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# The Heterogenous Labour Market Impact of the COVID-19 Pandemic

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# The Heterogeneous Labor Market Impacts of the Covid-19 Pandemic


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**Abstract**

We study the distributional consequences of the Covid-19 pandemic's impacts on employment, both during the onset of the pandemic and over recent months. Using cross-sectional and matched longitudinal data from the Current Population Survey, we show that the pandemic has exacerbated pre-existing inequalities. Although employment losses have been widespread, they have been substantially larger – and persistently so – in lower-paying occupations and industries. We find that Hispanics and non-white workers suffered larger increases in job losses, not only because of their over-representation in lower paying jobs, but also because of a disproportionate increase in their job displacement probability relative to non-Hispanic white workers with the same job background. Gaps in year-on-year job displacement probabilities between black and white workers have widened throughout the course of the pandemic recession, both overall and conditional on pre-displacement occupation and industry. These gaps are not explained by state-level differences in the severity of the pandemic or the associated response in terms of mitigation policies. We also find evidence that suggests that older workers have been retiring at faster rates.



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The Covid-19 pandemic led to a 10.3 percentage point increase in the unemployment rate in April 2020 (BLS, 2020). As we show below, a quarter of individuals who were employed in April 2019 were no longer employed as of April 2020. In this paper we ask: What are the distributional consequences of the Covid-19 pandemic's impact on employment? In particular, to what extent has employment in high and low paying occupations and industries been differentially impacted? Which demographic groups have been more impacted by the pandemic? And are the differential impacts across demographic groups explained by their pre-displacement occupation and industry affiliations? Are they driven by geographic variation in the severity of the pandemic and the associated response in terms of mitigation policies? Or were certain groups of workers disproportionately likely to transition out of work, even when compared to others in the same state who held the same occupation or industry before the onset of the pandemic? We explore the answers to these questions both in the immediate aftermath of the pandemic and over more recent months.

We use data through February 2021 from the Current Population Survey (CPS) – the primary source of labor force statistics for the United States, and take advantage of the rotating panel structure of the survey in order to track individuals' outcomes over time, both before and after the onset of the pandemic.

We first determine the extent to which the employment changes observed during the pandemic are due to individuals exiting employment, relative to reduced hiring. Next, in order to analyze the distributional impacts of the Covid shock, we rank occupations and industries according to their average pre-pandemic wages. We use a regression-based approach in order to isolate the impact of the pandemic on employment from occupation- or industry-specific seasonal and annual patterns, and determine the extent to which the impacts were concentrated in lower versus higher-paying occupations and industries, both at the onset of the pandemic and during more recent months.

We then turn to the heterogeneous impact of the pandemic across demographic groups. In particular, we investigate the differential impacts on employment outcomes across workers of different gender, age, education, and race/ethnicity. In order to put these findings into context, we compare the patterns observed during the pandemic to those observed during and after the Great Recession.

Given that the distribution of employment across occupations and industries differs between groups, one would expect that the impacts of the pandemic would differ according to the extent to which particular demographic groups tend to work in more impacted occupations and industries. We hence investigate the extent to which the increased rates of job loss that we identify for certain demographic groups can be explained by their pre-displacement industry and occupation affiliations, and the extent to which certain types of workers are more likely to lose their jobs during the pandemic period, even when compared to others in the same pre-displacement occupation and industry.

Demographic groups are differentially located across geographic areas, and the severity of the pandemic and the strictness of the associated mitigation policies varied across locations. We therefore also explore the extent to which differences between groups, conditional on pre-displacement occupation and industry, can be explained by differences in the impact of the pandemic across states and across areas with different population densities.

Our work contributes to the growing literature on the impacts of the Covid-19 pandemic by providing a detailed analysis of the distributional effects of the pandemic across occupations and industries, and of the disproportionate impacts on certain groups of workers. Our results show that the pandemic particularly impacted individuals who were already economically disadvantaged – an impact that has persisted nearly a year after the onset of the pandemic, and that can only be partially explained by pre-pandemic industry and occupation affiliations or by variation across geographic areas.

# 1 Related Literature and Contribution

The literature on the labor market impacts of Covid-19 has grown very rapidly. Here we briefly discuss some of the papers that are most related to our work, and highlight our key contributions.

Using data on occupational characteristics from datasets such as O*NET, a number of papers have focused on how the impacts of the pandemic differ across jobs according to the extent to which they can be performed remotely or are likely to be at risk due to social distancing requirements (e.g. Béland et al., 2020; Dingel & Neiman, 2020; Mongey et al., 2020). In this paper, we instead focus on the distributional consequences of the pandemic's employment impacts. In particular, we show that the decline in employment and the associated increase in the employment exit rate observed during the pandemic were disproportionately concentrated in lower-paying occupations and industries, especially during the onset of the pandemic in April 2020. Although the magnitudes have become more muted, the disproportionate impacts on lower-paying occupations and industries still persist as of February 2021. The pandemic has therefore exacerbated pre-existing inequalities in terms of labor market outcomes, with the impacts being most strongly felt among individuals in lower-paying jobs, and these inequality-exacerbating impacts have persisted nearly a year after the onset of the pandemic.[1]

A number of related papers developed concurrently to ours have also analyzed the heterogeneous effects of the pandemic across demographic groups. Several contributions have made use of "non-traditional" data sources, such as Cajner et al. (2020), who use data from ADP, a large U.S. payroll processing company; Coibion et al. (2020), who use data from the Nielsen Homescan panel; Bartik et al. (2020), who use data from Homebase; and Chetty et al. (2020), who build a database that tracks economic activity at a granular level in real time using anonymized data from various private companies. Alon et al. (2021), Bluedorn et al. (2021) and Albanesi & Kim (2021) focus on the gender dimension of the pandemic, while Montenovo et al. (2020) and Couch et al. (2020) also use CPS data to explore the heterogeneous employment impacts of the pandemic across demographic groups.

While in many regards our results are consistent with the existing literature, we also document a number of new facts. Methodologically, a key distinguishing feature of our approach is our focus on labor market flows. By taking advantage of the longitudinal matching of individuals records across nationally representative CPS samples we are able to analyze the employment transition patterns of individuals who were employed before the onset of the pandemic, and we can perform a detailed analysis of the role of pre-displacement occupation and industry affiliation (as well as geography) in determining the probability of transitioning out of employment. Importantly, and in contrast to most of the existing literature using CPS data, by focusing on flows, rather than cross-sectional data, we are able to consider not only individuals who transition towards unemployment, but also those who transition to non-participation. As we show below, the pandemic induced substantial excess worker flows towards both of these labor market states, as many individuals who left employment did not immediately search for new employment. Specifically, transitions to non-participation accounted for more than one-fifth of the excess outflows from employment between April 2019 and April 2020 (relative to 2015-2019 averages), and for close to half of the excess outflows

[1] An additional dimension through which these already stark inequalities may be exacerbated is the possibility that those who remain employed in these lower-paying occupations are increasingly exposed to the virus due to the limited possibilities of remote working offered by these occupations (see e.g. Mongey et al., 2020; Ruiz-Euler et al., 2020).

between February 2020 and February 2021. Using only cross-sectional data, it would not be possible to distinguish between the non-participants who were employed before the onset of the pandemic and those who were not. Moreover, the CPS does not generally record prior occupation and industry information for individuals classified as non-participants. By using the matched samples we have access to prior occupation and industry information for all matched individuals, including those who transition to non-participation, and this allows us to provide a detailed analysis of the extent to which flows out of employment are explained by individuals' prior occupation and industry affiliation.

In terms of our specific findings, we contribute a number of novel pieces of evidence about the impacts of the pandemic, both in its early stages, and over more recent periods. In particular, we show that individuals from racial and ethnic minorities experienced disproportionate job losses, not only because they tend to work in more affected occupations and industries, but also because they were more likely to transition out of employment even when compared to other workers who held similar jobs (based on detailed occupation and industry codes) before the onset of the pandemic. This finding still holds when using only within-state variation, implying that the gaps are not explained by differences in the state-level severity of the pandemic or the associated lockdown policies.

Perhaps most concerningly, we find that important gaps in job loss probabilities persist across demographic groups nearly a year after the onset of the pandemic – a pattern that differs from what was observed during the recovery from the Great Recession. Moreover, the fraction of these gaps that can be explained by workers' pre-displacement occupation or industry affiliation has decreased over time for most groups. For black workers, the gap in job loss probability relative to white workers has widened throughout the course of the pandemic recession in absolute terms (from around 2.8 percentage points in April to around 3.5 percentage points in February), and more than 75% of the gap as of February 2021 is observed among workers with the same pre-displacement industry and occupational affiliation – with none of this remaining gap explained by variation across states or between urban and rural areas. For Hispanic workers, although the gap has narrowed, less of the remaining difference can be explained by pre-displacement occupation and industry, or by geography. These results indicate that, on average, workers from minority groups have benefited much less from the employment recovery observed between April and February, even when compared to workers with the same occupation and industry background.

When comparing across genders, we find that women were disproportionately likely to exit employment at the onset of the pandemic, though this gap is largely explained by their pre-displacement occupation and industry affiliation, and the gender gaps in employment exit probabilities have largely disappeared by February 2021. We also find evidence that suggests that older workers have been retiring at faster rates. In particular, the gap in exit rates for workers aged 56 and older grew relative to those aged 36-55 (from 1.8 percentage points in April to 2.2 percentage points in February). Thus, while others have noted the initial increase in retirement (Coibion et al., 2020), we show that it has persisted (and grown) over the last year. Further, while in April one-third of the gap could be accounted for by occupation and industry background, by February only 9% of the gap could be explained, suggesting increased retirement also from occupations and industries that were less impacted by the pandemic.

Although the magnitude of the pandemic recession has been more severe then recent recessions, we find broadly similar patterns during the Great Recession in terms of which groups were disproportionately impacted. This is in line with the findings of Hoynes et al. (2012) regarding the disproportionate impacts of previous recessions on individuals who were already economically disadvantaged. However, we do find two key differences between the pandemic recession and the Great Recession: first, the pandemic recession has been much more severe for women then men, in part due to the impact of school and childcare closures and differences in the occupation and industry profile of the employment shock (Alon et al., 2021). Second, during the Great Recession we show employment exit did not increase for older individuals, perhaps due in part to the effect of the stock market crash on retirement savings leading workers to delay retirement.

## 2 Data and Aggregate Patterns

Our analysis is based on data from the monthly Current Population Survey (CPS), the official source for labor market statistics in the U.S. The CPS is sponsored jointly by the U.S. Census Bureau and the U.S. Bureau of Labor Statistics (BLS). We rely on the microdata made publicly available by IPUMS (Flood et al., 2020). We restrict the sample to non-institutionalized civilians aged 16 and older.

The CPS has a rotating panel structure, whereby households are surveyed for four consecutive months, then leave the sample for eight months, and are then surveyed for another four consecutive months. We take advantage of this rotating structure in our analysis and construct employment flows following Madrian & Lefgren (1999), by matching monthly files using administrative IDs and confirming matches based on sex, race, and age. Appendix Figure A.1 plots year-on-year changes in employment based on the stock data from the monthly CPS samples, and the corresponding changes constructed using flow rates from the matched samples. Typically, changes constructed from the flow data underestimate employment growth (as discussed by Frazis et al., 2005). During the pandemic period, both series move closely together.

The CPS records respondents' labor market status during the week that spans the 12th of each month. The majority of the major lock-down orders and other strict social distancing measures had not yet been implemented by the time of the March 2020 survey. Hence, the March 2020 CPS data only captures the very early effects of the Covid-19 pandemic. For most of the analysis, we focus on the patterns observed in April 2020, the month where the impacts of the pandemic were most acutely felt, and February 2021, the most recent period for which we can compute year-on-year changes relative to a pre-pandemic period. Where possible, we also show results to June 2021, the latest period of data available at the time of writing.

Between 95,000 and 100,000 working-aged individuals are sampled by the CPS each month. Response rates fell during the pandemic, from 83% in the 12-month period to February 2020 to 73% in March, then ranging from 65% to 70% between May and August, and recovering to around 80% in more recent months. The BLS has stated that "although the collection rates were adversely affected by pandemic-related issues, BLS was still able to obtain estimates that met our standards for accuracy and reliability".[2] All patterns shown are based on weighted outcomes using CPS composite weights. For the flow analysis, we weight using the most recent month's weights in order to account for attrition over the pandemic period.

Figure 1 displays overall aggregate patterns over time. Panel A shows the evolution of the employment rate since January 1976. The solid blue line is the standard official employment rate, using all individuals who are classified as employed in a given month divided by the population in that month. The dashed red line displays an adjusted employment rate which excludes certain individuals who are likely to have been misclassified as employed during the pandemic. Specifically, in April 2020, there was a large increase in the group of individuals who report that they were employed but absent

[2]See https://www.bls.gov/cps/employment-situation-covid19-faq-april-2020.pdf.

from work for reasons other than the ones enumerated by the CPS (such as vacation or illness). While this group is typically less than 0.5% of the population, it grew to almost 5% in April 2020. The BLS has argued that these individuals who are absent for "other" reasons should likely be classified as temporary layoffs. However, nearly one-quarter of individuals who were absent for "other" reasons in April 2020 report being paid by their employer for their time off. We therefore compute an adjusted employment rate (shown by the red dashed line) that excludes individuals who are classified as employed but (i) were absent from work during the reference week, (ii) report being absent for "other" reasons, and (iii) report that they were not paid by their employer for their time off. Workers satisfying these three criteria are instead classified as unemployed. For the remainder of our analysis, we use these adjusted measures of employment and unemployment.

Regardless of whether the standard or the adjusted employment rate is considered, Panel A of Figure 1 shows that the decline observed in April 2020 is very dramatic by historical standards. The official employment rate falls from 60.9% in February 2020 to 51.3% in April. The adjusted employment rate, which historically differs from the official employment rate only marginally, falls further, from 60.7% in February to 48.9% in April. As of February 2021, both measures have recovered to around 57%, with some slight further recovery to June 2021, but remaining close to the trough levels observed in the aftermath of the Great Recession, and well below pre-pandemic levels.

Panels B and C of Figure 1 illustrate the associated year-on-year labor market flows between employment and non-employment since September 1996. Each flow is expressed as a share of employment one year earlier. Panel B shows that outflows from employment to unemployment and not-in-the-labor-force (NILF) both increased dramatically in April 2020. From 2015 through 2019, the average exit rate to unemployment was 2.0%. This increased to 14.0% in April 2020, and although it declined sharply in the following months, it remains nearly twice as high as in the pre-pandemic period (at 3.9%) as of February 2021. Exits to NILF averaged 7.3% from 2015 through 2019, but increased to 10.6% in April 2020, and remain at 8.9% in February. In other words, 25% of individuals employed in April 2019 and 13% of individuals employed in February 2020 were no longer employed as of April 2020 and February 2021, respectively. It is important to note that the pandemic induced excess exits towards both unemployment and NILF, with the exit rate to NILF being particularly slow to recover to pre-pandemic levels. Hence, analyses that focus only on individuals classified as unemployed in the CPS will miss an important fraction of the pandemic-related job losses.

Panel C of Figure 1 displays the hire rates from unemployment and NILF as shares of employment one year earlier. Here we see that the inflow rate has also changed, but less dramatically. Hire rates from unemployment averaged 2.6% from 2015 to 2019, but fell to 1.2% in April 2020, recovering to 1.7% in February 2021. Hires from NILF averaged 6.1% from 2015 through 2019, but fell to 4.0% in April and recovered to 4.8% in February.

Compared to the increase in exit rates, hiring has remained comparatively robust during the pandemic. Over 80% of the dramatic initial rise in non-employment is due to exits from employment, rather than decreased hiring. This contrasts with the pattern typically observed during recessions, where a collapse in hiring is usually the dominant driver of increased unemployment rates (c.f. Elsby et al., 2009; Fujita & Ramey, 2009; Shimer, 2012). Given the magnitude of the decline in employment in April 2020 it is perhaps not surprising that separations must have played a major role (given that the typical volume of inflows is relatively small compared to the magnitude of the observed employment decline). The role of the hiring rate, however, is remarkably modest, as is the fact that it has recovered robustly.

### Isolating the impact of the pandemic from seasonal and annual patterns

Our paper explores heterogeneities in the employment effects of the pandemic across occupations, industries, and demographic groups. In order to isolate the pandemic-related changes from seasonal or annual patterns (which may be particularly important for certain occupations, industries, or demographic groups), we estimate a series of regressions using data from January 2015 onwards. The regressions are estimated using collapsed data at the group level for each month (where groups may be either occupations, industries or demographic categories), and are run separately for each group. The regression takes the following form:

$$Y_{gt} = \gamma_g D_{m(t)} + \alpha_g D_{y(t)} + \beta_g D_t^C + \epsilon_{gt} \tag{1}$$

$Y_{gt}$ is the outcome variable of interest for group $g$ in period $t$. For the stock analysis, this is the employment rate of group $g$ in a given month. For hires and exits, we use matched data over one-year windows, and calculate the rates of hiring and exiting as shares of the stock of employment at the beginning of the window. $D_{m(t)}$ is a vector of calendar month dummies. The coefficient $\gamma_g$ captures any seasonal variation in outcomes that are specific to the group being considered. $D_{y(t)}$ is a vector of year dummies, so that $\alpha_g$ accounts for year-by-year variation in the outcome of interest for the specific group.[3] $D_t^C$ is an indicator for the Covid-19 pandemic months, i.e. a vector of dummies for each individual month from March 2020 onwards.[4] Our coefficient of interest, $\beta_g$, is a vector capturing group-specific deviations in our outcome of interest during each pandemic month, once seasonal effects and annual patterns have been accounted for. While our analysis focuses on the estimated pandemic-related effects $\widehat{\beta}_g$ (and in particular the estimates for April 2020 and February 2021), results are qualitatively similar if focusing on raw changes over time, given that the resulting adjustments for seasonality and year effects are relatively small compared to the magnitude of the Covid shock. In all specifications, we report robust standard errors. By studying annual flows, we are able to use characteristics of pre-pandemic employment to study heterogeneity in the impact of the pandemic. However, since the pandemic began affecting employment in March 2020, we truncate our analysis at February 2021.

# 3 Distributional Impacts of the Covid-19 Pandemic

As is well known, the Covid-19 crisis forced many sectors of the economy to be shut down, at least temporarily, while also requiring production to be severely altered in other sectors. Under shelter-in-place orders only essential businesses were allowed to operate. Even in states that did not have strict shelter-in-place laws, consumer spending patterns showed a dramatic slowdown in business for restaurants, gyms, and hair salons.[5] Thus, we expect significantly heterogeneous impacts across different types of jobs, leading to differential impacts across workers, with potentially important distributional implications.

## 3.1 Heterogeneous Impacts across Occupations and Industries

Following a similar approach to the literature on job polarization (e.g. Acemoglu & Autor, 2011; Autor et al., 2006; Goos & Manning, 2007), we analyze the distributional

[3]Since all of 2021 is during the pandemic period, we extend the 2020 year dummy to include 2021 as well, since we cannot distinguish "normal" annual variation from the impact of the pandemic in that year.

[4]For the flow variables, the April 2020 dummy, for example, is equal to one for the flows between April 2019 and April 2020.

[5]See for instance https://slate.com/business/2020/05/south-reopening-restaurants-coronavirus-opentable.html

impacts of the pandemic by ranking occupations and industries based on their mean hourly wages in the pre-crisis period of January and February 2020.[6] For occupations, we focus on 22 2-digit SOC occupations, which are detailed in Appendix Table A.1 (ranked from lowest- to highest-paying).[7] The lowest-paying occupations include Food Preparation and Serving, Personal Care, and Cleaning and Maintenance Occupations, while the highest-paying occupations include Management, Legal, and Computer and Mathematical Occupations.

Figure 2 explores how the employment losses observed in aggregate as of April 2020 and February 2021 are distributed across these occupations. The figure plots the estimated coefficient $\widehat{\beta}_g$ from Equation (1) for each 2-digit occupation for the April 2020 and the February 2021 dummies (indicating the change in the dependent variable in the corresponding pandemic month after controlling for seasonality and year fixed effects), along with a 95% confidence interval based on robust standard errors. Occupations are ranked from lowest-paying on the left to highest-paying on the right.

Panel A plots the estimated impact of the pandemic on employment rates (employment in each occupation as a share of the total population). A clear pattern emerges: the impact of the pandemic is quite heterogeneous across occupations, with the employment contraction being disproportionately concentrated among lower-paying occupations. In particular, when looking at data to April 2020, we see that the 12 lowest-paying occupations experience statistically significant and in most cases quantitatively large declines in employment (with the main exception being Farming, Fishing and Forestry occupations which experience a relatively modest drop). When looking at outcomes to February 2021, we see that the employment declines have become much more modest (at least relative to April), but they are still disproportionately concentrated at the bottom of the distribution, in particular in Food Preparation and Serving, Personal Care and Personal Services, and Transportation Occupations.

Panel A of Appendix Figure A.2 shows analogous results when using each occupation's year-on-year employment growth rate as the dependent variable, allowing an interpretation of the impact of the pandemic in terms of the fraction of pre-pandemic

[6]The ranking is nearly identical if we use average wages for 2019. Hourly wages are taken directly from the data if available, or computed as weekly earnings divided by usual (or actual) hours worked per week. As in Lemieux (2006), top-coded earnings are adjusted by a factor of 1.4. We convert nominal values to June 2020 dollars based on the monthly Consumer Price Index (CPI, All Urban Consumers) from the BLS.

[7]The detailed occupational codes used in the CPS changed in January 2020 (from 2010 to 2018 Census code categories); however, the changes are relatively minor and do not affect the comparability over time at the 2-digit SOC level.

employment lost within each occupation (rather than the fraction of aggregate employment losses attributable to each occupation). The overall pattern is quite similar to the one in Panel A of Figure 2. As of February, some relatively high-paying occupations such as Arts, Entertainment and Media show large declines which are not reflected in Figure 2 because these occupations are small and hence do not account for a major fraction of aggregate employment losses.

Panels B and C of Figure 2 examine the hire rate from non-employment and the exit rate to non-employment for each occupation. These rates are calculated as a share of employment in that occupation one year earlier. This puts both inflows and outflows on the same denominator, which makes it easier to compare relative magnitudes.

Consistent with what we saw in Figure 1, the magnitude of the increase in exit rates shown in Panel C dwarfs the magnitude of the decrease in hiring in Panel B. Panel C also shows quite dramatic differences in exit rate changes across occupational wage rankings, especially in the early period. For Food Preparation and Serving, and Personal Care Occupations there is more than a 40 percentage point increase in the share of individuals exiting employment between April 2019 and April 2020. In contrast, all six of the highest paying occupations have exit rate increases of under 10 percentage points. When considering the impact as of February 2021, we still tend to observe a fairly monotonic relationship, with greater increases in exit rates and greater decreases in hiring rates among lower paying occupations.

Since 2-digit occupations are relatively broad, the trends in Figure 2 may be masking heterogeneity within 2-digit occupations. To show this is not the case, Figure 3 uses information at the more granular 4-digit occupation level, and plots raw changes (relative to February 2020) in employment as a share of the total population for occupations at each percentile of the occupational wage distribution. Consistent with the patterns at the 2-digit level, there is a strong monotonic relationship between wage rankings and the size of the employment losses in April. As of February 2021, employment losses still tend to be disproportionately larger in lower-paying occupations, with the main notable exception being "couriers and messengers", who experience strong employment growth between February 2020 and February 2021 (though far from enough to offset the major employment losses in most other low-paying occupations).

We next explore employment changes at the industry level. Figure 4 shows how employment losses are distributed across 13 major industry categories, once again ranked from lowest-paying on the left to highest-paying on the right, as detailed in Appendix Table A.2. As with occupations, the decline in employment tends to be concentrated in lower-paying industries. The largest employment decline is observed in the Leisure and Hospitality sector, which is the lowest-paying industry in the data. Employment declines are small in some high-paying sectors such as Information and Public Administration. Consistent with these patterns, we observe that workers in Leisure and Hospitality and Other Services industries experience the largest increases in exit rates (above 36 percentage points year-on-year to April, as shown in Panel C), while the highest-paying industries (Public Administration, Professional Services, and Financial Activities) saw much smaller increases in exit rates. Panel B of Appendix Figure A.2 shows analogous results when using each industry's year-on-year employment growth rate as the dependent variable, allowing an interpretation of the impact of the pandemic in terms of the fraction of pre-pandemic employment lost within each industry.

In Appendix Figure A.3, we show that if we look *within* the most heavily affected industries (Leisure and Hospitality, and Other Services), we find that the lowest-wage occupations (Food Preparation, Personal Care, and Cleaning) have substantially larger increases in exit rates compared to higher-wage managerial occupations. At the same time, for each of these occupational groups, exit rates are higher within the service sector than in other sectors. In other words, workers in a given occupation are more likely to be displaced if they are in a lower-paying sector, while workers in a given sector are more likely to be displaced if they are in a lower-paying occupation. This implies that both the occupation and the industry dimensions are informative about job loss, in both cases indicating higher job destruction rates for lower-paid jobs.

To summarize the results so far, we find that the pandemic has disproportionately affected low-wage jobs. The exacerbation of pre-existing inequalities induced by the pandemic is not only detectable when considering the immediate aftermath of the pandemic as of April 2020, but also when considering the longer-term effects as of February 2021, nearly a year after the onset of the pandemic.

It is interesting to note that these patterns are different from what has typically been observed during recent recession and recovery periods. As Jaimovich & Siu (2020) have documented, recent recessions have tended to disproportionately impact middle-wage routine task-intensive occupations, which have fallen during recessions and have not regained employment during subsequent recovery periods. In order to illustrate this pattern for the Great Recession period, we estimate a regression analogous to Equation (1), but using data for the years 2003–2014. We estimate the change in the employment rate in each month from January 2008 onwards (using 2007 as the base year), after controlling for seasonality and year effects. Figure 5 plots the estimated coefficients for December 2009 (close to the employment trough in the aftermath of the Great Recession) and December 2014 (several years into the recovery) for each occupation and industry, still ranked according to their January-February 2020 wages, in order to ease comparison with all of our other figures. In line with the Jaimovich & Siu (2020) evidence, the figure shows that the job losses during the Great Recession were disproportionately concentrated among middle-paying occupations and industries, both at the point of the employment trough, in December 2009, and also in the recovery period, in December 2014.

## 3.2 Heterogeneous Impacts across Demographic Subgroups

It is well known that the demographic composition of employment varies substantially between high- and low-paying jobs, with women and non-white, less educated, and younger workers over-represented in low-wage jobs. We show this directly in Appendix Figures A.4 and A.5.

Table 1 presents the estimated impact of the pandemic on the employment outcomes of different demographic groups. We focus on four dimensions of demographic heterogeneity: gender, education, age, and race/ethnicity. Column (1) displays the employment to population ratio for each group in the pre-pandemic period of February 2020. Columns (2) and (3) show the estimated impact of the pandemic on the year-on-year growth rate of the employment to population ratio of each group in April 2020 and February 2021. We estimate the impact of the pandemic using our regression approach, with the year-on-year growth rate of the employment to population ratio as the dependent variable, and with our month and year dummies accounting for group-specific seasonal and annual patterns.[8]

Beginning with gender, overall we see that the growth rate of the employment to population ratio fell by 22 percentage points (p.p.) for women in April, compared with 18 p.p. for men. As of February 2021, the reductions remain large, though much smaller in magnitude than in April (8 and 7 p.p. for women and men, respectively), and the gap between men and women has nearly disappeared.

[8] We have also generated results using the employment to population ratio (in levels) as the dependent variable. Those results yield estimates of the impact of the pandemic in terms of percentage point changes in the employment to population ratio of each group. Given the large differences in baseline employment to population ratios across demographic groups (as displayed in Column (1)), we prefer to focus on changes in the ratio as the dependent variable, since these results are readily interpretable in terms of the fraction of employment lost within each group.

When considering differences across education groups, we see a monotonic pattern in April as displayed in Column (2): the largest employment to population growth rate declines are among individuals with no high school degree, with a reduction of 31 p.p. The corresponding figure for workers with a college degree was less than half of this, at 12 p.p. By February, these declines have been mitigated for all groups.

The next set of rows of Table 1 shows substantially larger losses for workers under 25 compared to older workers in April, with important gaps remaining as of February. The final set of rows considers the impact across groups defined by race and ethnicity. We consider four mutually exclusive groups: non-Hispanic white, non-Hispanic black, non-Hispanic other, and Hispanic. The table shows larger declines in employment growth rates in April for non-white workers, with particularly large losses for Hispanics. Column (3) shows that larger declines persist for black and Hispanic workers relative to white workers in February 2021. This is consistent with previous evidence that employment of Hispanic and non-white groups is particularly hard-hit during recessions, likely due to hiring discrimination (Forsythe & Wu, 2020).

In Columns (4) through (7) we analyze the impact on labor market flows by demographic group. Flows are expressed relative to employment one year prior. We display the coefficients for April 2020 and February 2021, which reflect the change in year-over-year flows relative to employment one year prior, after controlling for typical transition rates for the corresponding demographic group. Beginning with April 2020, we see that, across demographics and consistent with the patterns observed for employment stocks, female workers, non-white workers (and particularly Hispanics), young workers, and those with less education experienced both larger increases in exit rates and larger decreases in hire rates.

By February 2021, the increases in exit rates are much smaller in magnitude, but still indicate substantial and statistically significant deviations from what would be expected based on demographic-group specific seasonal and annual patterns. Exit rates remain particularly elevated for black and Hispanic workers (6 p.p. for both groups) as well as for those with less education and for older workers. Meanwhile, hire rates remain lower for all groups, by about 1-4 percentage points in most cases. Workers under the age of 25 remain 6 p.p. less likely to be hired in February compared with their typical hire rates. Although employment changes are primarily driven by changes in exit rates, we do see that the decrease in youth hiring is more than six times that of older workers at the onset of the pandemic, and still remains high in February. This result is consistent with Forsythe (2020), which shows that firms disproportionately reduce hiring of young workers during recessions.

For most groups, the estimates in Columns (2) and (3) for the impact on the employment to population growth rate (which are based on cross-sectional stock data) are close to the differences between the estimated impacts on hires and exits in Columns (4) through (7). This indicates that the stock- and flow-based measures of employment contraction produce similar estimates, and confirms the reliability of an analysis based on flows in spite of the recent increase in attrition rates. For a few groups, however, there are some deviations between the patterns based on stocks and the patterns based on flows. In Appendix Figure A.6 we show that employment losses for black workers estimated from flow data are somewhat more severe than those estimated from stock data.[9] Nonetheless, regardless of whether we focus on the stock-based results in Columns (2) and (3) or the flow-based results in Columns (4) through (7) of Table 1, we find that black workers have suffered more severe employment losses than white workers during the pandemic period.

## 3.3 Comparison with the Great Recession

It is interesting to compare the unequal impact of the pandemic on employment across demographic groups to the patterns observed during the Great Recession. To do so, we first re-estimate the impact of the pandemic on the employment rates of each group, but using the last pre-pandemic month (i.e. February 2020) as a base. In other words, we perform our regression adjustment in order to estimate the pandemic impacts conditional on group-specific seasonal and annual patterns for each demographic group, but we now use the percentage change in the employment to population ratio for each demographic group relative to February 2020 (rather than the year-on-year change in the employment to population ratio) as the dependent variable. We then perform an analogous estimation for the Great Recession period using data for 2003–2014, with the percentage change in the employment to population ratio relative to December 2007 as the dependent variable. We use this alternative measure of employment changes given that the interpretation of the results based on our baseline year-on-year growth rate measure is less straightforward when considering periods that are more than one year after the onset of a downturn (given that it uses data from one year prior as a base).

[9] See also Cai & Baker (2021), who analyze bias from non-response rates by comparing stock and flow data from the CPS for the pre-pandemic period and find that the bias is particularly severe for black workers.

The much slower pace of the employment decline and subsequent recovery during the Great Recession period motivates us to consider outcomes that are more than one year after the start of the recession, and we hence turn to this alternative measure in this section.

Appendix Figures A.7 and A.8 plot the time series for the estimated changes in employment for each demographic group relative to the start of the recession. The figures highlight the fact that the speed and depth of the employment decline during the pandemic was dramatic, with a depth that exceeds the employment effects even two years into the Great Recession for all demographic groups. For almost all groups, by June 2021, the employment rate had recovered past the level of the Great Recession, 16 months in. This reflects the fact that, 16 months in, employment rates were still declining during the Great Recession (which had a contraction period lasting 18 months), whereas the contraction period during the Covid recession was sharp but brief, lasting only two months.

In order to provide a more rigorous comparison across the two recessions, Table 2 focuses on the impacts at key points in time. As before, we consider the impacts as of April 2020 (the trough of the pandemic recession) and February 2021. Given that with this alternative measure we are also able to consider periods that are more than one year after the onset of the pandemic, we also present results for the estimated impact as of June 2021 (the most recent period of data available at the time of writing). We contrast these impacts to those observed in December 2009, close to the employment trough in the aftermath of the Great Recession, and December 2014, several years after the end of the recession, when the aggregate employment rate had experienced a recovery that is roughly similar to what has been observed in the aftermath of the Covid shock.

First note that, in spite of the different approach to measuring employment losses, the estimates for the impact of the pandemic in April 2020 and February 2021 that are presented in Columns (2) and (3) are quite close to the estimates in Table 1, and the picture that emerges in terms of differences between demographic groups is similar. The estimates for June 2021 in Column (4) are broadly similar to those for February. Thus, although our year-over-year estimation strategy limits how far into the recovery we can analyze, as of June 2021 the demographic differences in employment do not appear to have changed substantively relative to February.[10]

[10]Recall that the main motivation for focusing on year-over-year changes is that this allows us to observe individuals' pre-pandemic occupation and industry affiliation, which we use extensively in our analysis below.

Columns (6) and (7) show that the Great Recession generated larger employment declines for men then women – the opposite of what we observe for the pandemic recession. When we examine age, we see a reversal of fortunes for under 25 year olds and over 55 year olds. During both recessions, employment rates initially declined more for the young compared with other workers. However, the trajectory of the recovery is quite different. If we compare December 2014 to June 2021, which are a similar point in the respective recoveries, we see that in December 2014 young workers' employment rates had fallen by 9 p.p. more than employment rates of 26-35 year old workers, while in June 2021 the employment rate impacts are statistically indistinguishable across these two groups. In contrast, while workers over 55 saw an initial employment rate decline that was larger than 26-55 year olds in April 2020, during the Great Recession these workers saw little employment decline. By June 2021, employment rates for workers over 55 remain depressed by 8 percentage points.

Interestingly, when considering the gaps in the impact across racial and ethnic groups, the Covid pandemic shares some similarities with the Great Recession. As we have highlighted, employment rates fell more for non-white workers relative to white workers at the start of the pandemic. During the nadir of the Great Recession we see a similar pattern. However, while by December 2014 the decline in employment rates had converged across racial and ethnic groups, as of June 2021 black and Hispanic workers continue to have employment rate declines that are 2-3 p.p. larger than those of white workers.

Overall, we observe similar patterns in job loss across demographics as in past recessions, in line with Hoynes et al. (2012), with the major exceptions being the results for men (which is consistent with the findings of Alon et al. (2021)), and the results for older workers (which is consistent with the findings of Coibion et al. (2020)). The other main difference is that the recovery has disproportionately benefited white workers, who are closer to their pre-pandemic employment rates than black and Hispanic workers – a pattern that was not observed in the aftermath of the Great Recession.

### 3.4 Do Occupations and Industries Explain Heterogeneous Impacts across Demographic Subgroups?

So far we have shown the dramatically differential impacts of the Covid-19 crisis across occupations and industries as well as across demographic groups. In this section, we investigate whether the disproportionate employment losses experienced by disadvantaged demographic groups are due to the fact that they are over-represented in the jobs that contracted most sharply (as shown in Appendix Figures A.4 and A.5), or if these workers experienced worse losses also *within* job categories.

In order to answer this question, we focus on outflows from employment, which, as shown above, are the dominant margin of adjustment driving the employment decline during the crisis. The key advantage of using outflow data is the ability to consider the pre-displacement occupation and industry for all workers switching out of employment, including those who transition out of the labor force.[11] We determine the extent to which the differential impact of the pandemic across demographic groups is accounted for by their pre-displacement occupation and industry by running a new set of regressions as follows:

$$\begin{aligned} Y_{it} =& \omega D_{demo(i)} + \beta D_{demo(i)} \times D_t^C + \gamma D_{demo(i)} \times D_{m(t)} + \alpha D_{demo(i)} \times D_{y(t)} \\ &+ \rho D_{occ(it)} + \delta D_t^C \times D_{occ(it)} + \epsilon_{it} \end{aligned} \tag{2}$$

Instead of running regressions using observations at the demographic group level, as in Equation (1), we now directly use the individual-level data, pooling all demographic groups together. $Y_{it}$ is an indicator variable which is equal to one for individuals who transition out of employment. We regress this on the interaction of demographic indicators, $D_{demo(i)}$, with a vector of dummy variables for each Covid-19 pandemic month (March 2020 through February 2021), indicated by $D_t^C$, while also controlling for demographic group fixed effects. We also allow for demographic group-specific seasonality (through the interaction of $D_{demo(i)}$ and $D_{m(t)}$) as well as demographic group-specific year effects (through the interaction of $D_{demo(i)}$ and $D_{y(t)}$). Our coefficient of interest, $\beta$, estimates differential changes in exit rates across demographic groups during the pandemic months. We then introduce successive occupation and industry fixed effects, both directly and interacted with the pandemic month indicators. This controls for differences in exit rates between job types under typical conditions, as well as differences in job loss by job type that are specific to the Covid-19 pandemic. To the extent that the differences between demographic groups are explained by their pre-displacement

[11] As we have seen, a substantial fraction of those exiting employment during the pandemic transitioned to being out of the labor force, and the CPS would not record the prior occupation or industry for the majority of these individuals in the cross-sectional data. An additional advantage of using prior occupation and industry affiliation from the flow data rather than the cross-sectional data is the fact that the occupational information for non-employed individuals is independently coded in the CPS. Independent coding is known to lead to substantial mismeasurement, even at highly aggregated levels of occupational classification (Kambourov & Manovskii, 2013; Moscarini & Thomsson, 2007).

occupation or industry affiliation, the estimated coefficient $\widehat{\beta}$ should be driven to zero once these controls are introduced. An estimate of $\widehat{\beta}$ that differs from zero even after controlling for occupations or industries would indicate differential exit rates across demographic groups occurring *within* job types.

Figures 6 and 7 plot the estimated $\widehat{\beta}$ coefficients from Equation (2), along with 95% confidence intervals (using robust standard errors), for our different demographic cuts. The figures on the left report estimates for April 2020, while those on the right report results for February 2021. We first show the baseline differentials between groups, before introducing any occupation or industry controls (blue bars). We then show results when introducing major industry groups (red bars), and 2-digit occupation fixed effects (green bars). Finally, in the orange bars, we show results from a specification that includes fixed effects at the most detailed occupation and industry levels available in the CPS (482 occupations and 96 industries), again interacted with a full set of fixed effects for each pandemic month. These detailed controls would account for the possibility that demographic groups are differentially sorted across detailed occupations and industries within the broader job categories. To the extent that the ability to work remotely varies primarily across (rather than within) detailed occupation and industry categories, these controls would also account for these differences. All coefficients reported are relative to the omitted group, which in the respective panels are males, whites, 36-55 year olds, and college graduates. In Table 3 we show the same results but translated into the share of the gap in employment exit rates for each demographic group that can be accounted for by individuals' pre-displacement occupation and industry affiliation.

The top left panel of Figure 6 shows that female employment exit rates increased by 3.6 percentage points more than male employment exit rates in April 2020. When we control for 2-digit occupations and major industry there is little difference in the gap, but once we control for detailed occupation and industry, the gap is substantially reduced. This means that most of the elevated exit rate for women is due to the types of jobs they work in (at a detailed level), rather than differences within narrowly defined jobs. The top right panel of Figure 6 shows this gap essentially disappears by February 2021, falling below 1 p.p. and indistinguishable from zero.

The bottom left panel of Figure 6 shows that two-digit occupations can explain about half of the increased exit rate for black workers relative to white workers in April 2020. For Hispanics, where we observe a large baseline gap in employment exit rates, the most detailed controls reduce the gap by about three-quarters. However, for all other non-white races, the most detailed controls can account for only 16% of the baseline gap, implying that most of the elevated exit rate for this group in April 2020 occurred within narrowly defined occupations and industries. Remarkably, the bottom right panel of Figure 6 shows that by February 2021, the gap in employment exit rates for black relative to white workers had actually increased, from 2.8 percentage points to 3.5 percentage points. Moreover, industry and occupation explain very little of this gap. Overall, there are sizeable gaps in employment exit rates as of February 2021 for black and Hispanic workers relative to white workers, and the vast majority of this gap is observed among workers with the *same* pre-displacement detailed occupation and industry.

In the top left panel of Figure 7 we see that workers under 25 had a 10 percentage point larger increase in exit rates compared to 36-55 year-olds in April 2020. This difference is reduced by 80% after controlling for detailed occupations and industries. For the 56 and up age category, exit rates increased by 2 percentage points more than for 36-55 year-olds, with detailed industries and occupations explaining around one-third of the gap. In the top right panel, we see that these exit rate differentials fell substantially by February 2021, with the exception of workers over age 56, for whom the gap increased slightly. Moreover, over 90% of the gap for these older workers remains after including industry and occupation controls.

In the bottom left panel of Figure 7 we see that individuals without a high school degree saw a pandemic-related increase in exit rates in April that was 12 percentage points larger than that of college graduates. Occupation and industry fixed effects leave 20% of the difference in exit rates unexplained. We see similar results for high school graduates and workers with some college, with the most detailed controls leaving 38% and 45% of the gaps unexplained, respectively. In the bottom right of Figure 7, we see that the gap in exit rates between less educated workers and college educated workers has narrowed substantially as of February 2021, with most of the gap explained by their pre-displacement industries and occupations.

As summarized in Table 3, while most of the gaps in exit rates between demographic groups have narrowed as of February 2021, the gap increased for black workers, and for both black and Hispanic workers over 70% of the gap is within detailed industry and occupational categories. This implies that, on average, workers from minority groups have benefited much less from the employment recovery observed between April and February 2021, even when compared to workers with the same occupation and industry background. In addition, the gap for older workers widened. This is consistent with disproportionate retirement rates among older workers, as documented by Coibion et al.

(2020), and may be due to the age profile of Covid-19, which is particularly dangerous for older individuals. The fact that very little of the gap is explained by pre-displacement occupation and industry suggests that older workers are disproportionately retiring from a wide range of jobs, regardless of how hard hit those jobs have been by the pandemic in terms of overall employment.

Finally, as an alternative way of visualizing the differential impacts across groups, Appendix Figure A.9 illustrates the change in the *within-occupation* employment share of different groups. The shares of female, young, less-educated and non-white workers declined in April 2020 (relative to a year earlier) within the vast majority of 2-digit occupations. This confirms that these workers are experiencing disproportionate job displacement even within 2-digit occupations. Similar patterns are observed across industries in Appendix Figure A.10.

## 3.5 The Role of Geography

So far we have focused on nation-wide estimates of the impact of the pandemic on the labor market, but the pandemic and the economic collapse differed across local labor markets. First, since Covid-19 is spread via close physical proximity, areas with more dense population are more at risk from the direct effect of the virus. Second, since mitigation policies such as lock-downs and capacity limitations were implemented at the state or local level, there were substantial differences across geographic areas and over time in the severity of the restrictions. Since there are large geographic differences in demographic composition, in this section we examine whether the residual gaps across demographic groups in the impact of the pandemic (for workers with the same occupation and industry background) can be explained by differences in the impact of the pandemic across geographical areas.

We first analyze how employment losses varied across areas with different population densities. As shown in Table 4, employment losses are somewhat larger in urban areas, with similar rates for both central city and outside-central city areas, but lower rates for non-metro areas. In line with this pattern, exit rates in April 2020 were higher for individuals in central cities and outside central cities compared to those in non-metropolitan areas, although the differences had narrowed by February 2021. Point estimates for individuals with unknown metro status fall between those for non-metro and metro, consistent with these individuals being drawn from a mix of urban and more rural areas. Thus, consistent with the viral risk, we do see a greater impact of the recession on individuals living in closer proximity to others.

We then investigate whether these differences can account for the unexplained gap in exit rates between demographic groups that we uncovered in Section 3.4. To do so, we run an additional set of fixed effect specifications, once again as in Equation (2), but now in addition to detailed industry and occupation fixed effects, we add metro status (non-metro, central city, outside central city, and unknown status) fixed effects, interacted with a full set of pandemic month dummies. Further, we consider a specification that includes a full set of state fixed effects, also interacted with a full set of pandemic month dummies. These fixed effects would account for any differences at the state level in the severity of the pandemic or the associated public policy restrictions at each point in time (as well as any other factors that vary at the state level over time). With this specification, we solely identify gaps between demographic groups using variation within a given state at a given point in time, after accounting for differences according to metro status, and differences according to detailed pre-displacement occupation and industry. The results in terms of the fraction of the gaps between demographic groups that can be explained based on these estimations are presented in the final two columns of Table 3.

The results for April 2020 show that density (metro status) can only explain a small additional fraction of the difference in employment exit rates across demographic groups defined by gender, age, or education (relative to what is explained by detailed occupation and industry controls). Remarkably, the final column of Table 3 shows that adding in a full set of state by month fixed effects also makes little difference in terms of the fractions explained across gender, age and education groups. Thus, although states had different lock-down policies and waves of the virus, employment responses appear to be mostly driven by national trends. This is consistent with other work finding modest labor market differentials across lockdown policies and virus spread (c.f. Forsythe et al., 2020).

Results when considering the gaps between race and ethnicity groups are quite interesting. When we look at black workers, we see that metro status increases the percent explained in April by 20 p.p.; however, including state fixed effects reduces the percent explained by 32 p.p. Thus, while some of the employment exit gap between black and white workers is due to the fact that black workers are more likely to live in urban areas that were more affected by the pandemic employment shock, conditional on their state of residence (as well as their metro status and their pre-displacement occupation and industry), black workers were disproportionately likely to lose their jobs in April. We see a similar pattern in February 2021. On net, only 36% of the employment exit gap between black and white workers in April 2020 can be explained by detailed occupation, industry, and geography controls, while in February 2021 this share is even lower, at 11%.

# 4 Conclusion

The economic fallout from the Covid-19 pandemic has been widespread. The magnitude of the employment losses, however, has differed substantially across different types of jobs and different types of workers. This paper shows that the pandemic has had the effect of exacerbating pre-existing inequalities: workers employed in lower-paying occupations and industries have been disproportionately impacted, given that employment declines have been significantly larger among lower-paying job categories. These asymmetric occupation- and industry-level effects may reflect heterogeneities in the extent to which different jobs can be performed remotely (see Brynjolfsson et al., 2020; Dingel & Neiman, 2020), as well as differences in the economic impacts of the pandemic across sectors.

Importantly, however, the differential impact on disadvantaged groups extends well beyond their exposure due to their pre-pandemic occupation and industry affiliation. Even within detailed job categories, and even when comparing individuals in the same state of residence, we find that Hispanic and non-white, less-educated, and younger workers suffered disproportionate increases in their job separation rates at the onset of the pandemic. Moreover, we find that black workers in particular have benefited substantially less from the employment recovery observed between April and February 2021, even when compared to workers with the same occupation and industry background and in the same state of residence.

Going forward, it will be important for policymakers to pay particular attention to these disadvantaged groups, who were not only more likely to be in a constrained economic situation before the pandemic, but have also been disproportionately likely to be impacted by it and to benefit less from the initial recovery.

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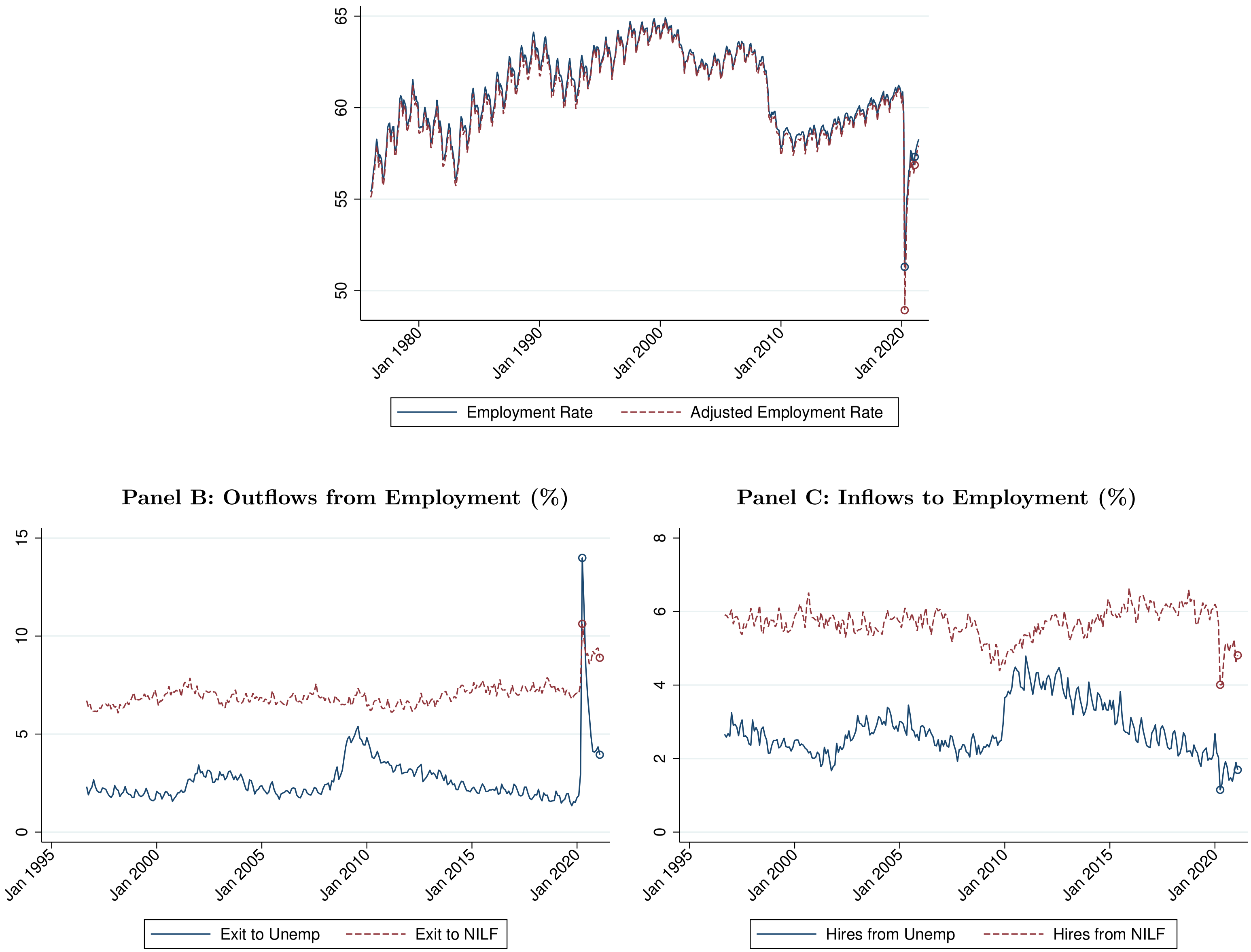
Figure 1: Aggregate Employment Rate and Labor Market Flows

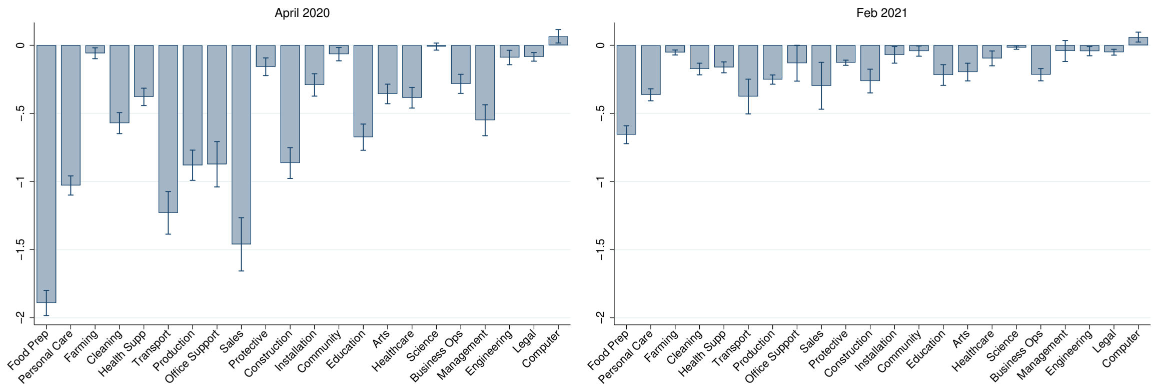
**Panel A: Employment Rate (%)**



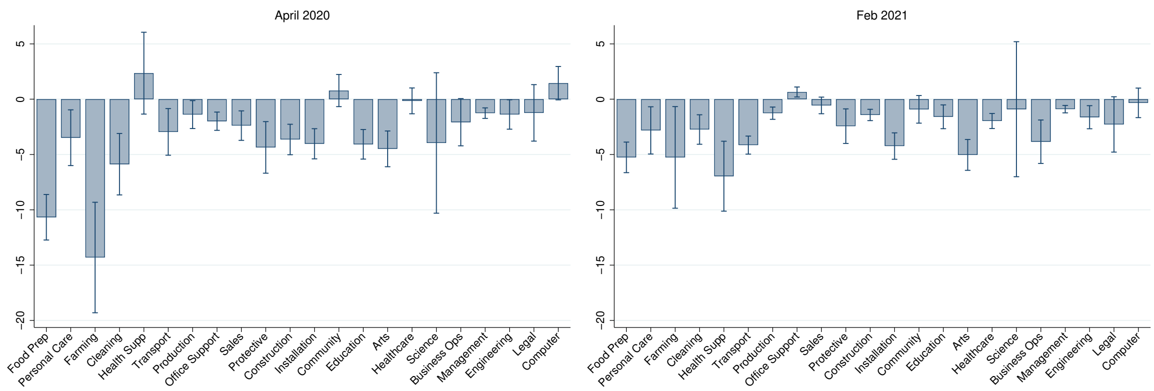

Note: The figure plots monthly employment rates and year-on-year labor market flows (percent of employed individuals who exit employment to non-employment, and percent of non-employed individuals who become employed as a share of employment one year earlier) based on monthly CPS data. The adjusted employment rate excludes individuals who are classified as employed, but were absent from work during the reference week for "other" reasons and report not being paid by their employer for their time off. These workers are instead classified as unemployed. The flow variables use the adjusted employment and unemployment classifications. The markers indicate data for April 2020 and February 2021.

Figure 2: Impact of the Pandemic across Occupations

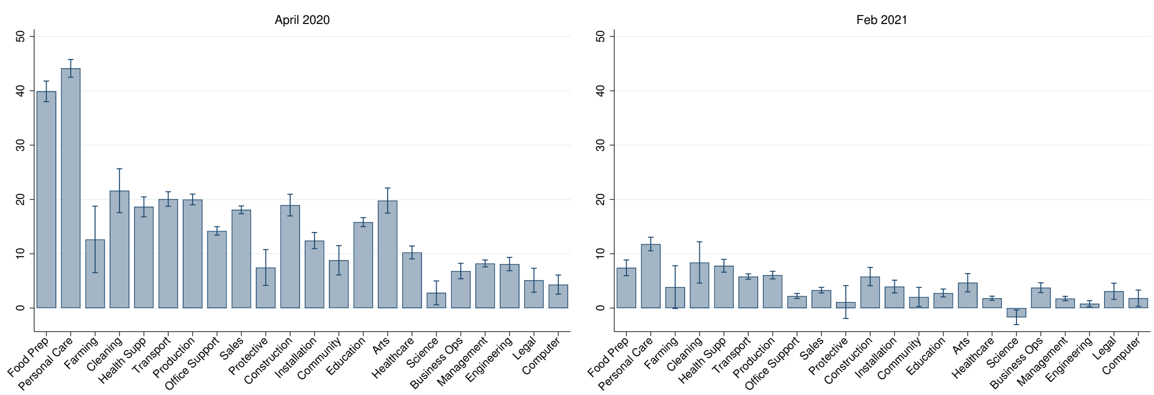
**Panel A: Adjusted Employment Rate**




**Panel B: Hires from Non-Employment**

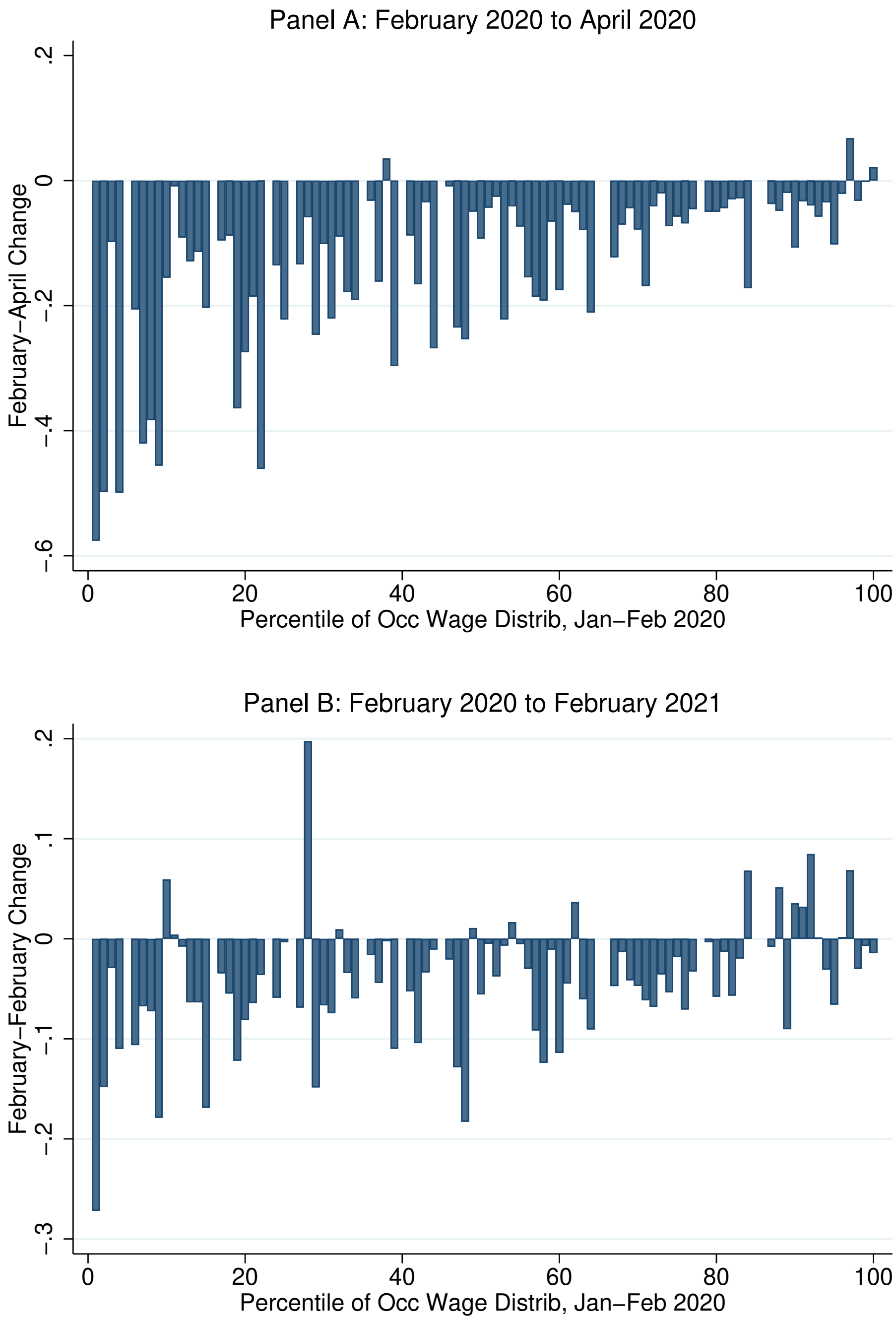



**Panel C: Exits to Non-Employment**




Note: Occupations are ranked from lowest- to highest-paying based on their mean wage in January and February 2020; see Table A.1 for details. The figure plots the estimated coefficient $\widehat{\beta}_g$ from Equation (1) for each 2-digit occupation, indicating the impact of the pandemic on the dependent variable in April 2020 and February 2021 after controlling for seasonality and year fixed effects. The lines represent 95% confidence intervals using robust standard errors.

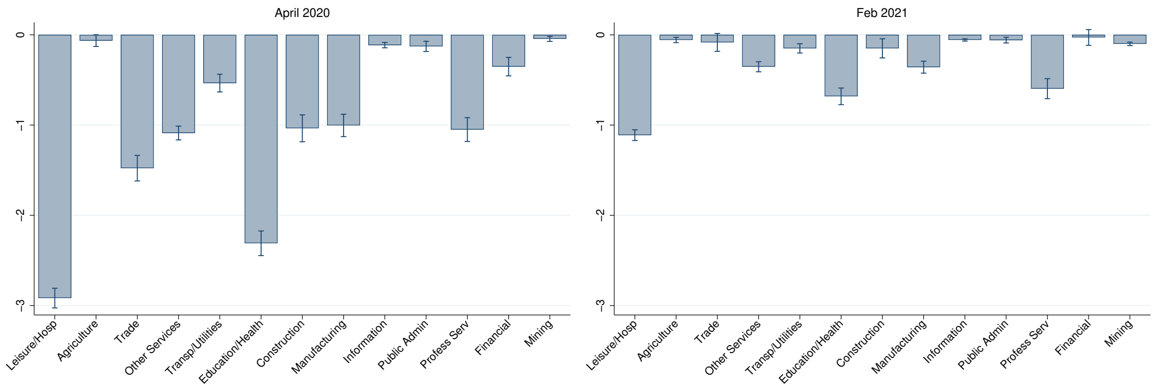
Figure 3: Changes in Employment across 4-Digit Occupations (as a share of the total population) since February 2020



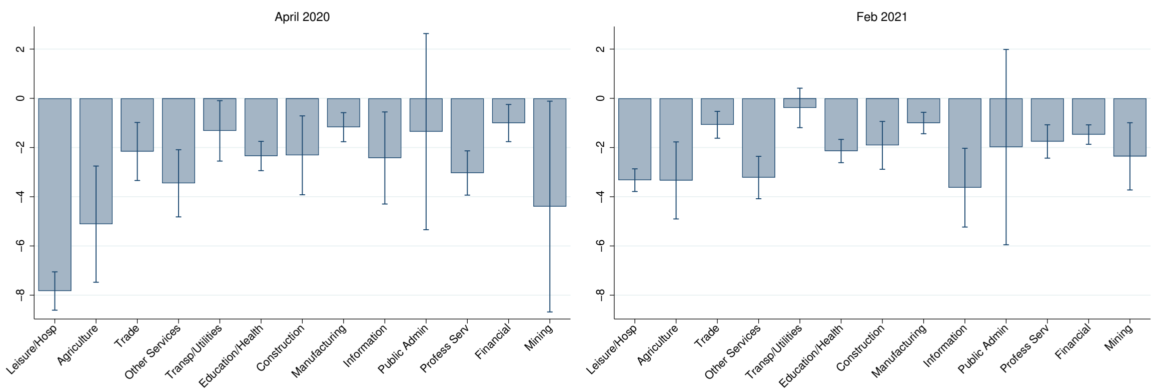

Note: The figure plots changes relative to February 2020 in employment rates (per capita) for occupations at each percentile of the employment-weighted occupational wage distribution (where the assignment to percentiles is based on employment and wages in the pre-pandemic period of January and February 2020). Our employment measure excludes individuals who were absent from work during the reference week for "other" reasons and report not being paid by their employer for their time off.

Figure 4: Impact of the Pandemic across Industries

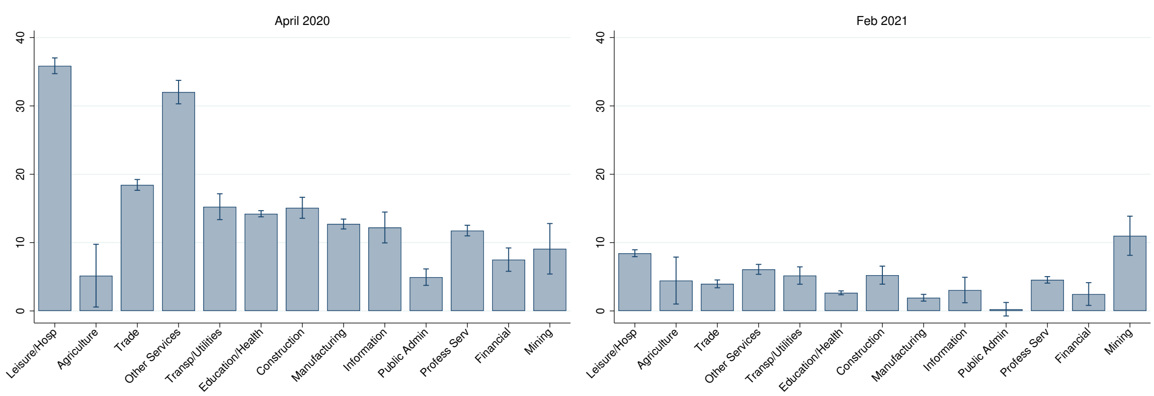
**Panel A: Adjusted Employment Rate**




**Panel B: Hires from Non-Employment**



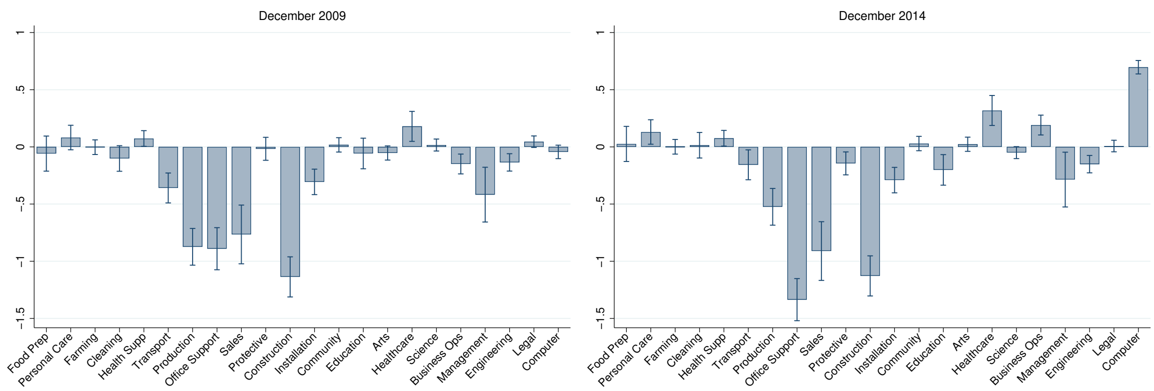

**Panel C: Exits to Non-Employment**



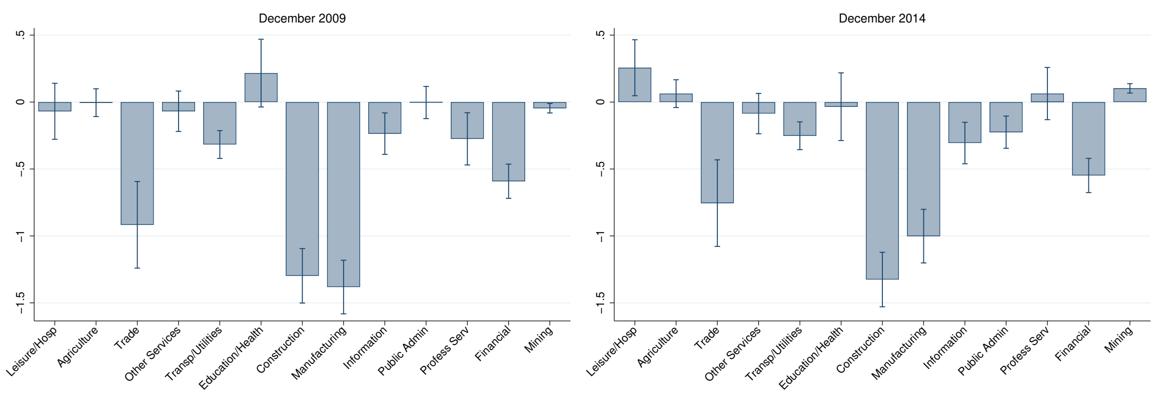

Note: Industries are ranked from lowest- to highest-paying based on their mean wage in January and February 2020; see Table A.2 for details. The figure plots the estimated coefficient $\widehat{\beta}_g$ from Equation (1) for each major industry category, indicating the impact of the pandemic on the dependent variable in April 2020 and February 2021 after controlling for seasonality and year fixed effects. The lines represent 95% confidence intervals using robust standard errors.

Figure 5: Differential Changes in Employment Rates across Occupations and Industries During and After the Great Recession

**Panel A: Across Occupations**

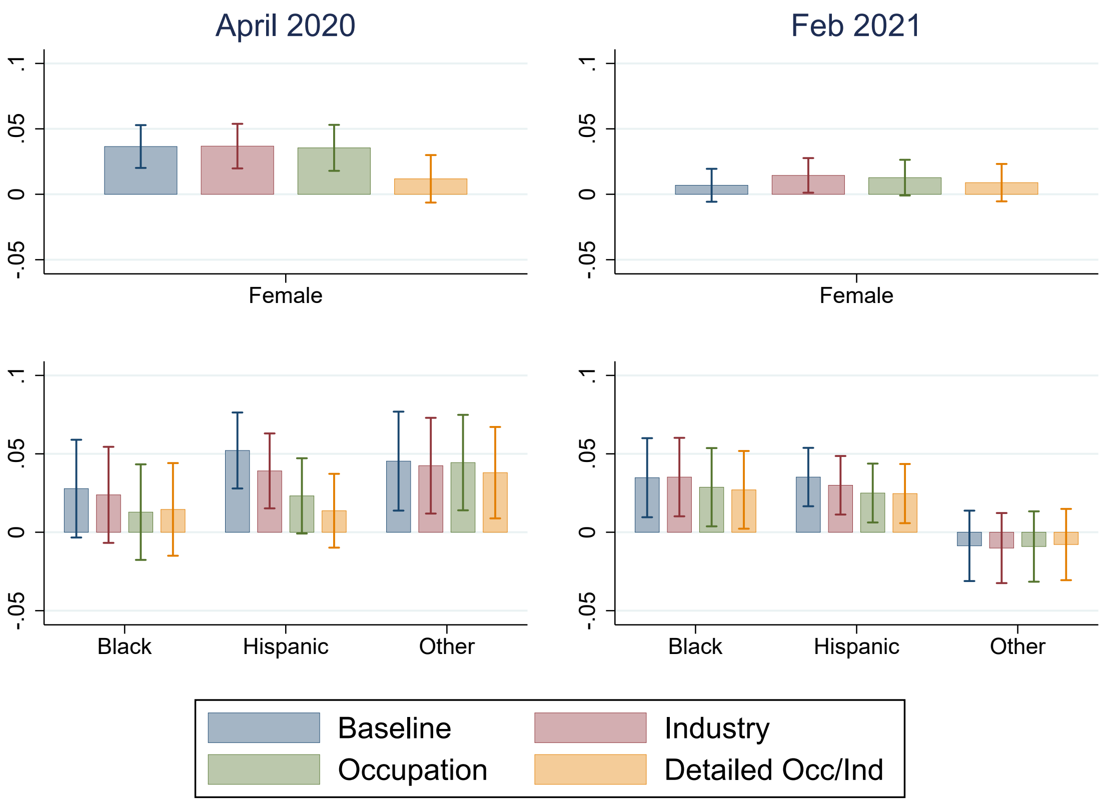



**Panel B: Across Industries**



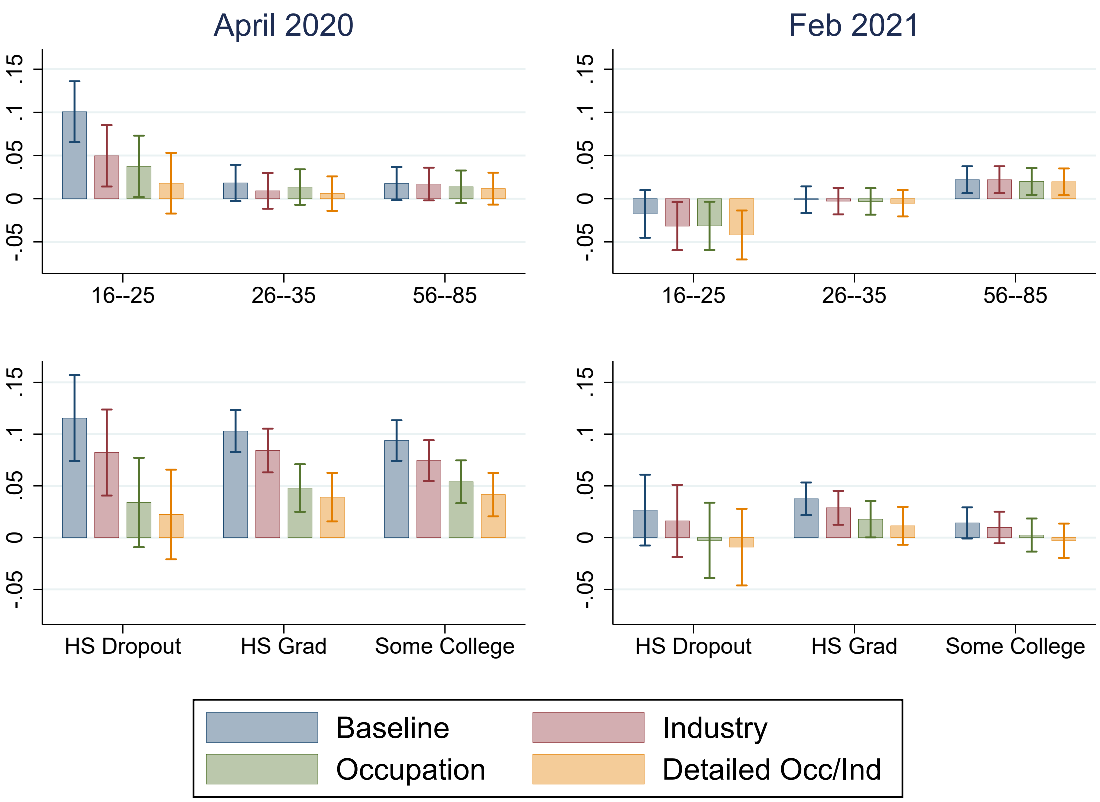

Note: Occupations and industries are ranked from lowest- to highest-paying based on their mean wage in January and February 2020. The figure plots the estimated coefficient $\widehat{\beta}_g$ from Equation (1) for each occupation or industry, using data for the period 2003–2014. The bars are estimates for the change in the employment rate of each occupation and industry as of December 2009 and December 2014, relative to 2007 levels, after controlling for seasonality effects. The lines represent 95% confidence intervals using robust standard errors.

Figure 6: Exits from Employment: Differentials across Demographic Groups with Different Sets of Fixed Effects




Note: The figure displays the estimated coefficients $\widehat{\beta}$ from Equation (2) across demographic groups, indicating the change in the probability of transitioning out of employment for each demographic group between April 2019 and April 2020 (left) and between February 2020 and February 2021 (right), relative to the omitted category (males and whites, respectively), after controlling for group-specific seasonality as well as year fixed effects. Each bar color represents the results from a regression that includes a different set of occupation or industry controls (directly and interacted with dummies for each pandemic month), as listed at the bottom of the graph. The lines represent 95% confidence intervals using robust standard errors.

Figure 7: Exits from Employment: Differentials across Demographic Groups with Different Sets of Fixed Effects




Note: The figure displays the estimated coefficients $\widehat{\beta}$ from Equation (2) across demographic groups, indicating the change in the probability of transitioning out of employment for each demographic group between April 2019 and April 2020 (left) and between February 2020 and February 2021 (right), relative to the omitted category (36-55 year olds and college graduates, respectively), after controlling for group-specific seasonality as well as year fixed effects. Each bar color represents the results from a regression that includes a different set of occupation or industry controls (directly and interacted with dummies for each pandemic month), as listed at the bottom of the graph. The lines represent 95% confidence intervals using robust standard errors.

Table 1: Impact of the Pandemic on Employment Growth Rates and Flows by Demographic Groups

| | Stocks | | | Flows | | | |
|---|---|---|---|---|---|---|---|
| | Feb 2020 | Emp Rate Chg (%) | | Exits | | Hires | |
| | Emp. Rate | April | Feb. | April | Feb. | April | Feb. |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Male | 0.65 | -0.18*** | -0.07*** | 0.14*** | 0.04*** | -0.02*** | -0.02*** |
| | | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| Female | 0.54 | -0.22*** | -0.08*** | 0.18*** | 0.04*** | -0.03*** | -0.02*** |
| | | (0.01) | (0.01) | (0.00) | (0.00) | (0.00) | (0.00) |
| No HS Deg. | 0.35 | -0.31*** | -0.08** | 0.22*** | 0.05*** | -0.06** | -0.04 |
| | | (0.03) | (0.03) | (0.01) | (0.01) | (0.02) | (0.02) |
| HS Grad. | 0.54 | -0.26*** | -0.11*** | 0.20*** | 0.06*** | -0.04*** | -0.01* |
| | | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) |
| Some Col. | 0.60 | -0.23*** | -0.07*** | 0.19*** | 0.04*** | -0.03*** | -0.02*** |
| | | (0.01) | (0.01) | (0.01) | (0.00) | (0.01) | (0.01) |
| Col. Grad. | 0.71 | -0.12*** | -0.04*** | 0.10*** | 0.02*** | -0.02*** | -0.02*** |
| | | (0.01) | (0.01) | (0.00) | (0.00) | (0.00) | (0.00) |
| 16 to 25 | 0.53 | -0.35*** | -0.10*** | 0.24*** | 0.02 | -0.12*** | -0.06** |
| | | (0.02) | (0.02) | (0.02) | (0.02) | (0.02) | (0.02) |
| 26 to 35 | 0.81 | -0.19*** | -0.07*** | 0.16*** | 0.03*** | -0.02*** | -0.01* |
| | | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) |
| 36 to 55 | 0.80 | -0.15*** | -0.05*** | 0.14*** | 0.03*** | -0.01** | -0.01*** |
| | | (0.01) | (0.01) | (0.00) | (0.00) | (0.00) | (0.00) |
| 56 to 85 | 0.38 | -0.19*** | -0.10*** | 0.16*** | 0.06*** | -0.02*** | -0.02*** |
| | | (0.01) | (0.01) | (0.01) | (0.01) | (0.00) | (0.00) |
| White | 0.59 | -0.18*** | -0.06*** | 0.14*** | 0.03*** | -0.02*** | -0.02*** |
| | | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| Black | 0.57 | -0.21*** | -0.10*** | 0.17*** | 0.06*** | -0.04** | -0.04** |
| | | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) |
| Hispanic | 0.63 | -0.25*** | -0.10*** | 0.20*** | 0.06*** | -0.05*** | -0.02* |
| | | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) |
| Other | 0.62 | -0.21*** | -0.06*** | 0.19*** | 0.02* | -0.03* | -0.02 |
| | | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) |

Note: The table lists the estimated coefficients $\widehat{\beta}_g$ from Equation (1) for each demographic group, indicating the change in the dependent variable (the year-on-year growth rate of the employment to population ratio in Columns (2) and (3); the year-on-year exit rate from employment in Columns (4) and (5); and the year-on-year hire rate from non-employment in Columns (6) and (7)) in April 2020 and February 2021 after controlling for seasonality and year fixed effects. Robust standard errors are in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 2: Comparison of the Employment Impacts of the Pandemic and the Great Recession across Demographic Groups

| | Covid Pandemic | | | | Great Recession | | |
|---|---|---|---|---|---|---|---|
| | Feb 2020 | Relative Emp Chg | | | Dec 2007 | Relative Emp Chg | |
| | Emp. Rate | April 20 | Feb 21 | June 21 | Emp. Rate | Dec 09 | Dec 14 |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Male | 0.65 | -0.16*** | -0.05*** | -0.07*** | 0.70 | -0.09*** | -0.07*** |
| | | (0.00) | (0.00) | (0.00) | | (0.01) | (0.01) |
| Female | 0.54 | -0.20*** | -0.06*** | -0.07*** | 0.57 | -0.04*** | -0.05*** |
| | | (0.00) | (0.00) | (0.01) | | (0.01) | (0.01) |
| No HS Deg. | 0.35 | -0.26*** | 0.00 | -0.10*** | 0.38 | -0.13*** | -0.08** |
| | | (0.01) | (0.01) | (0.02) | | (0.03) | (0.03) |
| HS Grad. | 0.54 | -0.24*** | -0.09*** | -0.15*** | 0.59 | -0.07*** | -0.09*** |
| | | (0.00) | (0.00) | (0.01) | | (0.01) | (0.01) |
| Some Col. | 0.60 | -0.22*** | -0.06*** | -0.06*** | 0.68 | -0.08*** | -0.10*** |
| | | (0.00) | (0.00) | (0.01) | | (0.01) | (0.01) |
| Col. Grad. | 0.71 | -0.11*** | -0.05*** | -0.06*** | 0.77 | -0.05*** | -0.06*** |
| | | (0.01) | (0.00) | (0.01) | | (0.01) | (0.01) |
| 16 to 25 | 0.53 | -0.34*** | -0.07*** | -0.05*** | 0.54 | -0.16*** | -0.11** |
| | | (0.01) | (0.01) | (0.01) | | (0.03) | (0.03) |
| 26 to 35 | 0.81 | -0.18*** | -0.06*** | -0.06*** | 0.80 | -0.06*** | -0.02+ |
| | | (0.00) | (0.00) | (0.00) | | (0.01) | (0.01) |
| 36 to 55 | 0.80 | -0.16*** | -0.04*** | -0.04*** | 0.82 | -0.06*** | -0.03*** |
| | | (0.00) | (0.00) | (0.00) | | (0.01) | (0.01) |
| 56 to 85 | 0.38 | -0.20*** | -0.09*** | -0.08*** | 0.37 | -0.01 | 0.01 |
| | | (0.00) | (0.00) | (0.00) | | (0.03) | (0.03) |
| White | 0.59 | -0.16*** | -0.05*** | -0.06*** | 0.64 | -0.06*** | -0.06*** |
| | | (0.00) | (0.00) | (0.00) | | (0.01) | (0.01) |
| Black | 0.57 | -0.18*** | -0.06*** | -0.10*** | 0.57 | -0.11*** | -0.06*** |
| | | (0.01) | (0.01) | (0.01) | | (0.01) | (0.01) |
| Hispanic | 0.63 | -0.24*** | -0.07*** | -0.09*** | 0.64 | -0.08** | -0.05* |
| | | (0.01) | (0.01) | (0.01) | | (0.02) | (0.02) |
| Other | 0.62 | -0.24*** | -0.04*** | -0.07*** | 0.63 | -0.09** | -0.05+ |
| | | (0.01) | (0.01) | (0.01) | | (0.03) | (0.03) |

Note: This table lists estimated coefficients $\widehat{\beta}_g$ from Equation (1) for each demographic group, where the dependent variable is the percentage deviation in the employment to population ratio relative to the beginning of the recession (February 2020 for the pandemic period and December 2007 for the Great Recession). Regressions for the Covid pandemic period use data from January 2015 onwards; regressions for the Great Recession period use data from 2003–2014. Estimates are adjusted for seasonality and year fixed effects. Robust standard errors are in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 3: Share of Exit Rate Differentials Explained by Occupation, Industry, and Geography

| | | Percent of gap explained by: | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Gap | 2-Dig SOC Occ. | Major Ind. | Both | Detailed Occ. | Detailed Ind. | Both Detailed | Occ./Ind. +Metro | Occ/Ind. +Metro +State |
| *April 2020* | | | | | | | | | |
| Female | 0.036 | 2.8% | -2.8% | 2.8% | 55.6% | 25.0% | 66.7% | 65.7% | 67.6% |
| Black | 0.028 | 53.6% | 14.3% | 53.6% | 53.6% | 28.6% | 46.4% | 67.9% | 35.7% |
| Hispanic | 0.052 | 55.8% | 25.0% | 63.5% | 63.5% | 44.2% | 73.1% | 86.5% | 78.8% |
| Other | 0.045 | 2.2% | 6.7% | 4.4% | 17.8% | 20.0% | 15.6% | 26.7% | 31.1% |
| 16 to 25 | 0.101 | 63.4% | 50.5% | 76.2% | 76.2% | 53.5% | 82.2% | 80.9% | 76.5% |
| 26 to 35 | 0.018 | 22.2% | 50.0% | 55.6% | 50.0% | 50.0% | 66.7% | 58.3% | 57.3% |
| 56 to 85 | 0.018 | 22.2% | 5.6% | 16.7% | 33.3% | 16.7% | 33.3% | 52.1% | 50.0% |
| No HS Deg. | 0.115 | 70.4% | 28.7% | 79.1% | 77.4% | 37.4% | 80.9% | 83.2% | 83.2% |
| HS Deg. | 0.103 | 53.4% | 18.4% | 57.3% | 61.2% | 25.2% | 62.1% | 72.2% | 77.8% |
| Some Col. | 0.094 | 42.6% | 21.3% | 47.9% | 55.3% | 22.3% | 55.3% | 33.3% | 33.3% |
| *February 2021* | | | | | | | | | |
| Female | 0.007 | -85.7% | -100.0% | -128.6% | 0.0% | -85.7% | -28.6% | -42.9% | -42.9% |
| Black | 0.035 | 17.1% | 0.0% | 14.3% | 25.7% | 20.0% | 22.9% | 31.4% | 11.4% |
| Hispanic | 0.035 | 28.6% | 14.3% | 31.4% | 31.4% | 17.1% | 28.6% | 40.0% | 51.4% |
| Other | -0.009 | 0.0% | -11.1% | -11.1% | 11.1% | -22.2% | 11.1% | -22.2% | -55.6% |
| 16 to 25 | -0.018 | -72.2% | -77.8% | -105.6% | -116.7% | -88.9% | -133.3% | -127.8% | -133.3% |
| 26 to 35 | -0.001 | -200.0% | -200.0% | -400.0% | -400.0% | -100.0% | -400.0% | -500.0% | -500.0% |
| 56 to 85 | 0.022 | 9.1% | 0.0% | 9.1% | 9.1% | 9.1% | 9.1% | 9.1% | 9.1% |
| No HS Deg. | 0.027 | 111.1% | 40.7% | 122.2% | 122.2% | 66.7% | 133.3% | 133.3% | 140.7% |
| HS Deg. | 0.038 | 52.6% | 23.7% | 60.5% | 65.8% | 36.8% | 71.1% | 65.8% | 63.2% |
| Some Col. | 0.014 | 85.7% | 28.6% | 85.7% | 107.1% | 64.3% | 121.4% | 114.3% | 107.1% |

Note: The first column displays the estimated gap in the impact of the pandemic on employment exit rates for each demographic group (in percentage points) relative to the omitted category (males, whites, 36-55 year olds, and college graduates, respectively) based on the regression results in Figures 6 and 7. The second group of columns displays the fraction of this gap that can be accounted for by workers' pre-displacement occupation and industry. The last two columns display the fraction that can be accounted for by whether the individual lives in a metropolitan area as well as the state of residence, after controlling for detailed occupation and industry fixed effects.

Table 4: Impact of the Pandemic on Employment Growth Rates and Flows by Urban Density

| | Stocks | | | Flows | | | |
|---|---|---|---|---|---|---|---|
| | Feb 2020 | Emp Rate Chg (%) | | Exits | | Hires | |
| | Emp. Rate | April | Feb. | April | Feb. | April | Feb. |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Non-Metro | 0.54 | -0.17*** | -0.05*** | 0.15*** | 0.04*** | -0.02* | -0.02* |
| | | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) |
| Central City | 0.60 | -0.20*** | -0.09*** | 0.18*** | 0.05*** | -0.03*** | -0.02*** |
| | | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) |
| Outside Central City | 0.60 | -0.21*** | -0.07*** | 0.16*** | 0.04*** | -0.03*** | -0.02*** |
| | | (0.01) | (0.01) | (0.01) | (0.00) | (0.00) | (0.00) |
| Unknown Status | 0.57 | -0.18*** | -0.04** | 0.12*** | 0.02 | -0.03** | -0.02** |
| | | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) |

Note: The table lists the estimated coefficients $\widehat{\beta}_g$ from Equation (1) for each level of metro density where the respondent resides, indicating the change in the dependent variable (employment to population ratio growth rate, exits or hires) in April 2020 and February 2021 after controlling for seasonality and year fixed effects. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

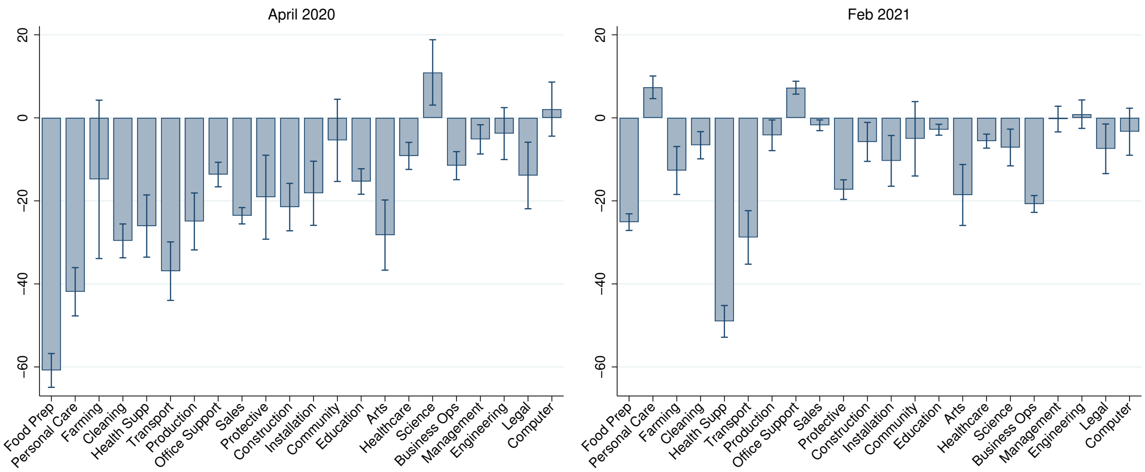
# A Appendix (For Online Publication)

Figure A.1: Year-on-Year Changes in Employment based on Stock and Flow Data

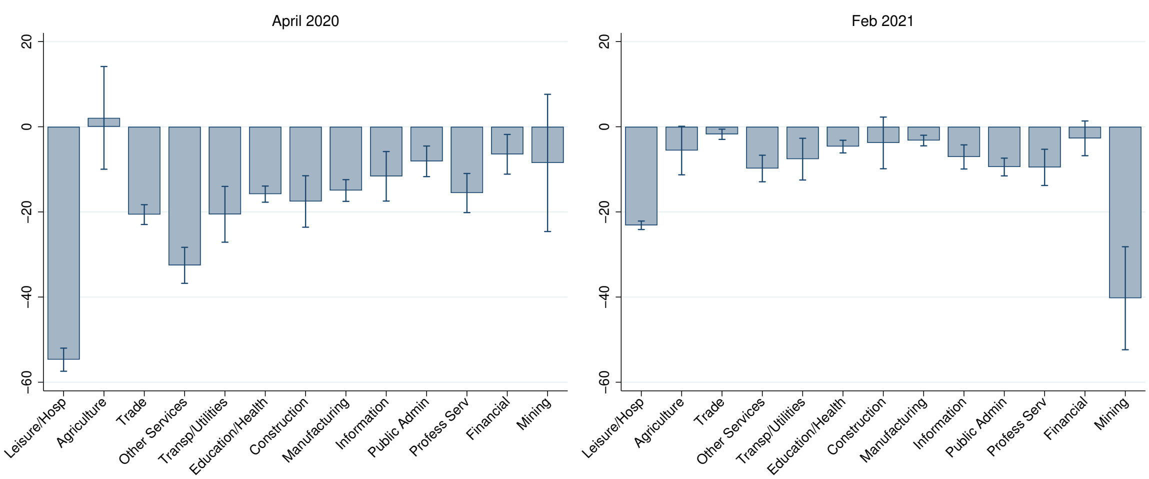

Note: The figure plots year-on-year changes in employment (in millions of people) based on the stocks from the monthly CPS data, and based on the flow rates constructed from the matched monthly samples. The markers indicate data for April 2020 and February 2021.

Figure A.2: Impact of the Pandemic on Year-on-Year Employment Growth Rates

**Panel A: Across Occupations**

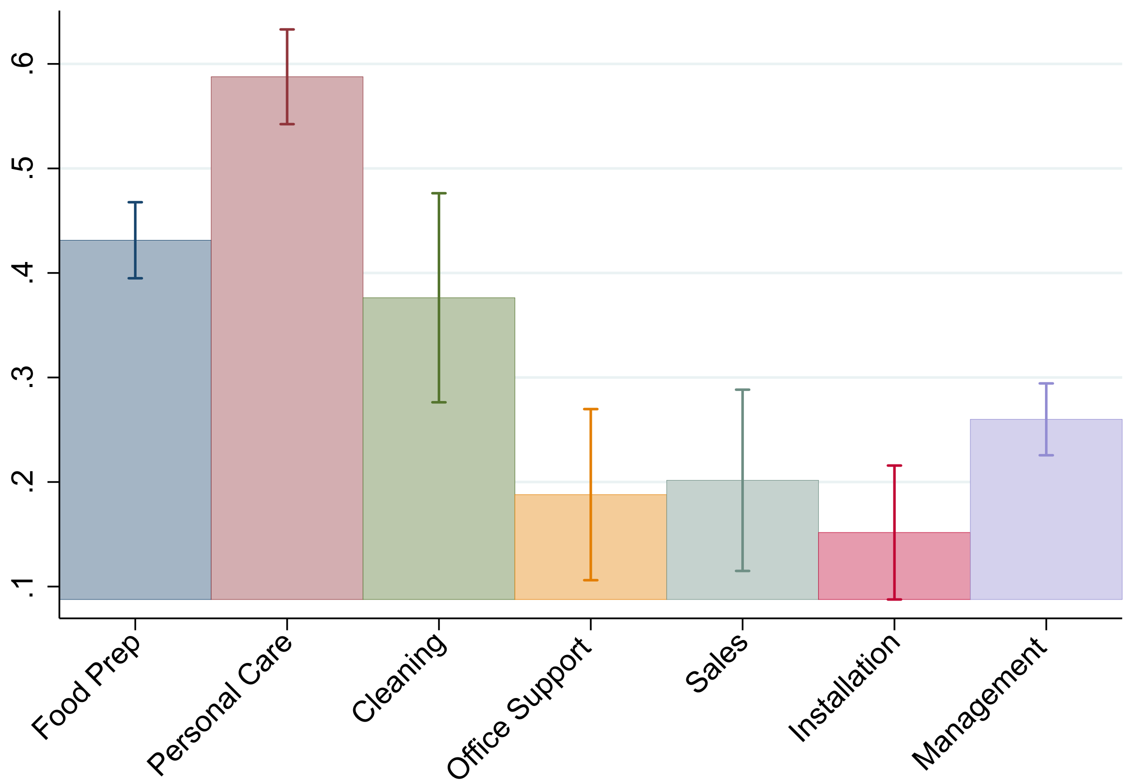



**Panel B: Across Industries**



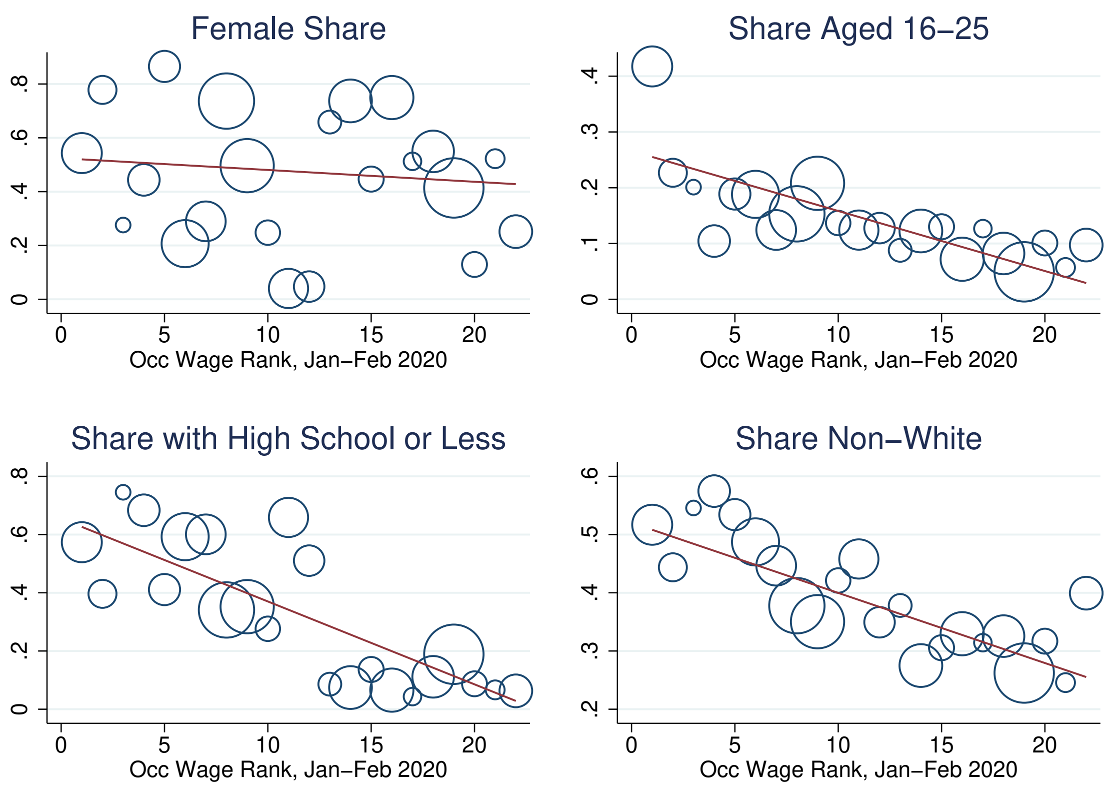

Note: Occupations and industries are ranked from lowest- to highest-paying based on their mean wage in January and February 2020. The figure plots the estimated coefficient $\widehat{\beta}_g$ from Equation (1) for each occupation or industry, indicating the impact of the pandemic on the year-on-year employment growth rate in April 2020 and February 2021 after controlling for seasonality and year fixed effects. The lines represent 95% confidence intervals using robust standard errors.

Figure A.3: Impact of the Pandemic on Employment Exit Rates across Occupations within Service Industries, April 2020



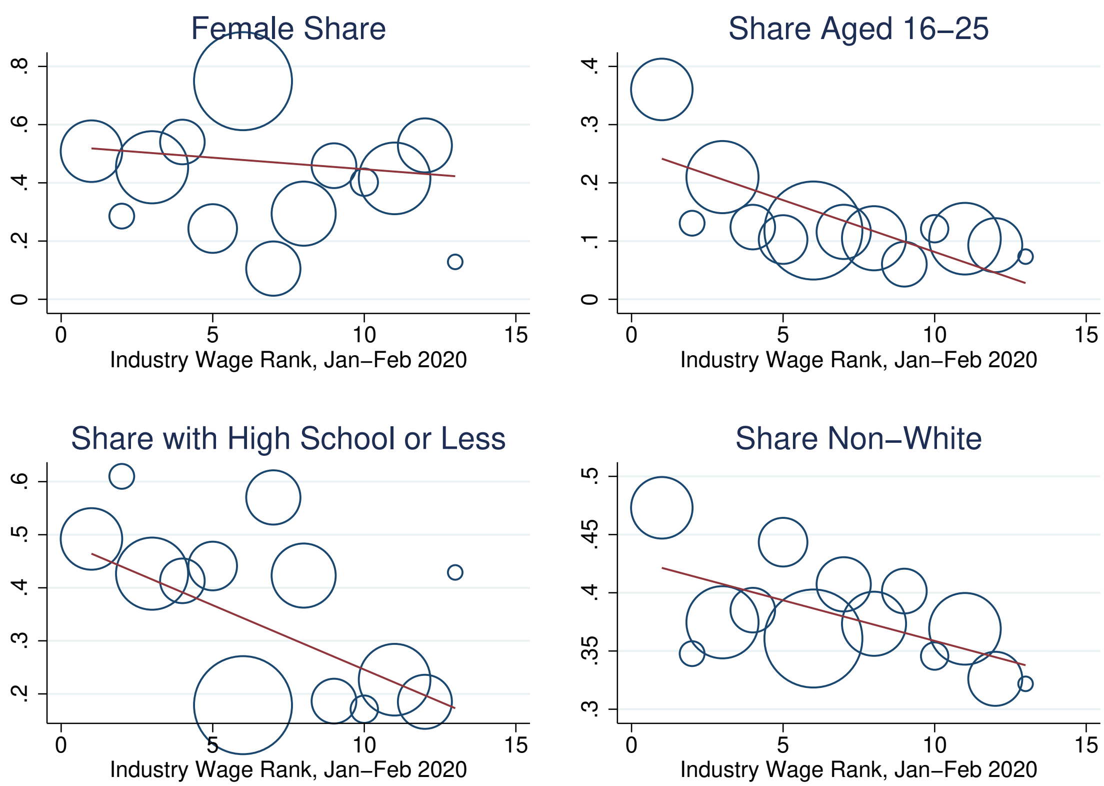

Note: Occupations are ranked from lowest- to highest-paying based on their mean wage in January and February 2020. The figure plots the estimated coefficient $\widehat{\beta}_g$ from Equation (1) for each occupation, using data from the Leisure and Hospitality, and Other Service industries only. The estimated coefficients indicate the change in the exit rate for each occupation in April 2020 after controlling for seasonality and year fixed effects. The lines represent 95% confidence intervals using robust standard errors.

Figure A.4: Demographic Shares within 2-digit Occupations, February 2020



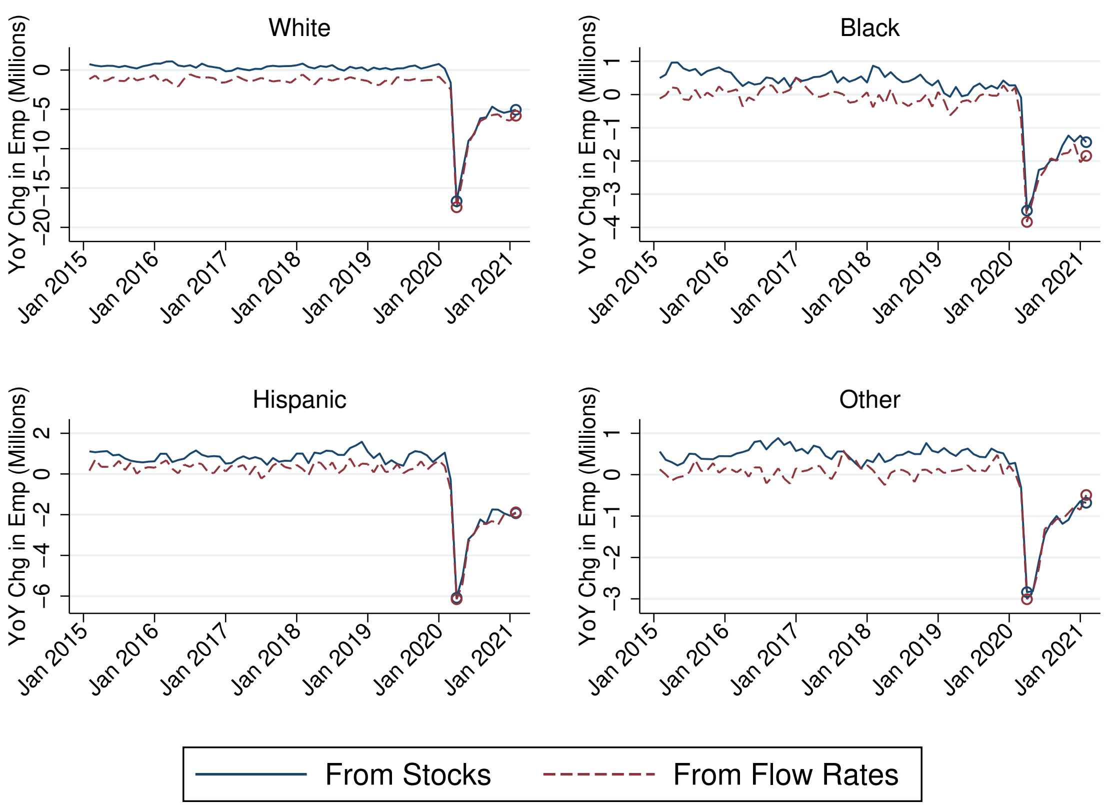

Note: The figure plots the share of different demographic groups among workers in each 2-digit occupation before the onset of the pandemic (February 2020). Occupations are ranked based on their average wages in the pre-pandemic period of January and February 2020. The size of each circle is proportional to the size of the occupation in February 2020.

Figure A.5: Demographic Shares within Major Industries, February 2020




Note: The figure plots the share of different demographic groups among workers in each major industry category before the onset of the pandemic (February 2020). Industries are ranked based on their average wages in the pre-pandemic period of January and February 2020. The size of each circle is proportional to the size of the industry in February 2020.

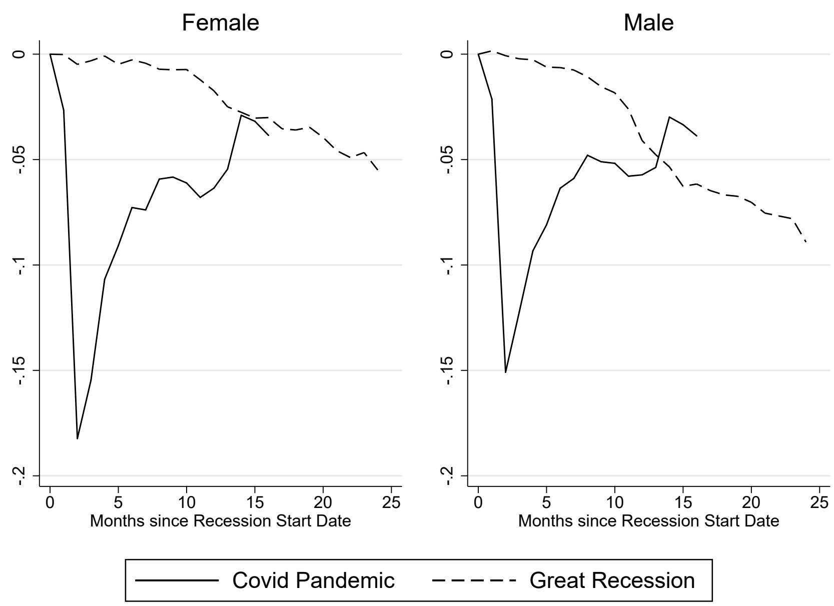
Figure A.6: Year-on-Year Changes in Employment for Racial and Ethnic Groups based on Stock and Flow Data



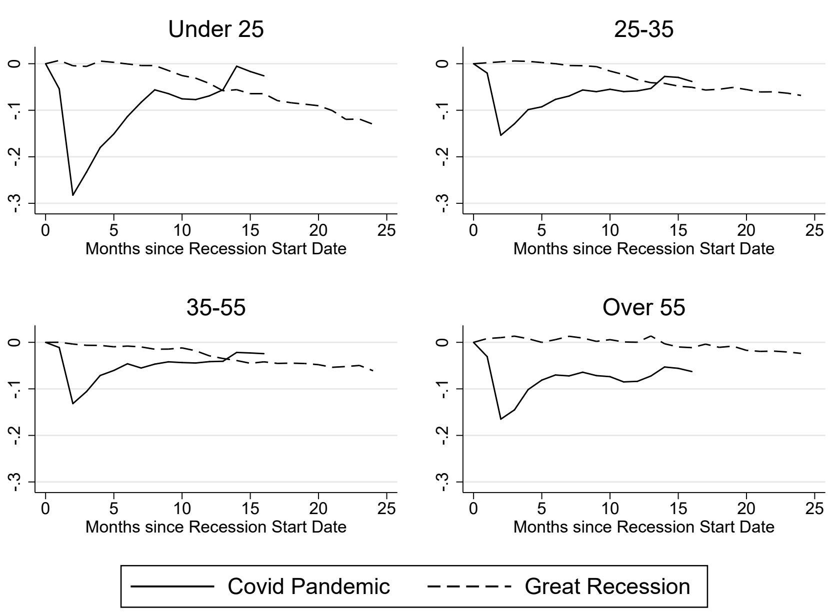

Note: The figure plots year-on-year changes in employment (in millions of people) based on the stocks from the monthly CPS data, and based on the flow rates constructed from the matched monthly samples. The markers indicate data for April 2020 and February 2021. Each demographic group is mutually exclusive.

Figure A.7: Comparison of Covid Pandemic with Great Recession, Percentage Point Change in Employment-to-Population Ratio by Group

**Panel A: Gender**



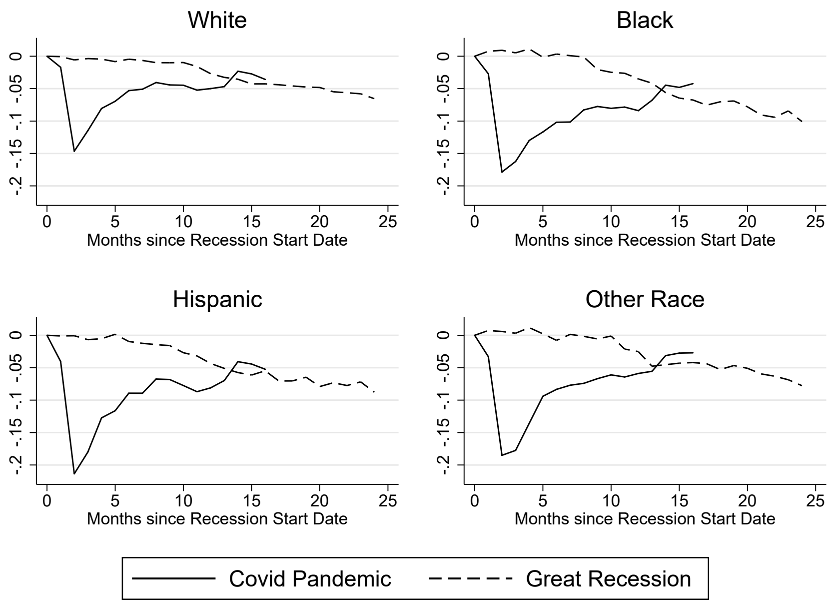

**Panel B: Age**



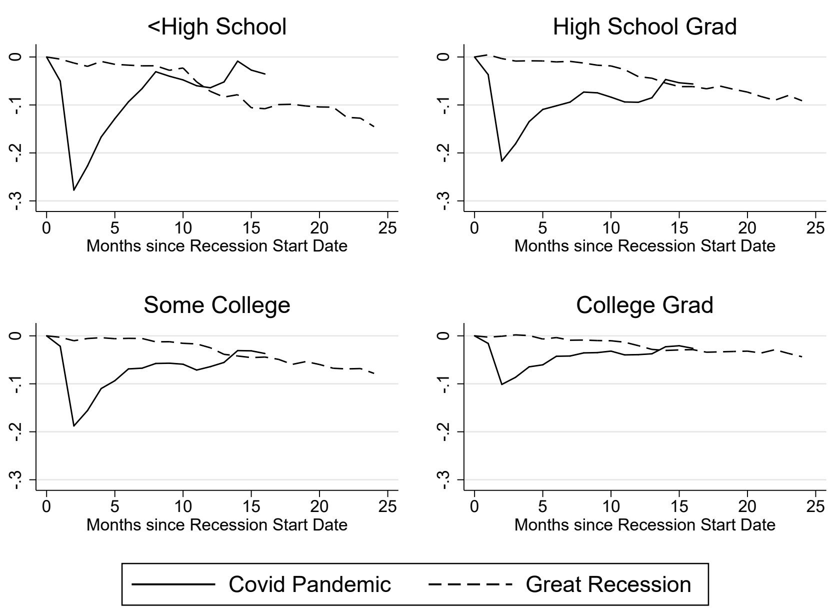

Note: Percentage point change in employment to population ratio for each demographic group, relative to December 2007 (dotted line) and February 2020 (solid line). Ratio is adjusted for classification error (see Section 2) and seasonally adjusted.

Figure A.8: Comparison of Covid Pandemic with Great Recession, Percentage Point Change in Employment-to-Population by Group

**Panel A: Race**




**Panel B: Education**




Note: Percentage point change in employment to population ratio for each demographic group, relative to December 2007 (dotted line) and February 2020 (solid line). Ratio is adjusted for classification error (see Section 2) and seasonally adjusted.

Figure A.9: Changes in demographic shares within 2-digit occupations, April 2019–April 2020


Note: The figure plots the change in the share of different demographic groups among workers in each 2-digit occupation at the onset of the pandemic (April 2020) relative to a year earlier. Occupations are ranked based on their average wages in the pre-pandemic period of January and February 2020. The size of each circle is proportional to the size of the occupation in April 2019.

Figure A.10: Changes in Demographic Shares within Major Industries, April 2019–April 2020


Note: The figure plots the change in the share of different demographic groups among workers in each major industry at the onset of the pandemic (April 2020) relative to a year earlier. Industries are ranked based on their average wages in the pre-pandemic period of January and February 2020. The size of each circle is proportional to the size of the industry in April 2019.

Table A.1: Changes in Employment by Occupation

| 2-digit SOC | Occupation | Wage Rank (1=lowest) | Log Real Wage (Jan-Feb 2020) | Δ Emp/Pop to: Apr 2020 | Δ Emp/Pop to: Feb 2021 |
|---|---|---|---|---|---|
| 35 | Food Prep and Serving | 1 | 2.41 | -1.87 | -0.68 |
| 39 | Personal Care, Service | 2 | 2.60 | -1.19 | -0.35 |
| 45 | Farm, Fish, Forestry | 3 | 2.63 | -0.07 | -0.06 |
| 37 | Cleaning, Maintenance | 4 | 2.64 | -0.70 | -0.19 |
| 31 | Healthcare Support | 5 | 2.69 | -0.24 | -0.18 |
| 53 | Transportation | 6 | 2.82 | -1.03 | -0.32 |
| 51 | Production | 7 | 2.87 | -0.93 | -0.24 |
| 43 | Office/Admin Support | 8 | 2.87 | -1.16 | -0.19 |
| 41 | Sales and Related | 9 | 2.92 | -1.49 | -0.21 |
| 33 | Protective Service | 10 | 3.03 | -0.13 | -0.13 |
| 47 | Construction, Extraction | 11 | 3.07 | -0.86 | -0.30 |
| 49 | Installation, Maintenance | 12 | 3.07 | -0.22 | -0.10 |
| 21 | Community/Social Service | 13 | 3.14 | -0.04 | -0.02 |
| 25 | Education | 14 | 3.16 | -0.66 | -0.18 |
| 27 | Arts, Entertainment, Media | 15 | 3.25 | -0.27 | -0.16 |
| 29 | Healthcare | 16 | 3.40 | -0.25 | -0.12 |
| 19 | Science | 17 | 3.45 | 0.01 | -0.02 |
| 13 | Business/Financial Op | 18 | 3.47 | 0.10 | -0.24 |
| 11 | Management | 19 | 3.52 | -0.48 | -0.07 |
| 17 | Architecture/Engineering | 20 | 3.59 | -0.12 | -0.05 |
| 23 | Legal | 21 | 3.62 | -0.08 | -0.04 |
| 15 | Computer/Mathematical | 22 | 3.62 | 0.19 | 0.07 |

Note: Occupations are ranked from lowest- to highest-paying based on their mean wage in January and February 2020. Real wages are expressed in June 2020 dollars. Changes in the employment to population ratio in the last two columns are calculated over 12-month horizons. Our employment measure excludes individuals who were absent from work during the reference week for "other" reasons and report not being paid by their employer for their time off.

Table A.2: Changes in Employment by Industry

| BLS Code | Industry | Wage Rank (1=lowest) | Log Real Wage (Jan-Feb 2020) | Δ Emp/Pop to: Apr 2020 | Feb 2021 |
|---|---|---|---|---|---|
| 11 | Leisure and Hospitality | 1 | 2.59 | -2.94 | -1.14 |
| 1 | Agriculture, Forestry, Fishing | 2 | 2.70 | -0.01 | -0.07 |
| 5 | Wholesale and Retail Trade | 3 | 2.85 | -1.43 | -0.05 |
| 12 | Other Services | 4 | 2.90 | -1.00 | -0.33 |
| 6 | Transportation and Utilities | 5 | 3.10 | -0.56 | -0.14 |
| 10 | Educational and Health Services | 6 | 3.11 | -2.24 | -0.65 |
| 3 | Construction | 7 | 3.12 | -0.86 | -0.20 |
| 4 | Manufacturing | 8 | 3.14 | -1.11 | -0.38 |
| 7 | Information | 9 | 3.26 | -0.09 | -0.05 |
| 13 | Public Administration | 10 | 3.26 | 0.01 | -0.06 |
| 9 | Professional/Business Services | 11 | 3.29 | -0.98 | -0.55 |
| 8 | Financial Activities | 12 | 3.35 | -0.25 | -0.07 |
| 2 | Mining | 13 | 3.46 | 0.00 | -0.10 |

Note: Industries are ranked from lowest- to highest-paying based on their mean wage in January and February 2020. Real wages are expressed in June 2020 dollars. Changes in the employment to population ratio in the last two columns are calculated over 12-month horizons. Our employment measure excludes individuals who were absent from work during the reference week for "other" reasons and report not being paid by their employer for their time off.