fact, changes in aggregate employment may reflect demand or supply shocks, but changes among high-risk workers (e.g. older workers and men) in high-exposure industries are more likely to reflect supply side factors. In April, we find little indication of a relative reduction of high-risk workers' employment in high-exposure industries, suggesting that labor supply factors have played a relatively small role in the employment response so far. However, in May, we show stronger evidence that high-risk workers are significantly less likely to be recently unemployed, and, with lower magnitudes, more likely to be absent from work. To assess the importance of caring for dependents as a factor in labor supply, we estimate changes in employment for families with children, and for women in particular. We find that women are more likely to become unemployed between February and April, and between February and May, and that women with young children experience substantially higher rates of absence from work, a concerning result given widespread closures of schools and childcare. Moreover, single parents, who are disproportionately female, are particularly likely to have lost jobs. Similarly, Alon et al. (2020) find that the social-distancing policies have a larger effect on women than men, unlike in a "regular" recession. They suggest that the impact of the epidemic on working mothers could be persistent.

Our fourth contribution is to decompose the gross differences in job losses across key demographic and social groups using an Oaxaca-Blinder decomposition. This analysis decomposes the difference in employment losses between two demographic groups into an unexplained component and components that are due to the observable characteristics of their occupations and their human capital characteristics. A significant share of differences in employment loss across demographic groups is explained by differences in pre-epidemic sorting across occupations. However, in most of our models, a non-negligible share of the difference in outcomes for the subgroups remains unexplained by either occupation sorting or other observable traits. These results are consistent with previous studies that find that social stratification and sorting mediate in labor outcomes (Busch 2020).

In addition to these substantive contributions, we also provide some analysis of recent concerns about anomalies in recent CPS data that are related to the classification of work absences vs unemployed workers U.S. Bureau of Labor Statistics (2020c). Our analysis shows that the treatment of work absences does have important implications for the overall assessment of the early labor market effects of the COVID-19 epidemic.

2 Related Research

The COVID-19 epidemic and the social distancing responses to it have already had profound effects in the United States. Between February and April 2020, the US witnessed a drastic reduction in the size and scope of economic activity. Large sectors of the economy – transportation, hospitality, and tourism – essentially shut down their normal operations during this time. During the shutdown phase, state governments implemented a range of social distancing mandates(Gupta et al. 2020; Goolsbee and Syverson 2020; Bartik et al. 2020; Coibion et al. 2020). In May, both the public and private sectors began to take steps to reopen some economic activities.

The literature on labor market impacts of the epidemics is evolving rapidly. Using cell phone data on mobility and interaction patterns, Gupta et al. (2020) document a massive, nationwide decline in multiple measures of mobility outside the home. Even states that had 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. Alon et al. (2020) find that the social-distancing policies have a larger effect on women than men, unlike in a “regular” recession. They suggest that the impact of the epidemic on working mothers could be persistent.

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. 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. These large declines happened across states, regardless of state policies or infection rates. Adams-Prassl et al. (2020) and Dasgupta and Murali (2020) study disparities in labor market impacts in other countries.

There is mounting evidence that layoff statistics may severely underestimate the extent of labor market adjustments. Using data from an early-April household survey, Coibion et al. (2020) estimate that unemployment greatly exceeds unemployment insurance claims. There is a growing literature that – like the present paper – uses O*NET occupational characteristics to capture the type of work conducted by each occupation and further investigate the employment variation attributed to occupational traits. Both Dingel and Neiman (2020) and Mongey and Weinberg (2020) use measures in O*NET to define high work-from-home occupations. Leibovici et al. (2020) takes a similar approach to measure occupations with high interpersonal contact.

However, given the nature of this health crisis, it is expected that the population of workers was differentially affected by the response policies that followed, and it is likely that these difference exacerbate the already deep social inequality in the US.

A large literature illustrates how existing patterns of social stratification shape socio-economic outcomes and the effects of large events and crises. Dudel and Myrskylä (2017); Cheng et al. (2019) and Killewald and Zhuo (2019) illustrate disparities in occupational wage gaps and other labor market outcomes on the basis of age, gender, and ethnicity both in the US and abroad. Dudel and Myrskylä (2017) show that the Great Recession shortened the life expectancy for senior workers specially among white men. Zissimopoulos and Karoly (2010) examine the short- and longer-term effects of Hurricane Katrina on labor market outcomes by subgroup of evacuees. Beyond labor market outcomes, large economic and social events also influence fertility (Grossman and Slusky 2019; Seltzer 2019), marriage (Schneider and Hastings 2015), migration (Sastry and Gregory 2014) and children's well-being (Cools et al. 2017; Schenck-Fontaine and Panico 2019).

In a study that is closely related to ours, Adams-Prassl et al. (2020) document unequal impacts of the COVID-19 pandemic on labor market outcomes in the US, UK and Germany. They suggest that countries – like Germany – which have more flexible unemployment insurance systems that allow workers to temporarily reduce worker hours without severing employment relationships, may weather the crisis better than countries with more conventional unemployment insurance systems. They also find that within countries, workers in less remote-workable occupations, less educated workers, and women are more affected by the crisis. Looking at the current crisis, Dasgupta and Murali (2020) study the disparities of job loss by high and low skilled workers in a developing economy. We explicitly contrast the pattern of labor impacts of the COVID-19 pandemic by social strata to other recent recessions.

Given the peculiarities of the COVID-19 economic crises, that derive from how the virus spreads, what measures can slow down the spread, and how quickly the crisis came about, it is necessary to investigate which population strata are particularly affected, and to what extent this is due to their occupational sorting. Understanding the most vulnerable workers' subgroups during the COVID-19 epidemic is paramount for a speedy and permanent recovery. In fact, there is substantial evidence about the long-lasting effects of economic crises can have on those who experience it and are directly affected. Hetschko et al. (2019) studies how involuntary unemployment affects negatively well-being after retirement using data German data. Considering the exposure of senior cohorts, Dudel and Myrskylä (2017) analyze how the Great Recession affected older workers and found that the working-life expectancy decreased and more so for old men. Seltzer (2019) looked at the Great Recession long lasting effects on fertility, despite the amelioration of the conventional economic indicators. Designing policies that are targeted at the subgroups mostly hit by the COVID-19 crisis will contribute to soften scarring effects that they would inevitably experience.

3 Data

3.1 Current Population Survey

Our main analysis uses data from the Basic Monthly CPS from February, April and May 2020. These surveys use a reference week that includes the 12th of the month (U.S. Census Bureau 2019). To focus on job losses related to the epidemic, we use a measure of *recent unemployment* that defines a worker as recently unemployed if he/she is coded as being unemployed in the focal week of April 2020, and reports having been unemployed for at most 10 weeks. For May 2020, recently unemployed workers are individuals who claim to be unemployed and have been so for at most 14 weeks. When creating this variable, we exclude individuals who list themselves as currently out of the labor force. Focusing on recent unemployment allows us to study the rate of recent job losses using only the April 2020 CPS cross section.[1] Appendix Figure 8.2 shows that the incidence of recent unemployment across demographic groups is very similar to month-over-month changes from February to April and from February to May in the employment-to-population ratio. The left graphs of both Panels of Appendix Figure 8.2 show the average change in employment rates from February 2020 to April 2020 (Panel A) and to May 2020 (Panel B) by demographic sub-population. The right graphs show the fraction of labor force participants who became unemployed recently as of the April CPS (Panel A) and May CPS (Panel B) reference weeks. The figure shows that changes in employment and recent unemployment rates convey similar information. Both employment outcomes are worse for younger workers, less educated workers, Hispanics, females, and workers with their own children in the household. Given the similarity between the two measures, we focus on recent unemployment.

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). During the epidemic, these employed-but-absent workers deserve particular attention for a few reasons. First, some employers released workers intending to rehire them (Bogage 2020; Borden 2020). 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

[1] During April, 12.1% of those aged 21 and above in the labor force reported being unemployed at the time and had lost their job sometime in the last 10 weeks. During May, 0.10% of the workers were recently unemployed (i.e. unemployed for at most 14 weeks). In contrast, in February only 2.1% did so.

of the March and April 2020 CPS. 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 (2020c), U.S. Bureau of Labor Statistics (2020b) and U.S. Bureau of Labor Statistics (2020a) explain that surveyors appeared to code at least some of them in the employed-but-absent category. These reasons contribute to a massive increase in the share of workers coded as employed-but-absent from work between February and April as well as May.[2] Therefore, we performed most of our analysis separately on measures of recent unemployment and employed-but-absent; see Appendix 9.3 and 9.4.

3.2 O*Net

We use the 2019 Occupational Information Network (O*Net) Work Context module, 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, and about the importance of different activities in their jobs. Some of the questions relate to the need for face-to-face interaction with clients, customers, and co-workers. Other questions assess how easily work could be done 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. To measure the extent to which an occupation involves tasks that may become riskier or more valuable during the COVID-19 epidemic, we developed indices for Face-to-Face interactions and the potential for Remote Work. Appendix Table 9.1 presents the specific O*Net questions used in each index. The value of each index for an occupation is a simple average of O*Net questions listed in the table. We standardized the indices to have a mean of zero and a standard deviation of one in our sample.

The O*Net data classifies occupations using SOC codes and the CPS data classifies occupation codes using Census Occupation codes. We cross-walked the two data sets to link the O*Net Face-to-Face and Remote Work indices with the CPS microdata. The April CPS contains workers from 526 unique Census Occupations. We were able to link the index variables to 524 occupation codes, leaving only 9 workers with missing indexes.[3]

[2] In our sample, the employed-but-absent share group rose by almost 150% from February to April, 2020, and by 82% from February to May, 2020.

[3] We were not able to link an O*Net Face-to-Face or Remote Work index to workers in Census Occupation Codes 1240 (Miscellaneous mathematical science occupations) and 9840 (Armed Forces).

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 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,[5] and to the CPS industry classification system. From the 287 industry categories at the four-digit level, 194 are identified as essential in 17 out of 20 NAICS sectors. Appendix Table 9.2 gives an abbreviated list of essential industries to clarify the classification scheme.

3.4 COVID-19 Exposure

To explore disparities in employment outcomes across states facing different epidemiological conditions, we linked CPS data to the average cumulative number of confirmed COVID-19 cases in a state during the focal week of the April and May CPS. We retrieve information on COVID-19 cases from The New York Times (2020).[6] We control for a state's population size using state level Census population estimates in our regression analyses.

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 (CCDC 2020). We applied the case-fatality rates to the U.S. workers in our sample by transforming the relative mortality rates by age and gender.[7] Our goal is to proxy for people's COVID-19 mortality expectations as of the second week of April and as of the second week of May. While mortality rates likely differ between the U.S. and China, these data are the best available at this time, and age and gender based mortality rates are likely primary factors in forming expectations.

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

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

[6] Last consulted on Jun 28, 2020.

[7] We use Bayes' theorem to infer mortality rates by age and gender from CCDC (2020). Specifically, we calculated:

$$Pr(Death|Gender, Age) = \frac{Pr(Age|Death) \cdot Pr(Gender|Death) \cdot Pr(Death)}{Pr(Gender) \cdot Pr(Age)}$$

Where: $Gender = \{Female, Male\}$ and $Age = \{20-29, ..., 70-79, 80+\}$. We normalize the variable to have mean of one and standard deviation of zero on the entire CPS sample.

4 Employment Disruptions in Three Recessions

Figure 1 shows the change in employment for the COVID-19 Recession compared with the peak-to-trough change in employment for the entire 2001 Recession (March 2001 to November 2001) and the entire Great Recession (December 2007 to June 2009). For COVID-19, we focused on two time periods that cover the initial "closing" phase of the pandemic (i.e. from February to April) and also a longer period that includes the ensuing "reopening" phase (i.e. from February to May). All estimates use CPS sampling weights and we limit the sample to CPS respondents who are at least 21 years old during the survey. When constructing the peak-to-trough change in employment rates for the 2001 Recession and the Great Recession, we adjust for seasonality by removing month fixed effects estimated from regressions of employment on month of year fixed effects using the Basic Monthly CPS data from January 2015 to December 2019.

By looking at the light grey lines on the figure, we see that the employment losses from February to April in the COVID-19 epidemic dwarf the declines for the other two recessions, which span nine and nineteen months respectively. Moreover, this remains true in May even after the re-opening, during which employment rebounded substantially. The size and unprecedented speed of the COVID-19 recession are reinforced in Appendix Figure 8.1, which shows seasonally-adjusted non-farm employment from March 2000 and May 2020. The bars in Figure 1 show the change in the employment rate for sub-populations defined by gender, presence of own children in the household, race, ethnicity, age group, and education achievement. Almost no group is spared from employment loss during any of the three recessions. However, the pattern of employment disruption is noticeably different in the early months of the COVID-19 recession.

Young (ages 21-24) and Hispanic workers have fared the worst so far. After the first two months of the COVID-19 epidemic, the fall in employment among young workers is almost 4.5 times larger than the employment losses experienced by young workers across the entire Great Recession. The change in employment rate for Hispanics was over 3.6 times larger between February and April 2020 than it was during the 19 months of the Great Recession. Our conjecture is that these two groups disproportionately work in industries that are particularly hit by social distancing measures, such as food service and construction. Women and respondents with own children in the household also experience larger employment declines than their counterparts without children. This could reflect labor supply constraints given school and daycare closures. During the COVID-19 outbreak, employment rates fell by 14 percentage points among Black workers and by 12 percentage points among White workers. A similar pattern arose during the 2001 Recession, but not during the Great Recession.

There is strong evidence of skill polarization effects during the current recession: high school dropouts and college graduates have experienced substantially smaller employment declines compared to the intermediate education groups. As we show below, highly-educated workers have better options to work remotely, without in-person interactions. In contrast, less educated workers are more likely to be in essential positions. While polarization is consistent with recent trends in the labor market, this kind of pattern was not a feature of the two previous recessions (Autor et al. 2006).

Comparing our results for the decrease in employment between February and April to those between February and May indicates that there were gains in employment between April and May as states ended the lock downs and began re-opening. The recovery in employment that the groups experienced between April and May were broadly proportional to the employment losses that occurred between February and April, so that the most hit subgroups remain such throughout May as well. This suggests that the distributional incidence of job loss and recovery are largely symmetric. There is, however, one notable exception. The employment of Blacks did not recover in May as much as would have been expected given the decline in employment in April, meaning that Blacks seem to have been re-employed relatively less in May than the other demographic categories.

In Figure 2, we report the same outcome as in Figure 1, employment change, by family structure. The sub-populations we consider are single individuals, married individuals, single parents, parents in two-parent households, single parents of a young child (up to 13 years old), and married parents of a young child (up to 13 years old). We coded as single all the respondents who claim to be in any category that is not "married with a spouse present in the household". Specifically, it includes respondents who are married with an absent spouse, widowed, divorced separated, or never married. "Married" workers responded to be married with a present spouse. We coded as parents all those respondents who reported having own children below 18 living in their household. We further divided this category to distinguish parents of young children (up to 13 years old).

Figure 2 shows that single workers experienced a larger decrease in employment during the epidemic than married ones, regardless of whether we compare April to February or May to February. Moreover, parents of own children living in the household fared worse than workers without dependents below 18 years old (i.e. own children). Single parents, whether of younger children or not, experienced the largest decrease in employment. Given that, in our sample for 2020, about 72% of the single parent category is female, it seems safe to say that single mothers represent the family category, among those we considered, that experienced the most negative employment shock during the epidemic. Throughout these estimates, the age of the child does not seem to strongly impact the change in employment during these months. Thus, single parents and single parents of young children appear roughly equally disadvantaged, as are married parents regardless of child age. The bar charts shown in this section highlight Hispanics, young workers (between 21 and 24 years old), and single parents to be the most vulnerable workers as a result of the epidemic, and those most in need of the policy protection.

5 Job Tasks and Recent Unemployment

In this section of the paper, we conduct descriptive and regression analyses to examine how recent unemployment rates depend on characteristics of the job (remote work compatibility, and face-to-face interaction), essential work designations, worker level COVID-19 risk, human capital, and family structure. We focus on a binary measure of recent unemployment, which is an indicator variable set to one if a person is unemployed and became unemployed within the past 10 weeks, as of the April CPS and within the past 14 weeks, as of the May CPS. Ignoring re-employment, this 10/14-week rate should capture the same employment disruptions as the overall change in employment rates between February and April, and February and May. Panel A of Appendix Figure 8.2 compares the recent unemployment rate in April 2020 with the February to April change in employment rates by sub-population, whereas Panel B shows the comparison for the months of February and May. The results in the figure confirm that the cross-sectional recent unemployment rates have nearly the same pattern across groups as the February-April employment rate change, and that this phenomenon remains unaltered during May.

Figure 3 shows the mean of the Remote Work and Face-to-Face indices across sub-populations in the February 2020 CPS. The graph shows how sub-populations were sorted into jobs with different remote work and face-to-face interaction attributes before the epidemic. The remote work index varies more across sub-populations than the face-to-face index. Women tend to work in jobs that both allow more remote work and involve more face-to-face activities than men. Sharp differences arise by ethnicity, with Hispanics disproportionately working in jobs that largely cannot be conducted remotely. Younger workers (age 21-24) are in jobs with fewer remote work prospects and in jobs that involve more face-to-face interaction, although the differentials are not very large. The most dramatic differences in occupational sorting arise across the four education groups. Workers with less than a college degree are in occupations with poor opportunities for remote work, and this is particularly true among high school dropouts.

Figure 4 shows the association between the remote work and face-to-face scores in an occupation and the rate of recent unemployment in that occupation in the April CPS. Figure 5, on the other hand, presents the results when looking at the cross-section in the May CPS. The diameter of the bubbles is proportional to the number of workers in that occupation. There are a total of 524 occupations in our sample and in April the occupation-specific recent unemployment rates range from 0% to over 30%. To improve readability, 52 occupations with recent unemployment rates of more than 36.17% (the 90th percentile of the distribution) are excluded from the figure but not from the regression below. For May, we also deleted occupations with extreme values of recent unemployment rates. By doing this, we drop 53 occupations with recent unemployment greater than 13.31%. The left panel in Figure 4 shows that the recent unemployment rate tends to be much lower in occupations with higher scores on the remote work index, suggesting that the ability to work remotely has helped protect employment during the early months of the epidemic. The second panel 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.

In May, as presented in Figure 5, we see that the relationship is attenuated and that the fitted lines have smaller slopes. While earlier on (i.e. April), recent unemployment was higher for occupations with lower remote work and higher face-to-face indices, during May this difference is less pronounced. This points to a deceleration of recent unemployment rates on those occupations most hardly hit at the beginning of the epidemics. Job tasks are not the only factors that may explain recent job losses. Essential work designations may help protect certain types of jobs, and school closures and reduced access to child care may have disrupted employment in households with children. Additionally, worker mortality risk from COVID-19 may have reduced labor supply among high-risk groups. To examine these possibilities in more detail, we fit OLS regressions of recent unemployment on a collection of worker and job characteristics:

$$\begin{aligned} y_{ijk} &= Face_j\beta_1 + Remote_j\beta_2 + Essential_k\beta_3 \\ &+ Mortality_i\beta_4 + Female_i\beta_5 + Child_i\beta_6 + (Child_i \times Female_i)\beta_7 + C19_s\beta_8 \\ &+ X_i\delta + \epsilon_{ij} \end{aligned} \quad (1)$$

In the model, y_{ij} is an indicator set to 1 if person i from occupation j is recently unemployed.[8] $Face_j$ and $Remote_j$are the indices for face-to-face work and remote work. $Essential_j$ is a dummy variable equal to one for people employed in an industry considered essential by DHS. We define an index of a person's COVID-19 mortality risk, denoted $Mortality_i$. $Female_i$ indicates that the person is female, $Child_i$ is an indicator set to 1 if person i has a child under age 6 in the household, and $C19_s$ is a measure of the log number of confirmed cases of COVID-19 in the state. X_i is a vector of covariates, including a quadratic in age, indicators for race/ethnicity, and indicators for

[8]We also fit models where the dependent variable indicates the worker reports being employed, but absent from work during the CPS reference week, and we report results in Tables 9.3 and 9.4

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.

We present the estimated coefficients in Tables 1 and 2 using April and May data respectively. Column (1) shows estimates from models that do not adjust for mortality risk or number of COVID-19 cases in the state, but do control for occupation and individual characteristics. Column (2) includes the mortality risk variable and logged state COVID cases. Column (3) accounts for the interactions between mortality risk and job task indices, and column (4) adds interactions between the state's COVID rate and job characteristics. Column (5) replaces the job task indices with occupation and industry fixed effects to account for any additional time-invariant job characteristics, as well as state fixed effects to control for additional local time-invariant conditions. In the appendix, we include the estimated coefficients for the same family of models using "employed but absent from work" as a dependent variable (Tables 9.3 and 9.4).

The results suggest that, even after adjusting for other covariates, people working in jobs with more potential for remote work are less likely to be recently unemployed, confirming what we presented above in Figure 4. The estimated coefficient on remote work in Column 1 implies that working in a job that scores one standard deviation above the mean on remote work reduces the risk of recent job loss by about 5.8 percentage points. The overall recent unemployment rate during the April sample was 13.1 percent. This implies that working in a job that scored one standard deviation above the average remote work score reduces the risk of recent unemployment rate by 44 percent. On the other hand, jobs where face-to-face interactions are important have higher recent unemployment rates. After adjusting for other factors, the model in column (1) implies that recent unemployment rates are 1.6 percentage points higher for people working in jobs that score 1 standard deviation above the mean on the face-to-face index. A 1 standard deviation increase in the face-to-face index is associated with a 12 percent increase in recent unemployment rates. The coefficient on "Essential" indicates that working in an essential industry substantially reduces the probability of recent unemployment. In particular, working in an industry classified as essential reduces recent unemployment rates by 8.9 percentage points, which is a 68 percent decrease relative to the mean. These results are quite stable across specifications, although the magnitude and precision naturally change when adding interactions between state level COVID-19 cases and these characteristics (Model 4).

When looking at the May CPS, the coefficient for the remote index drops to 4.6 percentage points (from from 5.8 in April), and the coefficient for Essential industry drops to 7.3 percentage points. In contrast, the coefficient for the Face-to-Face index, remains at the same level as in April. This associations remain significant for the same models with the exception of when we add interactions with the number of cases by state. May data shows an attenuated continuation of what the labor market experienced during April. This is due to the business reopening policies that most states implemented during May.

The regressions also suggest that recent unemployment rates vary substantially across demographic groups and with human capital. Recent unemployment rates are about 3 percentage points higher for women both in April and May, after adjusting for other covariates. The coefficient on the interaction term between female and children under age 6 is small and not statistically significant, suggesting that child care responsibilities have not explained much gender specific employment disruption so far. However, Appendix Table 9.3 shows that when the dependent variable is "employed but absent", the interaction between female and children under age 6 is large and statistically significant. Women with young children are 3.9 percentage points more likely to report being employed but absent than men with young children during April. During May, women with young children are still 3.6 percentage points more likely to fall into this category than their male counterparts. These results suggest that child care and family responsibility could play an important role in job losses downstream, if work absence is a leading indicator of future unemployment. Moreover, they show that May reopenings were not crucial in helping women with young children go back to work.

We used a quadratic function to approximate the age profile of recent unemployment rates. Taken literally, the coefficients from column (1) suggest that recent unemployment rates are quite high for younger workers and decline with age up to around age 49 in April and 50 in May. Then recent unemployment rates begin to rise again for older workers. Recent unemployment is lower among college educated workers: graduate degree holders are about 8 percentage points less likely to have become unemployed in the 10 weeks leading up to the April CPS, and college graduates are about 5 percentage points less likely to be recently unemployed. This relationship remains at the same level during May, when using a limit of 14 weeks for the unemployment spell.

Employment disruptions do seem to vary across geographic areas. Recent unemployment rates are about 3.3 percentage points lower among workers living in metropolitan areas, and 3.6 during May. The tables also include the level of positive COVID-19 cases in a state during the week of the CPS in April and interactions between COVID-19 cases and the job indices. We find that the recent unemployment rate falls by about 1.5 percentage points during April, and 1.1 percentage points during May, for each 1 percent increase in the number of confirmed COVID-19 cases in the state during the same week in April.

The results suggest that our proxy for COVID-19 mortality risk is not clearly related to job loss during April. The coefficient on mortality risk is only statistically significant in one out of the four specifications where it is included during April. However, during May, we find an inverse relationship that is significant across all specifications. According to column (2) in Table 2, a one standard deviation higher mortality risk is associated with 2.5 percentage points decrease in the recent unemployment rate in May. The interactions of our mortality risk measure with occupation indices are mostly insignificant both in April and in May, the only exception being the interaction between risk and remote work: in jobs that can be performed remotely, higher mortality risk seems associated with a slightly higher job loss rate in some specifications during both April and May.

One plausible interpretation of this result is the need to keep employer provided health insurance by those mostly at risk, considering that losing that protection in the middle of a pandemic might prove more calamitous for those affected. In contrast, when looking at the Absent from Work rate during May in Appendix Table 9.4, the evolution of the coefficients goes on the opposite direction to the one just described for recent unemployment, and the higher the mortality risk, the higher the Absent from Work rate, which could be the result of at risk workers calling off from work, either due to illness, or due to fear of contracting the disease. Still, we urge caution in interpreting these coefficients considering that our index could be an imperfect measure of the way people interpret their own mortality risk, as it is based only on the age and sex of COVID-19 related casualties in China.

6 Decomposing Group Differences in Recent Unemployment

Recent unemployment rates in April varied substantially across sub-populations. Some of these differences may reflect pre-epidemic sorting across occupations and industries, differences in human capital, and differences in demographic characteristics. However, it is also possible that the COVID-19 epidemic is affecting sub-populations differently. To shed light on these gaps, we used Oaxaca-Blinder models to decompose recent unemployment gaps into the share explained by pre-epidemic observable covariates, and an unexplained share which reflects differences across groups in how recent job loss is associated with those covariates.

Figure 6 summarizes the decomposition of the most significant gaps in our data. They appear ordered from smallest (left) to largest (right) for: white versus Black, high school graduate versus high school drop out, female versus male, non-Hispanic versus Hispanic, college graduate versus high school graduate, and older versus younger workers. Figure 7 shows the same decompositions, but applied to the May data for recent unemployment. The full results of the decompositions appear in Appendix Tables 9.5 and 9.7.

For each gap, we estimate three nested decomposition models. Each model includes basic demographic characteristics (age, gender, race, ethnicity, education, and presence of young children) and state controls. The three models are differentiated by how much detail we include regarding job characteristics. Model A includes the Face-to-Face, Remote Work, and Essential Job indices.

Model B adds a full set of 524 occupation dummies which, of course, absorb the variation from the Face-to-Face and Remote Work indices.[9] Finally, Model C adds a full set of 261 industry dummies, which absorb the variation from the Essential index.

Focusing first on Model A for the April data, the explanatory contributions of occupational task-based sorting and essential industry sorting push in different directions across groups. For example, the non-Hispanic/Hispanic gap is quite large at -4.4 percentage points, relative to a baseline recent unemployment rate of 12.1 percent. About 53.3 percent of the raw gap arises because Hispanic workers are overrepresented in jobs with little opportunity for remote work. However, these relative losses are partially offset by the fact the Hispanic workers are overrepresented in essential jobs, accounting for -11.7 percent of the raw gap. This pattern is similar for the gap between Black and white workers.

The gender gap is different. Continuing with the April data, most of the gender gap is unexplained, and in fact sorting on the basis of remote work predicts a smaller gap than actually appears in the data. Moving to Models B and C, we see that sorting by occupation and industry can explain a sizeable portion of the gender, race, and ethnic gaps in recent unemployment. However, there remain substantial unexplained differences in employment losses across groups even in these more detailed decompositions.

The largest gaps we observe are between college graduates and high-school graduates, and between older versus younger workers. In Model C, we observe that a majority of both raw gaps can be attributed to differences in the types of jobs workers held when the epidemic started. The less detailed Model A suggests that a large portion of that gap was associated with differences in capacity for remote work, and partially offset by employment in essential industries.

All of the patterns we observe are consistent from April to May except one: the gap in recent unemployment between Black and white workers. In May, the raw gap is -0.031 percentage points; nearly double the -0.016 gap from April. Curiously, all of the growth in the gap is from sources that are not explained by the individual or job characteristics included in the model. Overall, recent unemployment rates fell in May relative to April (as they did for headline unemployment). Consistent with this broad trend, recent unemployment also fell for white workers. However, recent unemployment rates increased slightly for Black workers. Our decomposition indicates that whatever prevented recent unemployment rates from falling as quickly for Black workers was unrelated to any of the individual or job characteristics included in our model. One possible

[9] For Model B, Table 9.6 in the Appendix reports the share of variation explained by sorting across five 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”, does not appear because the CPS is a survey of the civilian non-institutional population.

explanation is that, given the same characteristics, white workers are more likely to be re-employed than Black workers in a recovery. These patterns could also arise from changes in how the CPS classifies workers as unemployed relative to employed but absent across months.

Across the board, differential sorting into occupations and industries are highly relevant in explaining gaps in recent unemployment. This finding echoes recent work byAthreya et al. (2020), who find that the service sectors are most vulnerable to social-distancing. Nevertheless, the precise sources of employment losses vary across groups in ways that are not neatly summarized by differential exposure to particular types of tasks or sectors. Finally, we note that demographic controls do not explain a large part of any of the gaps, suggesting a limited role for labor supply effects in explaining recent job losses.

7 Conclusion

After only a few months, the COVID-19 job losses are larger than the total multi-year effect of the Great Recession. Moreover, there are large inequities in the job loss experiences across different demographic groups. The April and May CPS offer the first complete window into the employment disruptions produced by the COVID-19 epidemic. The April data provide detailed information about the distribution of job losses during the early part of the epidemic, and the May data give us some insights into the effect of work reopenings on job market patterns.

We find substantial differences in employment across jobs. For example, we find that, in April, recent unemployment rates are about 46% lower among workers in jobs that are more compatible with remote work. In contrast, workers in jobs that require more face-to-face contact are at higher risk of recent unemployment. A significant share of differences in employment loss across key racial, ethnic, age, and education sub-populations can be explained by differences in pre-epidemic sorting across occupations. However, in almost all cases, a large share of the gaps in job losses between social strata cannot be explained by either occupation sorting or other observable traits. There are at least 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.

An important implication of these impacts by job characteristic is the difference between employment rates and COVID-19 exposure. Thus, the employment of higher educated workers appears more secure due to the possibility of remote work in their jobs. While the least educated workers have also experienced less recent unemployment, largely due to their concentration in essential industries, these workers likely face greater exposure to COVID-19 itself. Thus, the smaller reduction in employment for both groups potentially masks other disparities. New government policies or private sector innovations that increase the viability of remote work for a larger share of the economy could be extremely valuable.

The early labor market evidence from the CPS suggests that many workers are separating from their employers, with the potential for long-term scarring effects known to befall displaced workers during recessions. Finding and forming productive employment matches is costly. Furthermore, workers receive health care and other benefits through employers. Assuming economic conditions 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 important.

The analysis of May CPS data show an uptick in employment that likely derives from the business reopenings implemented in most states during that month. Although rates of recent unemployment and absence from work are still very high in the May CPS data, reopening policies have reduced the negative impact of the epidemic on the labor market. The improvements in labor market outcomes are consistent with cell signal data, which show a rise in physical mobility starting in mid-April and continuing through May (Nguyen et al. 2020). Of course, it is unclear whether these returns to normalcy can be sustained in the face of more recent increases in COVID-19 cases and hospitalizations.

In the meantime, our results make clear that there are large disparities in the current labor market crisis, and they suggest a role for public policy that could target solutions on this basis. Although women with young children do not have statistically larger increases in recent unemployment compared to men with young children, despite the disruptions in school and child care, their higher rate of "employed but absent" is worrying and could indicate larger losses in future employment. Moreover, single parents, who are overwhelmingly women, experienced a larger decrease in employment between February and either April or May than their married counterparts. Efforts to support new child care options may be important in the next phase of the epidemic. In May, we found some evidence of racial disparities in the decline in recent unemployment. For example, Black workers seem to have experienced a smaller decline in recent unemployment during the reopening phase. The reasons for this appear to be unrelated to any of the individual or job characteristics we considered.

Our work also hints at deeper structural damage to the economy. Previous research documents large scarring effects of graduating from high school and college during a recession, and the longer term effects of early career setbacks may be even larger than the near term effects (Rothstein 2019). Our work shows that recent unemployment rates are very high among the youngest workers overall and in comparison to earlier recessions. Efforts to support early career workers as well as older displaced workers may need to be a particular target of policy in the near future.

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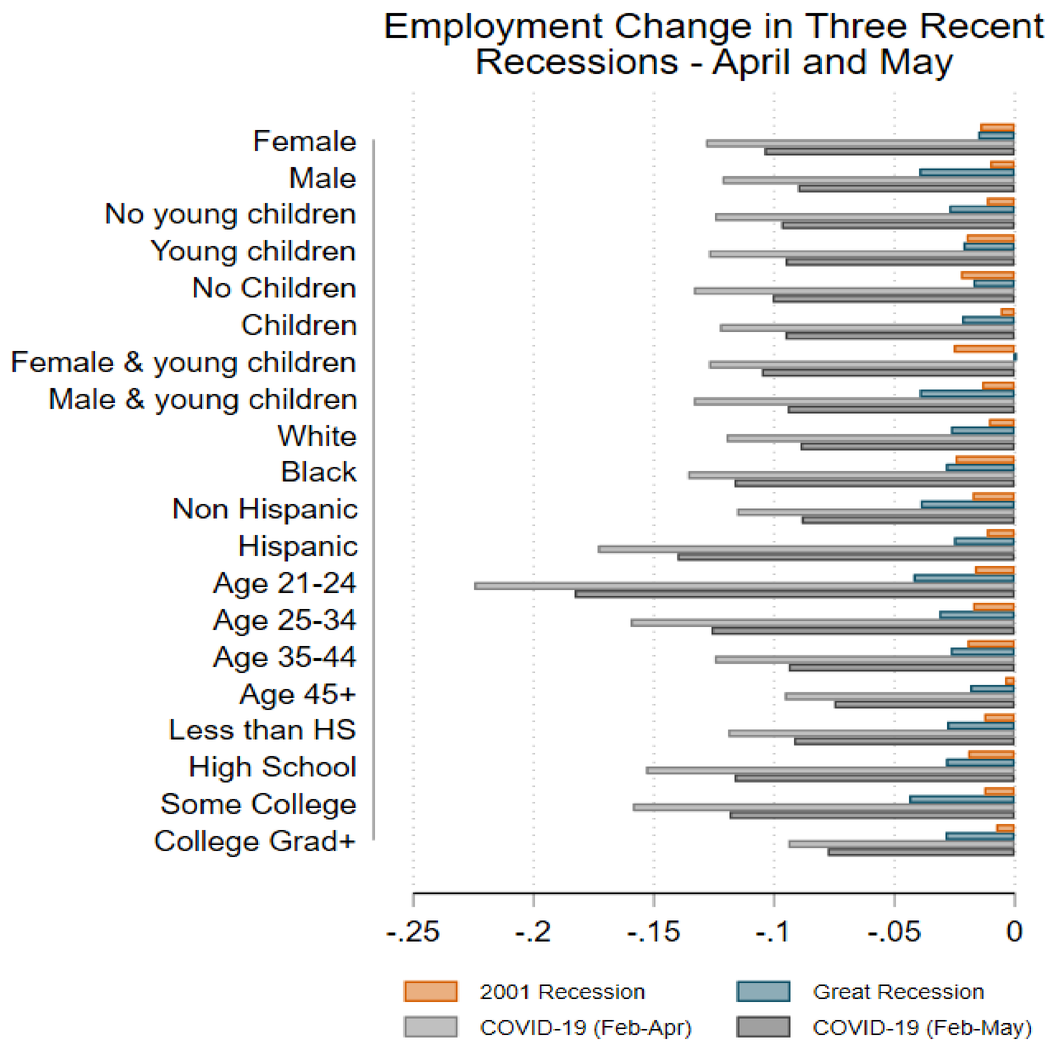
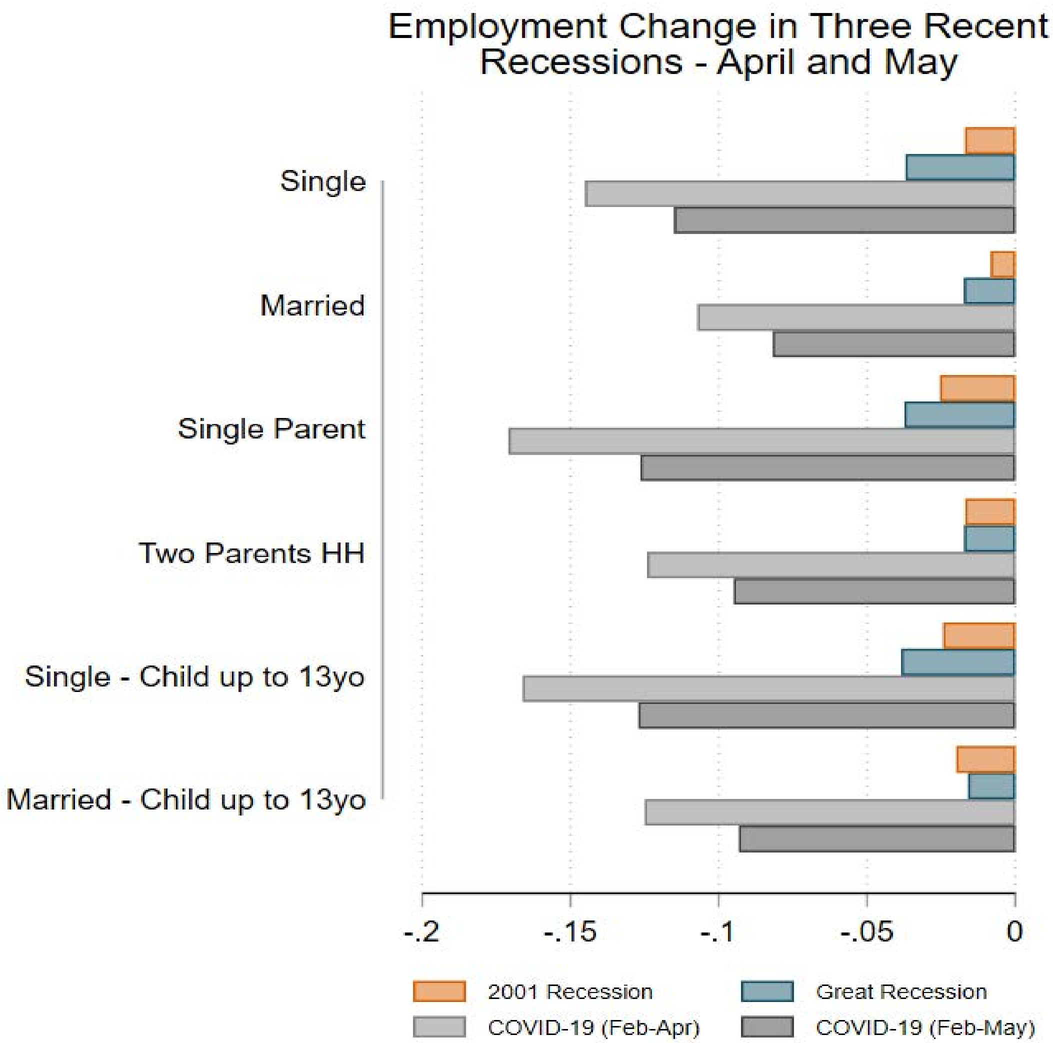
Tables and Figures

Figure 1



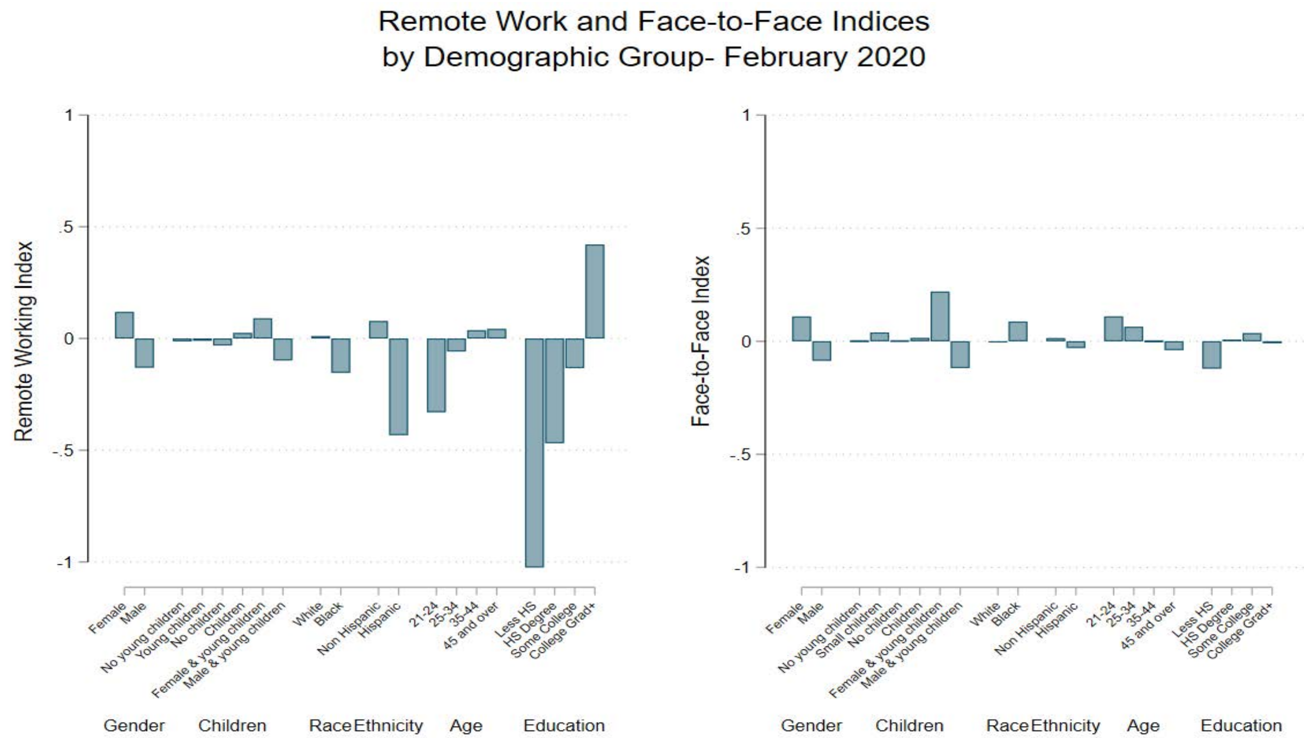
Notes: Sample consists of CPS respondents age 21 years and older. For each bar, we compute the difference in the percent of the demographic group that reports being employed and at work, between the start and end months of each recession pre COVID-19, and during COVID-19, by the two main months with data thus far (National Bureau of Economic Research 2012), where in one COVID-19 bar we compare April 2020 to February 2020 and in another, we compare May 2020 to February 2020. The estimates were weighted using the CPS composited final weights. To include a seasonal adjustment, monthly fixed effects were included in the computation of the average subgroups employment change for the 2001 Recession and the Great Recession.

Figure 2



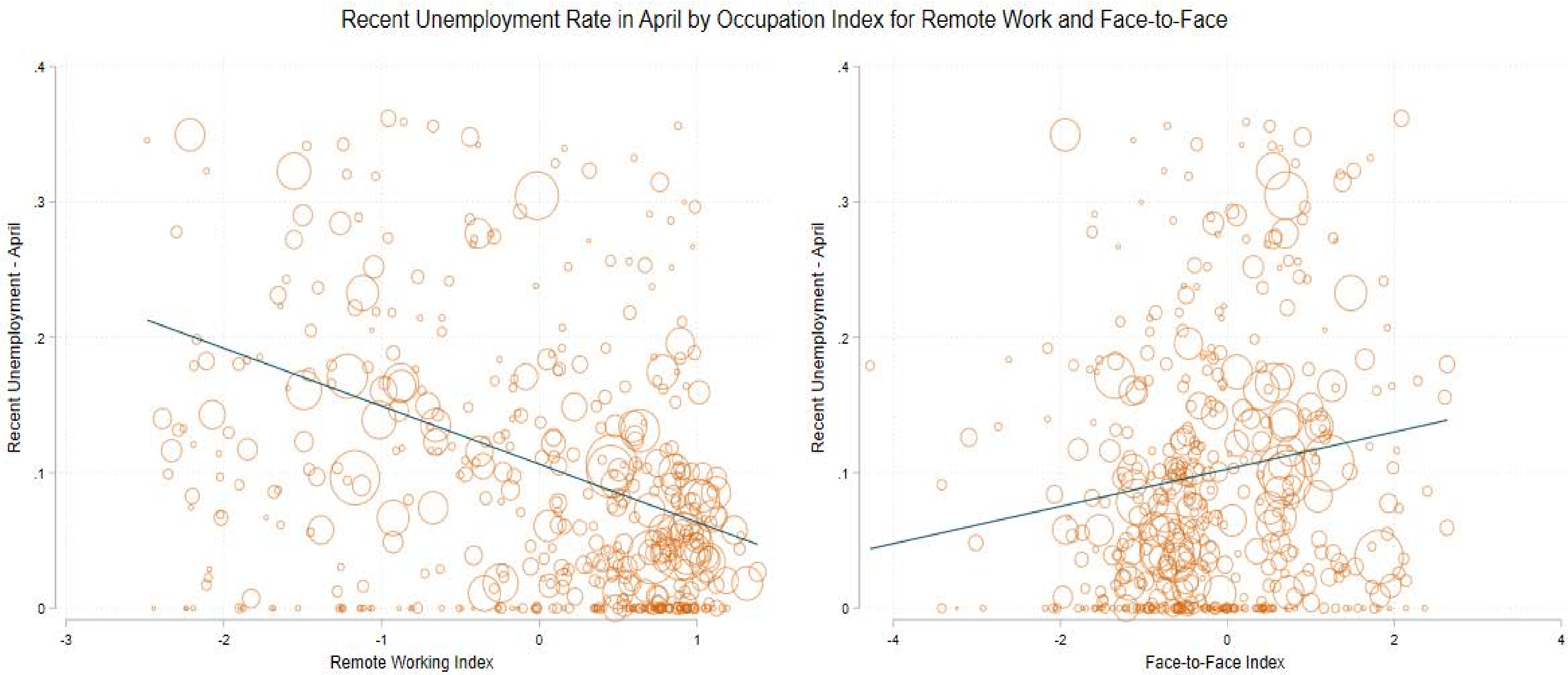
Notes: Sample consists of CPS respondents age 21 years and older. For each bar, we compute the difference in the percent of the demographic group that reports being employed and at work, between the start and end months of each recession pre COVID-19, and during COVID-19, by the two main months with data thus far (National Bureau of Economic Research 2012), where in one COVID-19 bar we compare April 2020 to February 2020 and in another, we compare May 2020 to February 2020. The estimates were weighted using the CPS composited final weights. To include a seasonal adjustment, monthly fixed effects were included in the computation of the average subgroups employment change for the 2001 Recession and the Great Recession.

Figure 3



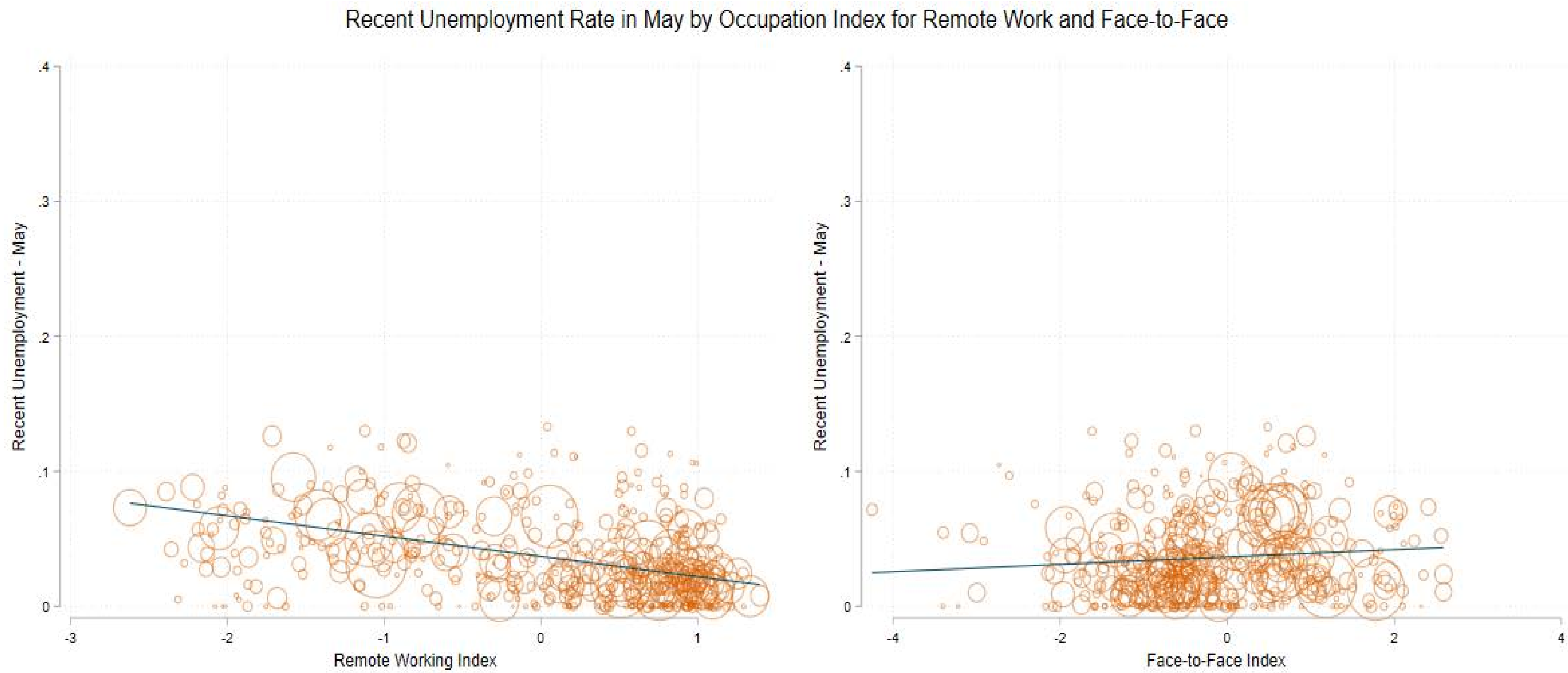
Note: Sample consists of CPS February 2020 respondents age 21 and above who are in the labor force. Each index has been standardized to have mean 0 and standard deviation 1. We compute the average of each occupation index by subgroup. Negative numbers indicate lack of that characteristic in the jobs of that group.

Figure 4



<u>Note:</u> Sample consists of April CPS 2020 respondents age 21 and above who are in the labor force. We compute the average percent recent unemployed in each occupation and plot that against the occupation's index value. Each occupational index has been standardized to have mean 0 and standard deviation 1. Each bubble represents a Census Occupation, and its dimension is proportional to the size of the workforce that holds that occupation in our sample. We include a line plotting the prediction from a linear regression of recently unemployed on each occupation index. To improve readability of the graphs, we excluded from the sample the 52 occupations whose recent unemployment rate is above the 90th percentile (i.e. greater than 36.17%).

Figure 5



<u>Note:</u> Sample consists of May CPS 2020 respondents age 21 and above who are in the labor force. We compute the average percent recent unemployed in each occupation and plot that against the occupation's index value. Each occupational index has been standardized to have mean 0 and standard deviation 1. Each bubble represents a Census Occupation, and its dimension is proportional to the size of the workforce that holds that occupation in our sample. We include a line plotting the prediction from a linear regression of recently unemployed on each occupation index. To improve readability of the graphs, we excluded from the sample the 53 occupations whose recent unemployment rate is above the 90th percentile (i.e. greater than 13.31%).

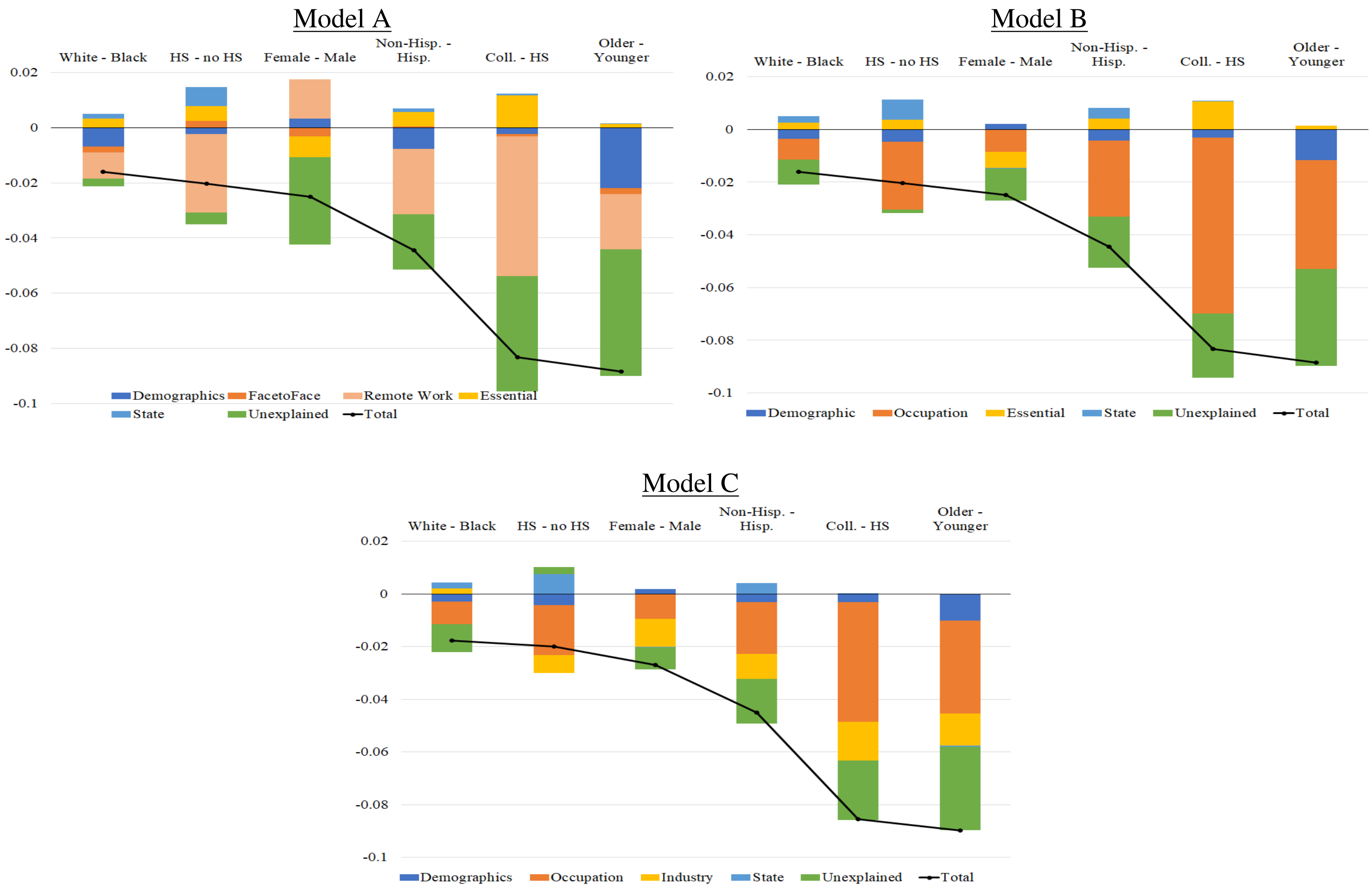
Table 1: Cross-Sectional Models: Characteristics of the Recently Unemployed Workers in April

Dependent = Recent Unemployed Apr Mean= 0.1306 ; Std. Dev = 0.3370	Mean (Std. Dev)	(1)	(2)	(3)	(4)	(5)
Face-to-Face	-0.017	0.016***	0.016***	0.017***	0.018	
	(0.988)	(0.006)	(0.006)	(0.005)	(0.012)	
Remote Work	0.071	-0.058***	-0.058***	-0.055***	-0.007	
	(0.953)	(0.009)	(0.008)	(0.008)	(0.021)	
Essential	0.706	-0.089***	-0.086***	-0.087***	-0.078*	
	(0.455)	(0.014)	(0.013)	(0.013)	(0.042)	
Mortality Risk Index	-0.315		-0.018***	-0.014	-0.014	-0.012
	(0.527)		(0.006)	(0.011)	(0.011)	(0.010)
Risk x Face-to-Face	-0.017			0.002	0.003	0.000
	(0.602)			(0.005)	(0.005)	(0.005)
Risk x Remote Work	-0.018			0.009*	0.009**	0.004
	(0.584)			(0.005)	(0.005)	(0.004)
Risk x Essential	-0.222			-0.006	-0.006	-0.001
	(0.463)			(0.011)	(0.011)	(0.009)
Ln(COVID cases in State)	9.370		0.015***	0.015***	0.016**	
	(1.291)		(0.005)	(0.005)	(0.007)	
Ln(COVID cases) x Face-to-Face	-0.166				-0.000	0.000
	(9.355)				(0.001)	(0.001)
Ln(COVID cases) x Remote	0.715				-0.005**	-0.004**
	(8.991)				(0.002)	(0.002)
Ln(COVID cases) x Essential	6.600				-0.001	-0.003
	(4.393)				(0.005)	(0.005)
Fem x Child-U6	0.062	-0.003	0.001	0.002	0.002	-0.009
	(0.241)	(0.011)	(0.010)	(0.010)	(0.010)	(0.010)
Child under 6	0.137	-0.013*	-0.011*	-0.011*	-0.011*	-0.001
	(0.344)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)
Female	0.468	0.034***	0.029***	0.030***	0.030***	0.007
	(0.499)	(0.008)	(0.008)	(0.008)	(0.008)	(0.005)
Black	0.126	-0.003	-0.003	-0.003	-0.003	0.012
	(0.331)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Hispanic	0.178	0.005	0.007	0.007	0.006	0.009
	(0.382)	(0.009)	(0.009)	(0.009)	(0.009)	(0.008)
Age/100	0.428	-1.002***	-1.076***	-1.050***	-1.057***	-0.708***
	(0.143)	(0.144)	(0.149)	(0.147)	(0.147)	(0.098)
$(Age/100)^2$	0.204	1.029***	1.177***	1.146***	1.152***	0.794***
	(0.130)	(0.154)	(0.168)	(0.165)	(0.165)	(0.116)
Less-than HS	0.067	Omitted	Omitted	Omitted	Omitted	Omitted
	0.250					
HS	0.249	-0.003	-0.001	-0.002	-0.001	-0.002
	(0.432)	(0.013)	(0.014)	(0.014)	(0.014)	(0.011)
Some College	0.274	-0.003	-0.001	-0.002	-0.001	-0.005
	(0.446)	(0.013)	(0.014)	(0.014)	(0.014)	(0.010)
BA Degree	0.259	-0.047***	-0.044***	-0.044***	-0.044***	-0.027**
	(0.438)	(0.014)	(0.014)	(0.014)	(0.014)	(0.011)
Post D	0.151	-0.081***	-0.080***	-0.080***	-0.079***	-0.037***
	(0.358)	(0.015)	(0.015)	(0.015)	(0.015)	(0.013)
Metropolitan	1.114	-0.033***	-0.026***	-0.026***	-0.026***	-0.010
	(0.318)	(0.009)	(0.009)	(0.009)	(0.009)	(0.008)
Ln(State Population)	16.130	0.005	-0.010	-0.010	-0.010	
	(0.914)	(0.005)	(0.008)	(0.008)	(0.008)	
Constant		0.377***	0.468***	0.465***	0.456***	0.307***
		(0.093)	(0.100)	(0.100)	(0.108)	(0.048)
State + Occup. + Industry F.E.						Yes
Observations		47146	46237	46237	46237	46232
R-squared		0.069	0.067	0.067	0.068	0.184

Table 2: Cross-Sectional Models: Characteristics of the Recently Unemployed Workers in May

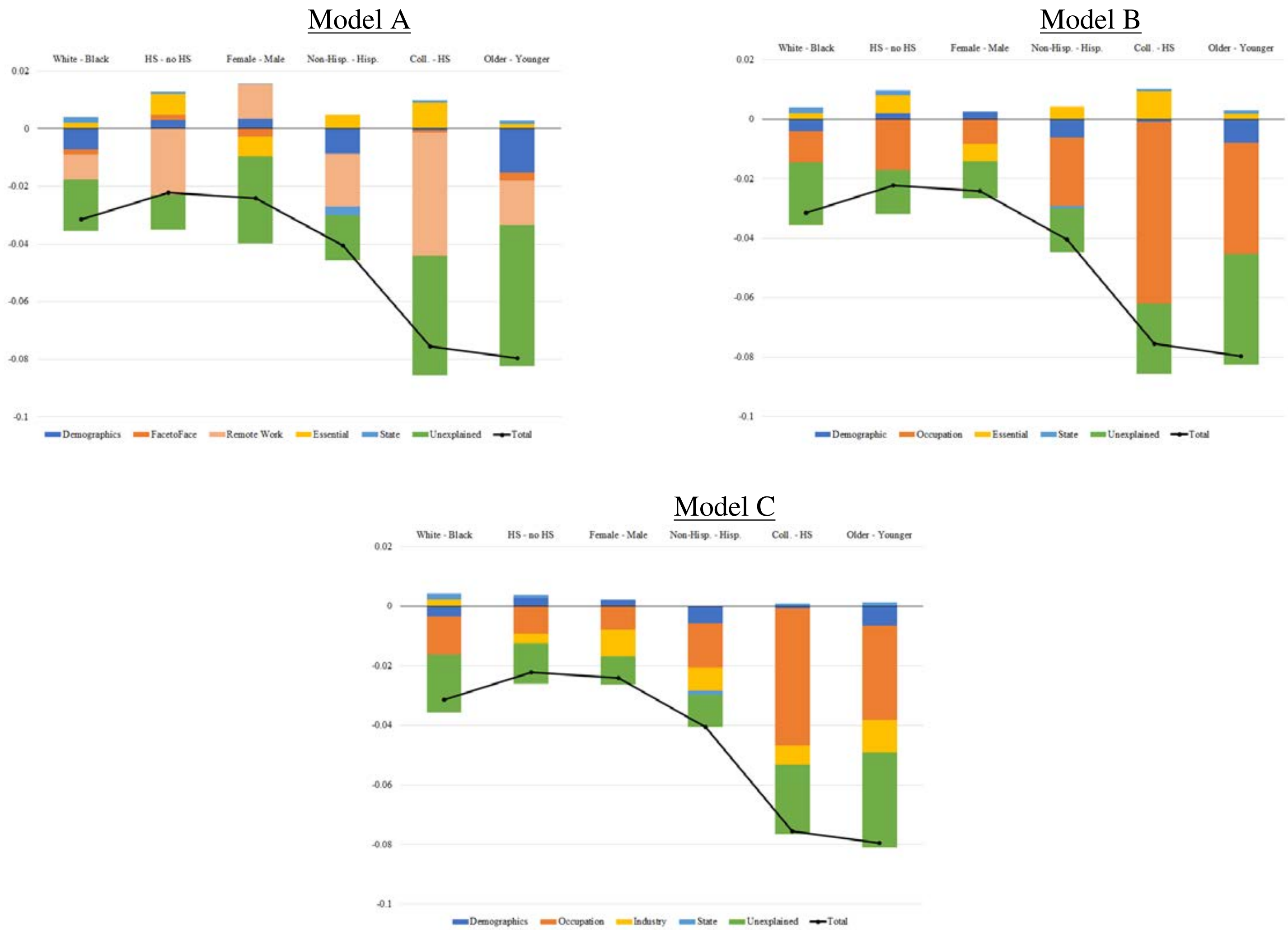
Dependent = Recent Unemployed May Mean= 0.1118 ; Std. Dev = 0.3152	Mean (Std. Dev)	(1)	(2)	(3)	(4)	(5)
Face-to-Face	-0.010	0.016***	0.016***	0.017***	-0.003	
	(0.984)	(0.005)	(0.005)	(0.005)	(0.015)	
Remote Work	0.062	-0.046***	-0.048***	-0.046***	0.018	
	(0.955)	(0.008)	(0.008)	(0.007)	(0.020)	
Essential	0.707	-0.073***	-0.068***	-0.067***	-0.053	
	(0.455)	(0.012)	(0.011)	(0.011)	(0.038)	
Mortality Risk Index	-0.320		-0.025***	-0.028**	-0.028**	-0.030***
	(0.519)		(0.008)	(0.011)	(0.011)	(0.008)
Risk x Face-to-Face	-0.016			0.003	0.003	0.001
	(0.604)			(0.004)	(0.004)	(0.004)
Risk x Remote Work	-0.018			0.007*	0.007	0.001
	(0.577)			(0.004)	(0.004)	(0.003)
Risk x Essential	-0.224			0.005	0.005	0.015*
	(0.460)			(0.008)	(0.008)	(0.008)
Ln(COVID cases in State)	10.312		0.011***	0.011***	0.013***	
	(1.192)		(0.004)	(0.004)	(0.005)	
Ln(COVID cases) x Face-to-Face	-0.117				0.002	0.002
	(10.223)				(0.002)	(0.001)
Ln(COVID cases) x Remote	0.680				-0.006***	-0.005***
	(9.903)				(0.002)	(0.002)
Ln(COVID cases) x Essential	7.275				-0.001	-0.004
	(4.792)				(0.004)	(0.004)
Fem x Child-U6	0.060	0.002	0.008	0.008	0.008	-0.002
	(0.237)	(0.015)	(0.015)	(0.015)	(0.015)	(0.012)
Child under 6	0.135	-0.004	-0.005	-0.005	-0.005	0.005
	(0.341)	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)
Female	0.468	0.031***	0.026***	0.026***	0.026***	0.006
	(0.499)	(0.008)	(0.008)	(0.008)	(0.008)	(0.005)
Black	0.126	0.011	0.009	0.009	0.009	0.018**
	(0.332)	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)
Hispanic	0.179	0.012	0.010	0.010	0.009	0.009
	(0.383)	(0.009)	(0.009)	(0.009)	(0.009)	(0.006)
Age/100	0.426	-0.840***	-1.034***	-1.016***	-1.023***	-0.673***
	(0.143)	(0.131)	(0.152)	(0.150)	(0.150)	(0.096)
$(\text{Age}/100)^2$	0.202	0.848***	1.143***	1.120***	1.126***	0.759***
	(0.129)	(0.140)	(0.182)	(0.181)	(0.180)	(0.117)
Less-than HS	0.065	Omitted	Omitted	Omitted	Omitted	Omitted
	0.247					
HS	0.254	-0.003	-0.001	-0.002	-0.001	-0.002
	(0.435)	(0.013)	(0.014)	(0.014)	(0.014)	(0.011)
Some College	0.275	-0.003	-0.001	-0.002	-0.001	-0.005
	(0.446)	(0.013)	(0.014)	(0.014)	(0.014)	(0.010)
BA Degree	0.255	-0.047***	-0.044***	-0.044***	-0.044***	-0.027**
	(0.436)	(0.014)	(0.014)	(0.014)	(0.014)	(0.011)
Post D	0.152	-0.081***	-0.080***	-0.080***	-0.079***	-0.037***
	(0.359)	(0.015)	(0.015)	(0.015)	(0.015)	(0.013)
Metropolitan	1.115	-0.033***	-0.026***	-0.026***	-0.026***	-0.010
	(0.320)	(0.009)	(0.009)	(0.009)	(0.009)	(0.008)
Ln(State Population)	16.129	0.005	-0.010	-0.010	-0.010	
	(0.911)	(0.005)	(0.008)	(0.008)	(0.008)	
Constant		0.377***	0.468***	0.465***	0.456***	0.307***
		(0.093)	(0.100)	(0.100)	(0.108)	(0.048)
State + Occup. + Industry F.E.						Yes
Observations		45712	44787	44787	44787	44779
R-squared		0.059	0.058	0.059	0.059	0.167

Figure 6: Oaxaca-Blinder Decomposition for April: A Graphical Representation



Note: The three figures are the graphical representation of the Oaxaca decomposition estimates shown in Table 9.5 and obtained through three different models. All the decomposition models include socio-demographic controls (i.e. age, gender, race, ethnicity, and education), state fixed effects, and a dummy for the presence of children under 6. Model A includes the Face-to-Face, Remote Work, and Essential Job indices. Model B adds a full set of 524 occupation dummies. Model C includes a full set of 261 industry dummies, and report the share of each gap explained by sorting into industries classified as Essential vs Non-essential. Each shaded area represents the share that is, depending on the color, explained by the different sets of variables reported in the legend.

Figure 7: Oaxaca-Blinder Decomposition for May: A Graphical Representation

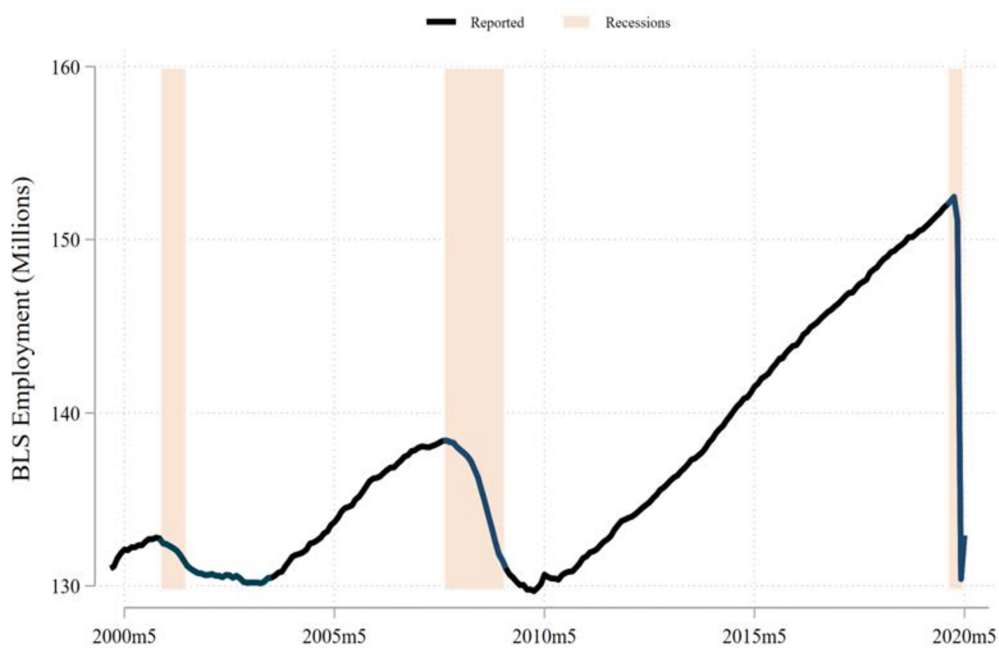


Note: The three figures are the graphical representation of the Oaxaca decomposition estimates shown in Table 9.7 and obtained through three different models. All the decomposition models include socio-demographic controls (i.e. age, gender, race, ethnicity, and education), state fixed effects, and a dummy for the presence of children under 6. Model A includes the Face-to-Face, Remote Work, and Essential Job indices. Model B adds a full set of 524 occupation dummies. Model C includes a full set of 261 industry dummies, and report the share of each gap explained by sorting into industries classified as Essential vs Non-essential. Each shaded area represents the share that is, depending on the color, explained by the different sets of variables reported in the legend.

8 Appendix

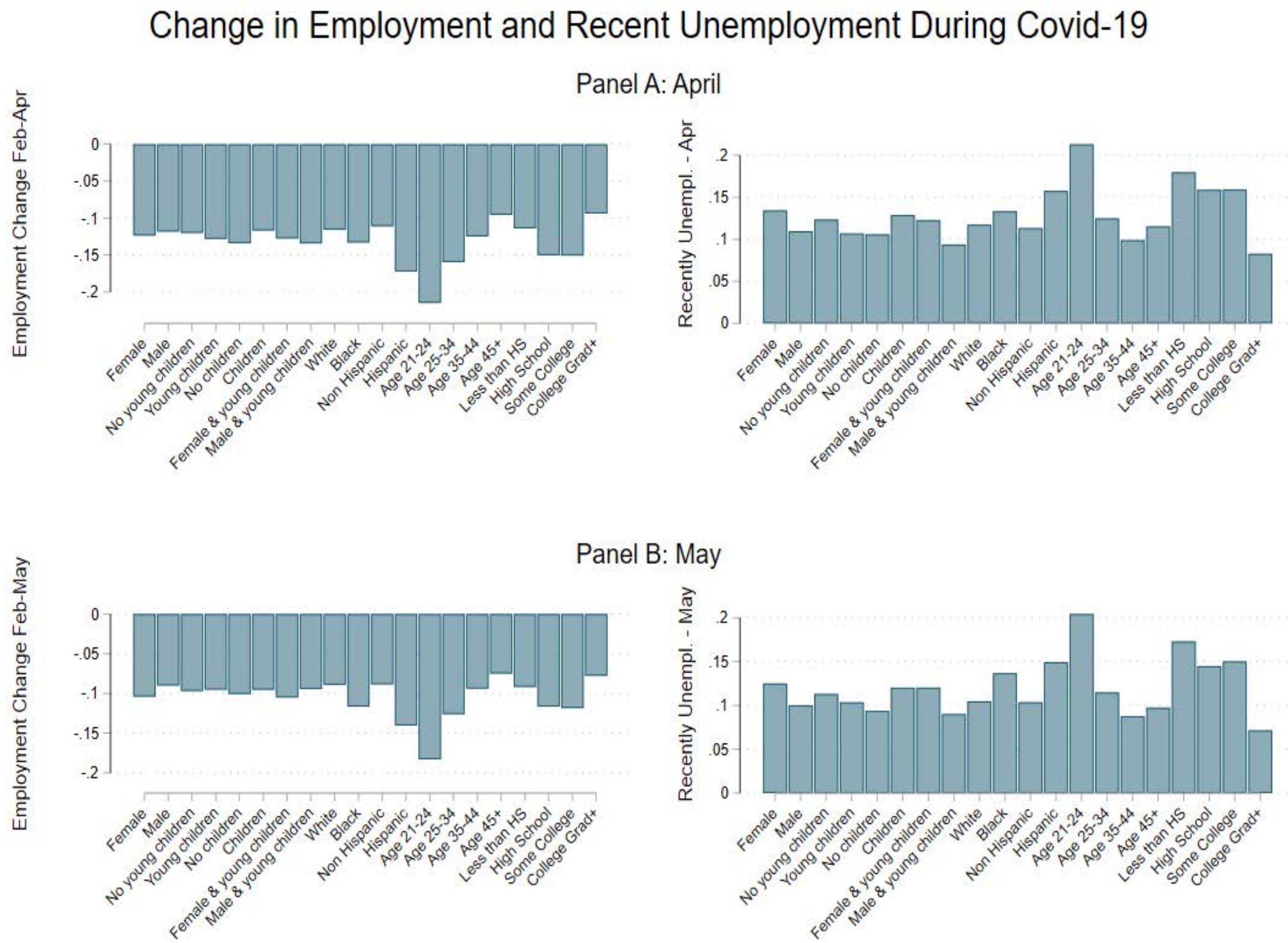
8.1 Employment Rates Over Time

Figure 8.1: BLS Employment Series (Seasonally Adjusted)



Note: The figure presents the seasonally adjusted series for All Employees in non-farm jobs (millions) between January 2000 and May 2020. The shaded areas represent the 2001 Recession (March 2001 to November 2001), the Great Recession (December 2007 to June 2009), and the COVID-19 Recession. The figure implies that jobs lost during April and May 2020 exceed jobs lost in either of the two previous recessions.

Figure 8.2



<u>Note:</u> In Panel A, Employment Change is computed as the February employment rate minus the April rate. Recently Unemployed is reported only from the April CPS (coded as Recently Unemployed if unemployed in April, and became unemployed at most 10 weeks before the CPS April survey week).

In Panel B, Employment Change is computed as the February employment rate minus the May rate. Recently Unemployed is reported only from the May CPS (coded as Recently Unemployed if unemployed in April, and became unemployed at most 14 weeks before the CPS May survey week). In both panels, the change in employment is computed excluding workers who are employed but absent from work. The panel on recent unemployed in April and May 2020 has been produced selecting on the same sample used in the models shown in Tables 1 and 2.

9 Additional Tables and Figures

Table 9.1: 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?

Note: The O*Net "Work Context" module (2019 version: available www.onetcenter.org) 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 9.2: Industry Sectors and Categories defined as Essential

Sector	Sector Name	Examples
11	Agriculture, Forestry, Fishing and Hunting	Crop production; Animal production; Forestry; Logging; Fishing, Hunting and trapping; Agriculture and forestry support activities
21	Mining, Quarrying, and Oil and Gas Extraction	Oil and gas extraction; Coal mining; Metal ore mining; Nonmetallic mineral mining and quarrying; Not specified mining; Mining support activities
22	Utilities	Electric power generation, transmission and distribution; Natural gas distribution; Electric and gas, and other combinations; Water, steam, air-conditioning, and irrigation,; Sewage; Other not specified
23	Construction	All in construction
31-33	Manufacturing	All Food manufacturing; All Animal food manufacturing; Industries: All in Paper related; Petroleum; Rubber & Tires; Pharma; Plastics; Chemicals; Pottery and ceramics; Cement; Glass; Iron; Aluminum; Nonferrous metal; Foundries; Forgings; Cutlery; Coating; All machinery and equipment manufacturing; Household appliance manufacturing; Motor vehicles & parts; Aircraft & parts; Railroad; Ship and boats; other transportation; Sawmills; Wood manufacturing; Medical Supplies.
42	Wholesale Trade	Paper; Machinery and equipment; Hardware; Household appliances; Lumber and construction; Grocery and related products; Drugs; sundries and chemical and allied products; Farm product raw material; Petroleum products; Alcoholic beverages; Farm supplies; other non-durable goods; electronic markets, agents and brokers.
44-45	Retail Trade	Automotive parts and accessories; Electronics; Building materials; Lawn and garden equipment; Grocery stores; Supermarkets; Convenience stores; Specialty food stores; Beer, wine and liquor stores; Pharmacies and drug stores; Health and personal care stores; Gas stations; General merchandise stores; Electronic shopping and mail-order houses; Fuel dealers.
48-49	Transportation and Warehousing	Air, Rail T., Water, Truck, Transportation; Bus service and urban transit; Taxis; Pipeline transportation; Services incidental to transportation; Postal Service; Couriers; Warehousing and storage.
51	Information	Newspapers, periodicals, book and directory publishers; Software publishers; Broadcasting; Internet publishing and broadcasting; Wired telecommunication carriers; Telecomm.; Data processing, hosting and related; Other information services, except libraries and archives.
52	Finance and Insurance	Banking; Saving institutions; Credit Unions; Non-depository credit activities; Securities, commodities, funds, trusts; Other financial investments, Insurance carriers.
53	Real Estate and Rental and Leasing	Real State; Lessors, agents brokers; Property managers; Appraisers offices; Other related.
54	Professional, Scientific, and Technical Services	Accounting, tax preparation, bookkeeping and payroll services; Management, scientific and technical consulting services; Scientific research and development; Veterinary
56	Admin. & Waste Manag. Services	Security and investigation; Services to buildings; landscaping; waste management and remediation
62	Health Care and Social Assistance	Physicians, dentists, chiropractors, optometrists, other; Outpatient care centers; Home health care services; Other health care; Hospitals; Psychiatric and substance abuse hospitals; Nursing care facilities; Residential care facilities; Individual and family services; Child day care.
72	Accommodation and Food Services	Traveler accommodation; Restaurants and other food services.
81	Other Services (except Public Administration)	Automotive repair and maintenance; Machinery and equipment repair and maintenance; Funeral homes, cemeteries and crematories.
92	Public Administration	All in Public Administration.

Note: Following Blau et al. (2020) and Census NAICS 2017 Industry Descriptions, we coded the DHS essential workforce definition. The table is presented for reference using consolidated 4-digit industry categories for brevity and do not necessarily match NAICS complete names. In these sectors, Education Services; Arts, Entertainment, and Recreation and Management of Companies and Enterprises, no subcatergories are classified as essential workforce. 194 categories out of 287 at the 4 digit level are declared as jobs in Essential by the DHS. Available at: www.cisa.gov.

9.1 Additional Labor Outcomes

Table 9.3: Cross-Sectional Models: Employed - Absent in April 2020

Dependent = Absent from Work Apr Mean= 0.0734 ; Std. Dev = 0.2607	(1)	(2)	(3)	(4)	(5)	
Face-to-Face	-0.017	0.015***	0.015***	0.016***	0.004	
	(0.988)	(0.004)	(0.004)	(0.004)	(0.013)	
Remote Work	0.071	-0.014***	-0.014***	-0.013***	0.018**	
	(0.953)	(0.004)	(0.004)	(0.004)	(0.009)	
Essential	0.706	-0.034***	-0.034***	-0.036***	-0.029	
	(0.455)	(0.007)	(0.007)	(0.007)	(0.025)	
Mortality Risk Index	-0.315		0.007	0.013	0.013	0.014*
	(0.527)		(0.007)	(0.009)	(0.008)	(0.008)
Risk x Face-to-Face	-0.017			0.002	0.003	0.002
	(0.602)			(0.003)	(0.003)	(0.003)
Risk x Remote Work	-0.018			0.004	0.004	0.002
	(0.584)			(0.004)	(0.004)	(0.003)
Risk x Essential	-0.222			-0.007	-0.007	-0.011**
	(0.463)			(0.005)	(0.005)	(0.005)
Ln(COVID cases in State)	9.370		0.013***	0.013***	0.014***	
	(1.291)		(0.002)	(0.003)	(0.004)	
Ln(COVID cases) x Face-to-Face	-0.166				0.001	0.001
	(9.355)				(0.001)	(0.002)
Ln(COVID cases) x Remote	0.715				-0.003***	-0.002**
	(8.991)				(0.001)	(0.001)
Ln(COVID cases) x Essential	6.600				-0.001	-0.002
	(4.393)				(0.003)	(0.003)
Fem x Child-U6	0.062	0.039***	0.037***	0.038***	0.038***	0.036***
	(0.241)	(0.008)	(0.008)	(0.008)	(0.008)	(0.007)
Child under 6	0.137	0.001	0.001	0.000	0.000	0.002
	(0.344)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Female	0.468	0.008*	0.009**	0.010**	0.009**	0.002
	(0.499)	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)
Black	0.126	0.003	-0.000	-0.000	-0.000	0.003
	(0.331)	(0.005)	(0.006)	(0.006)	(0.006)	(0.005)
Hispanic	0.178	-0.006	-0.004	-0.004	-0.005	-0.007
	(0.382)	(0.009)	(0.009)	(0.009)	(0.009)	(0.008)
Age/100	0.428	-0.169**	-0.110	-0.094	-0.099	-0.080
	(0.143)	(0.074)	(0.087)	(0.089)	(0.089)	(0.091)
$(Age/100)^2$	0.204	0.290***	0.199*	0.179	0.183	0.171
	(0.130)	(0.084)	(0.111)	(0.113)	(0.114)	(0.113)
Less-than HS	0.067	Omitted	Omitted	Omitted	Omitted	Omitted
	(0.250)					
HS	0.249	0.005	0.007	0.007	0.007	0.011
	(0.432)	(0.009)	(0.009)	(0.009)	(0.009)	(0.010)
Some College	0.274	-0.003	-0.001	-0.002	-0.001	0.006
	(0.446)	(0.009)	(0.009)	(0.009)	(0.009)	(0.011)
BA Degree	0.259	-0.026**	-0.025**	-0.025**	-0.025**	-0.010
	(0.438)	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)
Post D	0.151	-0.043***	-0.043***	-0.043***	-0.043***	-0.019
	(0.358)	(0.011)	(0.011)	(0.011)	(0.011)	(0.012)
Metropolitan	1.114	-0.011	-0.007	-0.007	-0.007	-0.002
	(0.318)	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)
Ln(State Population)	16.130	0.009***	-0.004	-0.004	-0.004	
	(0.914)	(0.002)	(0.003)	(0.003)	(0.003)	
Constant		-0.015	0.062	0.061	0.055	0.089***
		(0.040)	(0.043)	(0.044)	(0.042)	(0.028)
State + Occup. + Industry F.E.						Yes
Observations		47146	46237	46237	46237	46232
R-squared		0.019	0.021	0.021	0.021	0.074

Table 9.4: Cross-Sectional Models: Employed - Absent in May 2020

Dependent = Absent from Work May Mean= 0.0529 ; Std. Dev = 0.2238	(1)	(2)	(3)	(4)	(5)	
Face-to-Face	-0.010	0.010***	0.010***	0.012***	0.008	[t]
	(0.984)	(0.003)	(0.003)	(0.003)	(0.009)	
Remote Work	0.062	-0.010***	-0.011***	-0.009***	0.021	
	(0.955)	(0.003)	(0.003)	(0.003)	(0.020)	
Essential	0.707	-0.021***	-0.021***	-0.023***	-0.041**	
	(0.455)	(0.006)	(0.006)	(0.007)	(0.020)	
Mortality Risk Index	-0.320		0.009	0.017*	0.017*	0.012
	(0.519)		(0.006)	(0.009)	(0.009)	(0.008)
Risk x Face-to-Face	-0.016			0.007***	0.008***	0.007***
	(0.604)			(0.003)	(0.003)	(0.003)
Risk x Remote Work	-0.018			0.006**	0.006**	0.005*
	(0.577)			(0.003)	(0.003)	(0.003)
Risk x Essential	-0.224			-0.007	-0.007	-0.007
	(0.460)			(0.006)	(0.006)	(0.005)
Ln(COVID cases in State)	10.312		0.011***	0.011***	0.010**	
	(1.192)		(0.003)	(0.003)	(0.004)	
Ln(COVID cases) x Face-to-Face	-0.117				0.000	0.001
	(10.223)				(0.001)	(0.001)
Ln(COVID cases) x Remote	0.680				-0.003	-0.002
	(9.903)				(0.002)	(0.002)
Ln(COVID cases) x Essential	7.275				0.002	0.001
	(4.792)				(0.002)	(0.002)
Fem x Child-U6	0.060	0.036***	0.035***	0.036***	0.035***	0.035***
	(0.237)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
Child under 6	0.135	-0.000	-0.001	-0.001	-0.001	-0.000
	(0.341)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Female	0.468	0.009***	0.011***	0.012***	0.012***	0.007**
	(0.499)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)
Black	0.126	0.004	0.003	0.003	0.003	0.006
	(0.332)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Hispanic	0.179	-0.005	-0.004	-0.004	-0.005	-0.004
	(0.383)	(0.006)	(0.005)	(0.005)	(0.006)	(0.004)
Age/100	0.426	-0.157*	-0.089	-0.062	-0.065	-0.108
	(0.143)	(0.081)	(0.094)	(0.094)	(0.094)	(0.077)
$(Age/100)^2$	0.202	0.261***	0.154	0.118	0.120	0.180*
	(0.129)	(0.088)	(0.113)	(0.113)	(0.113)	(0.091)
Less-than HS	0.065	Omitted	Omitted	Omitted	Omitted	Omitted
	(0.247)					
HS	0.254	-0.005	-0.006	-0.006	-0.006	-0.007
	(0.435)	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)
Some College	0.275	0.004	0.004	0.004	0.004	0.004
	(0.446)	(0.008)	(0.009)	(0.009)	(0.009)	(0.008)
BA Degree	0.255	-0.012	-0.014	-0.013	-0.013	-0.009
	(0.436)	(0.009)	(0.009)	(0.009)	(0.009)	(0.007)
Post D	0.152	-0.028***	-0.030***	-0.030***	-0.030***	-0.017**
	(0.359)	(0.009)	(0.009)	(0.009)	(0.009)	(0.007)
Metropolitan	1.115	-0.006	-0.003	-0.003	-0.003	0.001
	(0.320)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
Ln(State Population)	16.129	0.004	-0.007	-0.007	-0.007	
	(0.911)	(0.003)	(0.005)	(0.005)	(0.005)	
Constant		0.027	0.083	0.080	0.091	0.056**
		(0.057)	(0.062)	(0.062)	(0.066)	(0.022)
State + Occup. + Industry F.E.						Yes
Observations		45712	44787	44787	44787	44779
R-squared		0.012	0.015	0.015	0.016	0.064

Table 9.5: Oaxaca-Blinder Decomposition for April

	Male/Female		Non-hispanic/Hispanic		White/Black		Older/Younger		HS/non-HS		Coll/non-Coll	
	Estimate	Share	Estimate	Share	Estimate	Share	Estimate	Share	Estimate	Share	Estimate	Share
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Raw Gap	**-0.0249**	**100.00%**	**-0.0444**	**100.00%**	**-0.0161**	**100.00%**	**-0.0884**	**100.00%**	**-0.0203**	**100.00%**	**-0.0832**	**100.00%**
					Model A							
Explained	0.0068	-27.11%	**-0.0243**	**54.72%**	**-0.0134**	**82.98%**	**-0.0425**	**48.07%**	**-0.0159**	**78.30%**	**-0.0414**	**49.80%**
Socio-demographic	**0.0034**	**-13.78%**	**-0.0080**	**17.99%**	**-0.0069**	**42.87%**	**-0.0181**	**20.43%**	-0.0030	14.59%	**-0.0018**	**2.18%**
Children under 6	-0.0001	0.41%	0.0003	-0.69%	0.0000	-0.08%	**-0.0039**	**4.36%**	0.0008	-3.72%	**-0.0005**	**0.60%**
FacetoFace	**-0.0030**	**12.18%**	0.0005	-1.06%	**-0.0020**	**12.37%**	**-0.0020**	**2.30%**	**0.0026**	**-12.80%**	**-0.0008**	**0.92%**
Remote Work	**0.0142**	**-56.98%**	**-0.0237**	**53.30%**	**-0.0096**	**59.76%**	**-0.0202**	**22.90%**	**-0.0285**	**140.61%**	**-0.0507**	**60.96%**
Essential	**-0.0075**	**30.25%**	**0.0052**	**-11.70%**	**0.0033**	**-20.19%**	0.0014	-1.54%	**0.0052**	**-25.60%**	**0.0118**	**-14.16%**
State	-0.0002	0.81%	0.0014	-3.11%	0.0019	-11.75%	0.0003	-0.38%	**0.0071**	**-34.78%**	0.0006	-0.70%
Unexplained	**-0.0317**	**127.11%**	**-0.0201**	**45.28%**	-0.0027	16.77%	**-0.0459**	**51.93%**	-0.0044	21.70%	**-0.0418**	**50.20%**
					Model B							
Explained	**-0.0127**	**50.89%**	**-0.0251**	**56.50%**	**-0.0066**	**40.85%**	**-0.0516**	**58.43%**	**-0.0190**	**93.52%**	**-0.0589**	**70.72%**
Socio-demographic	**0.0021**	**-8.63%**	**-0.0043**	**9.64%**	**-0.0035**	**21.63%**	**-0.0100**	**11.29%**	-0.0050	24.82%	**-0.0029**	**3.53%**
Children under 6	0.0000	0.12%	0.0001	-0.21%	0.0000	-0.03%	-0.0018	1.99%	0.0005	-2.23%	-0.0003	0.31%
All Occupations	**-0.0084**	**33.84%**	**-0.0290**	**65.21%**	**-0.0080**	**49.78%**	**-0.0411**	**46.53%**	**-0.0258**	**127.06%**	**-0.0666**	**79.97%**
Essential	**-0.0061**	**24.44%**	**0.0042**	**-9.45%**	**0.0026**	**-16.25%**	0.0013	-1.52%	**0.0037**	**-18.39%**	**0.0107**	**-12.80%**
State	-0.0003	1.11%	**0.0039**	**-8.69%**	0.0023	-14.28%	-0.0001	0.13%	**0.0077**	**-37.75%**	0.0002	-0.29%
Unexplained	**-0.0122**	**49.11%**	**-0.0193**	**43.50%**	-0.0095	59.15%	**-0.0367**	**41.57%**	-0.0013	6.48%	**-0.0244**	**29.28%**
					Model C							
Explained	**-0.0166**	**66.75%**	**-0.0276**	**62.01%**	-0.0055	34.39%	**-0.0567**	**64.14%**	**-0.0229**	**112.82%**	**-0.0607**	**72.94%**
Socio-demographic	**0.0018**	**-7.14%**	-0.0032	7.28%	**-0.0029**	**17.81%**	**-0.0083**	**9.43%**	-0.0049	24.32%	**-0.0029**	**3.45%**
Children under 6	0.0000	0.17%	0.0001	-0.28%	0.0000	-0.04%	-0.0018	2.09%	0.0006	-2.75%	-0.0003	0.32%
All Occupations	**-0.0095**	**38.25%**	**-0.0197**	**44.27%**	**-0.0087**	**54.18%**	**-0.0353**	**39.97%**	**-0.0189**	**93.13%**	**-0.0455**	**54.65%**
Industry-Essential	**0.0062**	**-24.76%**	**-0.0122**	**27.40%**	-0.0014	8.48%	-0.0074	8.39%	**-0.0132**	**65.34%**	**-0.0183**	**21.93%**
Industry-nonEssential	**-0.0168**	**67.52%**	0.0027	-6.07%	0.0034	-21.08%	-0.0048	5.43%	0.0064	-31.62%	0.0036	-4.28%
State	-0.0002	0.95%	0.0041	-9.30%	0.0023	-14.43%	-0.0004	0.41%	**0.0075**	**-37.11%**	0.0003	-0.31%
Unexplained	**-0.0083**	**33.25%**	**-0.0169**	**37.99%**	-0.0106	65.61%	**-0.0317**	**35.86%**	0.0026	-12.82%	**-0.0225**	**27.06%**

Notes: This table shows Oaxaca decomposition of gap in the proportion of workers recently unemployed in April. Entries in bold are statistically significant at the 5% level. Model A includes two indexes describing occupational characteristics: the Face-to-Face index and Remote Working index. Model B includes a full set of 524 occupation dummies. Model C includes a full set of 524 occupation dummies and 261 industry dummies. All models include basic socio-demographic controls, including age, age squared, gender, race, ethnicity, education, and state fixed effects. All regressions use CPS sample weights. In Models B and C, we reported the aggregated shares of explanation by the 524 occupations, while we list the shares of explanation by five occupation categories in Table 9.6. For Model C, we report the shares of explanation of industries in two groups: essential industry and non-essential industry.

Table 9.6: Oaxaca-Blinder Decomposition for April: Five Occupation Groups

	Male/Female		Non-hispanic/Hispanic		White/Black		Older/Younger		HS/non-HS		Coll/non-Coll	
	Estimate	Share	Estimate	Share	Estimate	Share	Estimate	Share	Estimate	Share	Estimate	Share
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Raw Gap	**-0.0249**	**100.00%**	**-0.0444**	**100.00%**	**-0.0161**	**100.00%**	**-0.0884**	**100.00%**	**-0.0203**	**100.00%**	**-0.0832**	**100.00%**
Model B												
Mgmt/Tech/Arts	**-0.0070**	**28.02%**	0.0031	-7.07%	0.0024	-14.83%	0.0009	-0.98%	**0.0060**	**-29.77%**	0.0069	-8.28%
Service	**-0.0176**	**70.51%**	**-0.0160**	**35.98%**	**-0.0061**	**38.06%**	**-0.0286**	**32.33%**	**-0.0174**	**85.71%**	**-0.0335**	**40.21%**
Sales/Office	**-0.0086**	**34.67%**	-0.0013	2.84%	-0.0015	9.54%	**-0.0127**	**14.33%**	**0.0109**	**-53.85%**	**-0.0075**	**8.97%**
Constr/Nat. Res.	**0.0148**	**-59.19%**	**-0.0103**	**23.19%**	**0.0046**	**-28.27%**	0.0004	-0.47%	**-0.0193**	**95.38%**	**-0.0134**	**16.14%**
Prod./Trans.	**0.0100**	**-40.18%**	**-0.0046**	**10.27%**	**-0.0073**	**45.27%**	-0.0012	1.32%	**-0.0060**	**29.59%**	**-0.0191**	**22.93%**
Model C												
Mgmt/Tech/Arts	**-0.0083**	**33.22%**	0.0057	-12.77%	0.0020	-12.37%	0.0048	-5.40%	**0.0083**	**-41.06%**	0.0122	-14.62%
Service	**-0.0144**	**57.96%**	**-0.0106**	**23.89%**	**-0.0062**	**38.77%**	**-0.0278**	**31.43%**	**-0.0136**	**67.12%**	**-0.0235**	**28.24%**
Sales/Office	**-0.0078**	**31.17%**	**-0.0009**	**2.07%**	**-0.0017**	**10.64%**	**-0.0101**	**11.42%**	**0.0128**	**-62.96%**	**-0.0060**	**7.20%**
Constr/Nat. Res.	**0.0124**	**-49.72%**	**-0.0094**	**21.08%**	**0.0039**	**-24.36%**	0.0002	-0.18%	**-0.0195**	**96.24%**	**-0.0112**	**13.51%**
Prod./Trans.	**0.0086**	**-34.38%**	**-0.0044**	**10.00%**	**-0.0067**	**41.50%**	-0.0024	2.71%	**-0.0069**	**33.79%**	**-0.0169**	**20.31%**

Notes: This table reports the share of variation explained by sorting across five 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”, does not appear because the CPS is a survey of the civilian non-institutional population. The shares of the five categories of occupations add up to the share of “All Occupation" in Model B and Model C in Table 9.5. Entries in bold are statistically significant at the 5% level.

Table 9.7: Oaxaca-Blinder Decomposition for May

	Male/Female		Non-hispanic/Hispanic		White/Black		Older/Younger		HS/non-HS		Coll/non-Coll	
	Estimate	Share	Estimate	Share	Estimate	Share	Estimate	Share	Estimate	Share	Estimate	Share
Raw Gap	**-0.0241**	**100.00%**	**-0.0405**	**100.00%**	**-0.0314**	**100.00%**	**-0.0796**	**100.00%**	**-0.0222**	**100.00%**	**-0.0755**	**100.00%**
					Model A							
Explained	**0.0062**	**-25.58%**	**-0.0251**	**61.87%**	**-0.0135**	**42.95%**	**-0.0307**	**38.56%**	**-0.0101**	**45.70%**	**-0.0342**	**45.22%**
demographic	**0.0035**	**-14.34%**	**-0.0086**	**21.28%**	**-0.0071**	**22.78%**	**-0.0161**	**20.25%**	0.0031	-13.79%	-0.0003	0.40%
Children under 6	0.0000	0.08%	0.0000	-0.10%	0.0000	-0.01%	0.0009	-1.19%	0.0000	0.22%	-0.0001	0.18%
FacetoFace	**-0.0029**	**11.85%**	0.0002	-0.40%	**-0.0018**	**5.58%**	**-0.0029**	**3.61%**	**0.0019**	**-8.69%**	**-0.0008**	**1.07%**
Remote Work	**0.0121**	**-50.11%**	**-0.0184**	**45.35%**	**-0.0087**	**27.75%**	**-0.0154**	**19.33%**	**-0.0230**	**103.87%**	**-0.0428**	**56.72%**
Essential	**-0.0066**	**27.30%**	**0.0048**	**-11.84%**	**0.0021**	**-6.84%**	0.0017	-2.15%	**0.0071**	**-32.05%**	**0.0090**	**-11.87%**
State	0.0001	-0.36%	-0.0031	7.59%	0.0020	-6.32%	0.0010	-1.28%	0.0009	-3.86%	0.0010	-1.26%
Unexplained	**-0.0303**	**125.58%**	**-0.0155**	**38.13%**	**-0.0179**	**57.05%**	**-0.0489**	**61.44%**	-0.0120	54.30%	**-0.0414**	**54.78%**
					Model B							
Explained	**-0.0118**	**48.73%**	**-0.0257**	**63.42%**	**-0.0106**	**33.63%**	**-0.0425**	**53.37%**	-0.0074	33.44%	**-0.0518**	**68.61%**
demographic	**0.0023**	**-9.46%**	**-0.0061**	**15.16%**	**-0.0040**	**12.89%**	**-0.0096**	**12.12%**	0.0023	-10.18%	-0.0010	1.28%
Children under 6	0.0000	-0.19%	-0.0001	0.23%	0.0000	0.00%	**0.0017**	**-2.19%**	-0.0003	1.31%	0.0000	-0.01%
All Occupations	**-0.0082**	**34.06%**	**-0.0228**	**56.24%**	**-0.0106**	**33.74%**	**-0.0375**	**47.09%**	**-0.0171**	**77.11%**	**-0.0610**	**80.75%**
Essential	**-0.0059**	**24.35%**	**0.0043**	**-10.56%**	**0.0019**	**-6.06%**	0.0017	-2.17%	**0.0061**	**-27.70%**	**0.0095**	**-12.52%**
State	0.0000	-0.04%	**-0.0010**	**2.35%**	0.0022	-6.95%	0.0012	-1.49%	0.0016	-7.10%	0.0007	-0.89%
Unexplained	**-0.0124**	**51.27%**	**-0.0148**	**36.58%**	-0.0208	66.38%	**-0.0371**	**46.63%**	-0.0148	66.56%	**-0.0237**	**31.39%**
					Model C							
Explained	**-0.0148**	**61.40%**	**-0.0297**	**73.18%**	**-0.0119**	**37.85%**	**-0.0477**	**59.91%**	-0.0086	38.80%	**-0.0524**	**69.34%**
demographic	**0.0020**	**-8.17%**	**-0.0056**	**13.93%**	**-0.0034**	**10.96%**	**-0.0086**	**10.83%**	0.0030	-13.59%	-0.0008	1.01%
Children under 6	0.0001	-0.24%	-0.0001	0.30%	0.0000	0.01%	0.0021	-2.67%	-0.0002	1.03%	0.0000	-0.03%
All Occupations	**-0.0079**	**32.69%**	**-0.0149**	**36.67%**	**-0.0128**	**40.68%**	**-0.0316**	**39.69%**	**-0.0093**	**42.06%**	**-0.0459**	**60.79%**
Industry-Essential	0.0029	-12.00%	**-0.0111**	**27.37%**	0.0014	-4.45%	-0.0059	7.40%	**-0.0161**	**72.72%**	**-0.0096**	**12.76%**
Industry-nonEssential	**-0.0119**	**49.32%**	**0.0034**	**-8.38%**	0.0009	-2.84%	-0.0051	6.41%	**0.0130**	**-58.49%**	0.0031	-4.06%
State	0.0000	-0.19%	-0.0013	3.28%	0.0020	-6.51%	0.0014	-1.76%	0.0011	-4.92%	0.0009	-1.13%
Unexplained	**-0.0093**	**38.60%**	**-0.0109**	**26.82%**	**-0.0195**	**62.15%**	**-0.0319**	**40.09%**	-0.0136	61.20%	**-0.0232**	**30.66%**

Notes: This table shows Oaxaca decomposition of gap in the proportion of workers recently unemployed in May. Entries in bold are statistically significant at the 5% level. Model A includes two indexes describing occupational characteristics: the Face-to-Face index and Remote Working index. Model B includes a full set of 524 occupation dummies. Model C includes a full set of 524 occupation dummies and 261 industry dummies. All models include basic socio-demographic controls, including age, age squared, gender, race, ethnicity, education, and state fixed effects. All regressions use CPS sample weights. In Models B and C, we reported the aggregated shares of explanation by the 524 occupations, while we list the shares of explanation by five occupation categories in Table 9.8. For Model C, we report the shares of explanation of industries in two groups: essential industry and non-essential industry.

Table 9.8: Oaxaca-Blinder Decomposition for May: Five Occupation Groups

	Male/Female		Non-hispanic/Hispanic		White/Black		Older/Younger		HS/non-HS		Coll/non-Coll	
	Estimate	Share	Estimate	Share	Estimate	Share	Estimate	Share	Estimate	Share	Estimate	Share
Raw Gap	**-0.0241**	**100.00%**	**-0.0405**	**100.00%**	**-0.0314**	**100.00%**	**-0.0796**	**100.00%**	**-0.0222**	**100.00%**	**-0.0755**	**100.00%**
						Model B						
Mgmt/Tech/Arts	**-0.0062**	**24.78%**	0.0022	-4.96%	**0.0025**	**-15.45%**	**-0.0029**	**3.29%**	**0.0060**	**-29.66%**	0.0050	-6.04%
Service	**-0.0162**	**65.11%**	**-0.0111**	**24.97%**	**-0.0057**	**35.46%**	**-0.0257**	**29.11%**	**-0.0122**	**60.14%**	**-0.0265**	**31.83%**
Sales/Office	**-0.0092**	**36.90%**	-0.0004	0.96%	-0.0006	3.77%	**-0.0107**	**12.15%**	**0.0118**	**-58.31%**	**-0.0067**	**8.11%**
Constr/Nat. Res.	**0.0125**	**-50.11%**	**-0.0082**	**18.42%**	**0.0035**	**-21.98%**	0.0009	-1.03%	**-0.0136**	**66.88%**	**-0.0131**	**15.79%**
Prod./Trans.	**0.0109**	**-43.69%**	**-0.0053**	**11.90%**	**-0.0103**	**63.94%**	0.0010	-1.11%	**-0.0092**	**45.27%**	**-0.0196**	**23.61%**
						Model C						
Mgmt/Tech/Arts	**-0.0073**	**29.34%**	**0.0044**	**-9.94%**	**0.0025**	**-15.51%**	-0.0038	4.30%	**0.0069**	**-33.82%**	0.0101	-12.17%
Service	**-0.0137**	**54.78%**	**-0.0059**	**13.20%**	**-0.0062**	**38.71%**	**-0.0203**	**22.97%**	**-0.0079**	**39.01%**	**-0.0203**	**24.42%**
Sales/Office	**-0.0084**	**33.66%**	-0.0003	0.71%	-0.0014	8.47%	**-0.0086**	**9.71%**	**0.0133**	**-65.47%**	**-0.0060**	**7.18%**
Constr/Nat. Res.	**0.0112**	**-45.05%**	**-0.0076**	**17.10%**	**0.0033**	**-20.64%**	0.0007	-0.74%	**-0.0130**	**63.99%**	**-0.0118**	**14.23%**
Prod./Trans.	**0.0102**	**-41.06%**	**-0.0055**	**12.38%**	**-0.0110**	**68.23%**	0.0004	-0.49%	**-0.0086**	**42.28%**	**-0.0179**	**21.52%**

Notes: This table reports the share of variation explained by sorting across five 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”, does not appear because the CPS is a survey of the civilian non-institutional population. The shares of the five categories of occupations add up to the share of “All Occupation" in Model B and Model C in Table 9.7. Entries in bold are statistically significant at the 5% level.