HETEROGENEOUS LABOR MARKET IMPACTS OF THE COVID-19 PANDEMIC

GUIDO MATIAS CORTES AND ELIZA FORSYTHE*

The authors study the distributional consequences of the COVID-19 pandemic's impact on employment, both during the onset of the pandemic and over subsequent months. Using cross-sectional and matched longitudinal data from the Current Population Survey, they show that the pandemic has exacerbated pre-existing inequalities. Although employment losses have been widespread, they have been substantially larger—and more persistent—in lower-paying occupations and industries. 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 over 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 nor by the associated response in terms of mitigation policies. In addition, evidence suggests that older workers have been retiring at faster rates.

The COVID-19 pandemic led to a 10.3 percentage point (p.p.) 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 article 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 affected by the pandemic? And are the differential impacts

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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 subsequent months.

We use data through June 2021 from the Current Population Survey (CPS), the primary source of labor force statistics for the United States. We take advantage of the rotating panel structure of the survey 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 attributable to individuals exiting employment, relative to reduced hiring. Next, we 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 subsequent months. We then turn to the heterogeneous impact of the pandemic across demographic groups. 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 specific demographic groups tend to work in more affected 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 also varied across locations. We therefore explore the extent to which differences between groups, conditional on pre-displacement occupation and industry, can be explained by differences in the effect 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 effects on certain groups of workers. Our results show that the pandemic particularly affected 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.

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 articles that are most related to our work, and we highlight our key contributions.

Using data on occupational characteristics from data sets such as O*NET, a number of articles 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, Brodeur, and Wright 2020; Dey, Frazis, Loewenstein, and Sun 2020; Dingel and Neiman 2020; Mongey, Pilossoph, and Weinberg 2021). In this article, we instead focus on the distributional consequences of the pandemic's employment impacts and contribute a number of novel pieces of evidence about the influence of the pandemic, both in its early stages and over more recent periods.

Several related articles 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 used data from ADP, a large US payroll processing company; Coibion, Gorodnichenko, and Weber (2020), who used data from the Nielsen Homescan panel; Bartik et al. (2020), who used data from Homebase; and Chetty et al. (2020), who built 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 and Kim (2021) examined the gender dimension of the pandemic, while Montenovo et al. (2020) and Couch, Fairlie, and Xu (2020) also used CPS data to explore the heterogeneous employment impacts of the pandemic across demographic groups. Cortes and Forsythe (2020) and Dalton et al. (2021) examined heterogeneity across the individual and establishment wage distribution.

Although 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 individual 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. In contrast to most of the existing literature using CPS data, by focusing on flows rather than on cross-sectional data, we are able to consider not only individuals who transition into unemployment but also those who transition to non-participation. As we show below, the pandemic induced substantial excess worker flows toward both of these labor market states, as many individuals who left employment did not immediately search for new employment. 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. We also provide new results on which groups have benefited from the economic recovery observed between April 2020 and February 2021.

Data and Aggregate Patterns

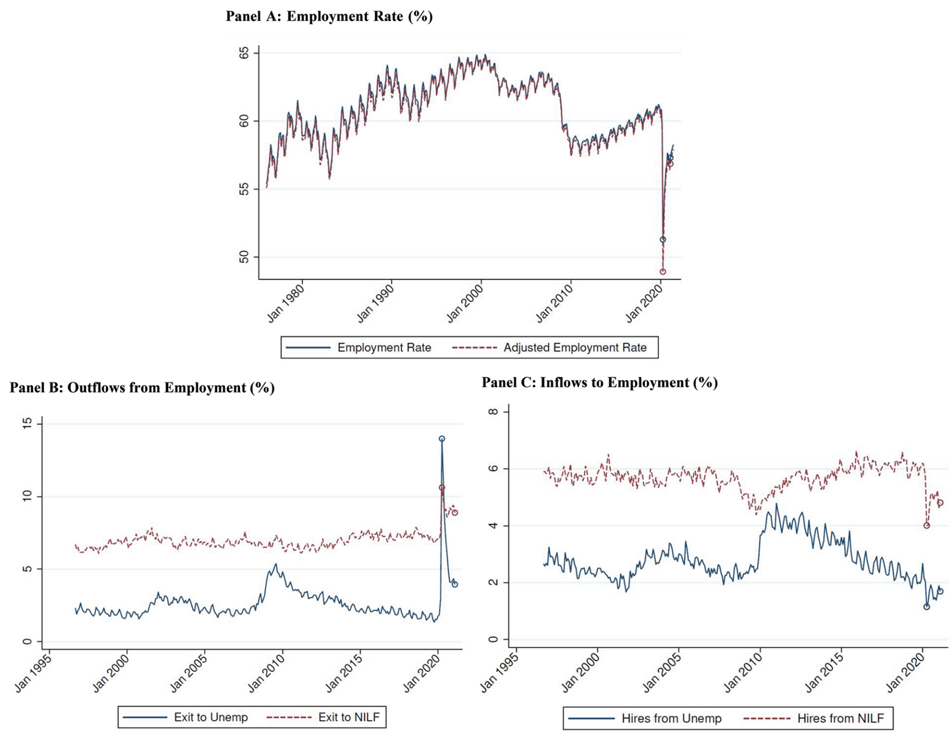
Our analysis is based on data from the monthly Current Population Survey (CPS), the official source for labor market statistics in the United States. The CPS is sponsored jointly by the US Census Bureau and the US Bureau of Labor Statistics (BLS). We rely on the microdata made publicly available by IPUMS (Flood et al. 2020). We restrict the sample to non-institutionalized civilians age 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 and Lefgren (1999) by matching monthly files using administrative IDs and confirming matches based on sex, race, and age. Online Appendix Figure A.1 (hereafter, numbering for Online Appendix material is prefaced with an "A.") 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, Robison, Evans, and Duff 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 lock-down orders and other strict social distancing measures had not yet been implemented at the time of the March 2020 survey. Hence, the March 2020 CPS data captures only 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 when the impacts of the pandemic were most acutely felt, and in February 2021, the most recent period for which we can compute year-on-year changes relative to a pre-pandemic period. When 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

Figure 1. Aggregate Employment Rate and Labor Market Flows



Notes: The figure plots monthly employment rates and year-on-year labor market flows (percentage of employed individuals who exit employment to non-employment, and percentage 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 circles indicate data for April 2020 and February 2021. NILF, not-in-the-labor-force.

the 12-month period prior to and including February 2020 to 73% in March, then ranging from 65% to 70% between April and August, and recovering to approximately 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."[1] 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

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

classified as employed in a given month divided by the population in that month. The dashed, red line displays an adjusted employment rate that excludes certain individuals who are likely to have been misclassified as employed during the pandemic. Specifically, in April 2020, a large increase is observed in the group of individuals who report that they were employed but absent 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 1) were absent from work during the reference week, 2) report being absent for "other" reasons, and 3) 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 farther, from 60.7% in February to 48.9% in April. As of February 2021, both measures have recovered to approximately 57%, with some slight further recovery in 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 2021. 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 toward 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. More than 80% of the dramatic initial rise in non-employment is attributable to exits from employment, rather than decreased hiring. This outcome contrasts with the pattern typically observed during recessions, in which a collapse in hiring is usually the dominant driver of increased unemployment rates (see Elsby, Michaels, and Solon 2009; Fujita and 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 article explores heterogeneities in the employment effects of the pandemic across occupations, industries, and demographic groups. 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 onward. The regressions are estimated using collapsed data at the group level for each month (for which groups may be either occupations, industries, or demographic categories) and are run separately for each group. The regression takes the following form:

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

The outcome variable of interest is denoted Y_{gt} for group g in period t. For the stock analysis, this variable is the employment rate of group g in a given month. For hires and exits, we use matched data over one-year windows, and we calculate the rates of hiring and exiting as shares of the stock of employment at the beginning of the window. Indicator $D_{m(t)}$ is a vector of calendar month dummies. The coefficient γ_g captures any seasonal variation in outcomes that are specific to the group being considered. Indicator $D_{y(t)}$ is a vector of year dummies, so that α_g accounts for year-by-year variation in the outcome of interest for the specific group.[2] Indicator

[2]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.

D_t^C is an indicator for the COVID-19 pandemic months, that is, a vector of dummies for each individual month from March 2020 onward.[3] Our coefficient of interest, β_g, is a vector that captures 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 β_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.

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.[4] Thus, we expect significantly heterogeneous impacts across jobs, leading to differential impacts across workers, with potentially important distributional implications.

Heterogeneous Impacts across Occupations and Industries

Following a similar approach to the literature on job polarization (e.g., Autor, Katz, and Kearney 2006; Goos and Manning 2007; Acemoglu and Autor 2011), we analyze the distributional 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.[5] For occupations, we focus on 22, 2-digit Standard Occupational Classification (SOC) occupations, which are detailed in Table A.1 (ranked from lowest to highest paying).[6] 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.

[3]For the flow variables, the April 2020 dummy, for example, is equal to 1 for the flows between April 2019 and April 2020.

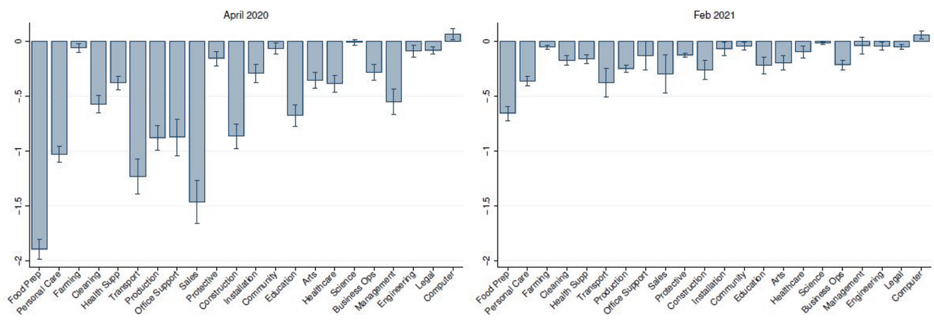
[4]See, for instance, https://slate.com/business/2020/05/south-reopening-restaurants-coronavirus-opentable.html.

[5]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.

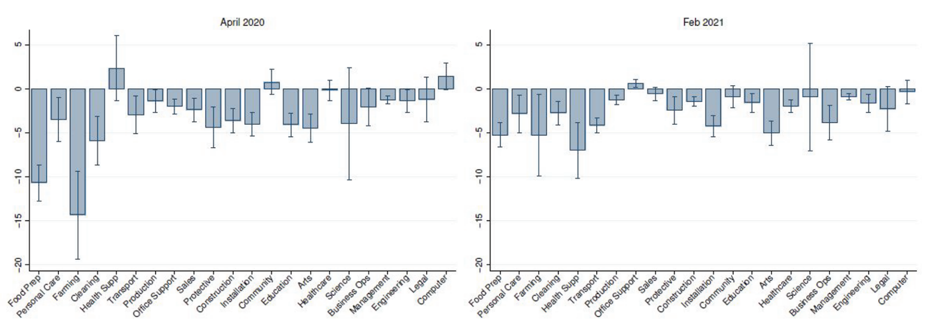
[6]The detailed occupational codes used in the CPS changed in January 2020 (from 2010 to 2018 Census code categories); however, the changes are relatively minor and do not affect the comparability over time at the 2-digit SOC level.

Figure 2. Impact of the Pandemic across Occupations

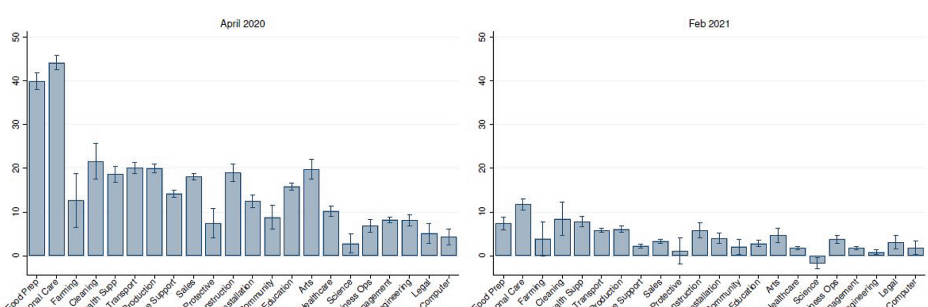
Panel A: Adjusted Employment Rate



Panel B: Hires from Non-Employment



Panel C: Exits to Non-Employment



Notes: 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 vertical lines represent 95% confidence intervals using robust standard errors.

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. Specifically, 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.[7]

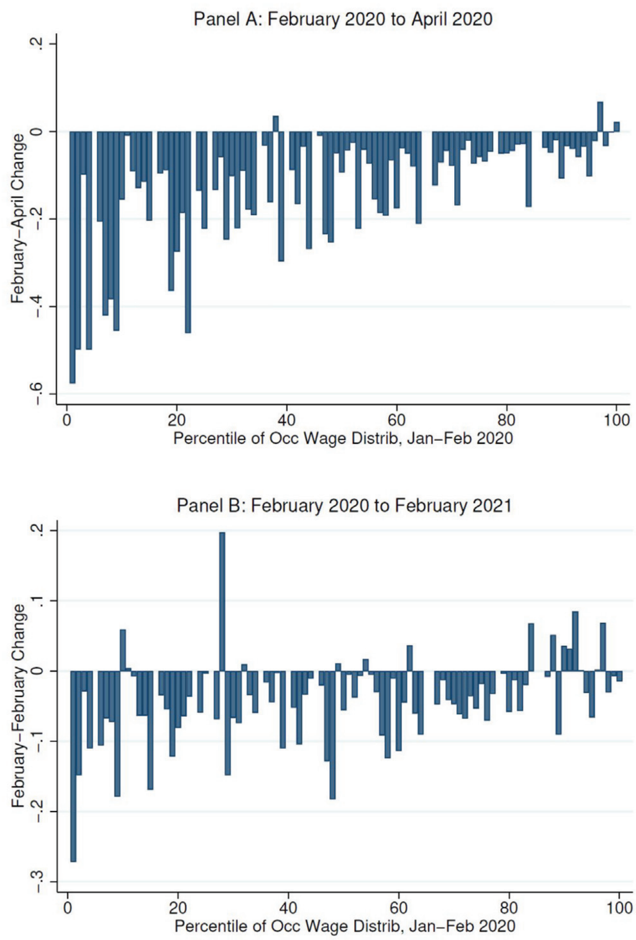
Panels B and C of Figure 2 examine the hire rate from non-employment and the exit rate to non-employment for each occupation. These rates are calculated as a share of employment in that occupation one year earlier. This approach puts both inflows and outflows on the same denominator, which makes it easier 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 for Personal Care occupations, more than a 40 p.p. increase occurs in the share of individuals exiting employment between April 2019 and April 2020. By contrast, all six of the highest-paying occupations have exit rate increases of less than 10 p.p. When considering the impact as of February 2021, we still observe a relationship between occupational wage rankings and the magnitude of the impact of the pandemic, with generally 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, a fairly monotonic relationship between wage rankings and the size of the employment losses is apparent in April. As of February 2021, employment losses still tend to be disproportionately larger in lower-paying occupations,

[7]Panel A of 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 employment lost within each occupation (rather than the fraction of aggregate employment losses attributable to each occupation).

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



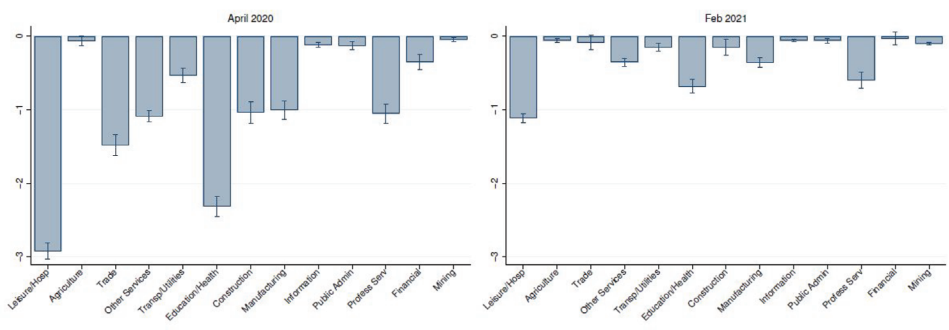
Notes: The figure plots change relative to February 2020 in employment rates (per capita) for occupations at each percentile of the employment-weighted occupational wage distribution (the assignment to percentiles is based on employment and wages in the pre-pandemic period of January and February 2020). 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.

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).

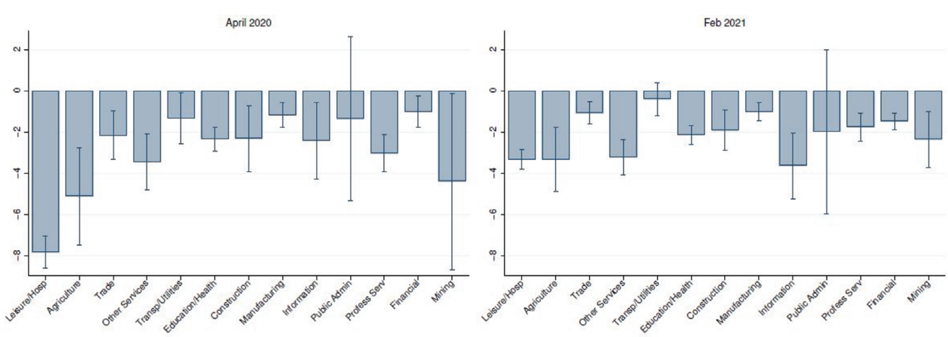
We next explore employment changes at the industry level. Figure 4 shows how employment losses are distributed across 13 major industry categories, once again ranked from lowest paying on the left to highest paying on the right, as detailed in Table A.2. As with occupations, the decline in employment tends to be concentrated in lower-paying industries. The largest employment decline is observed in the Leisure and Hospitality sector, which

Figure 4. Impact of the Pandemic across Industries

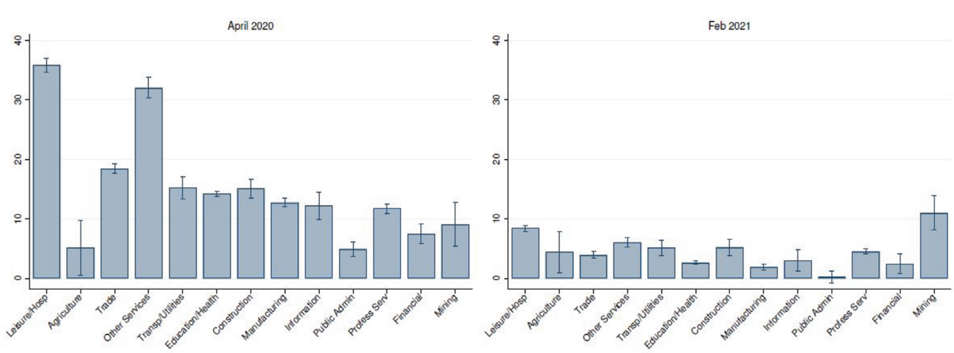
Panel A: Adjusted Employment Rate



Panel B: Hires from Non-Employment



Panel C: Exits to Non-Employment



Notes: 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 vertical lines represent 95% confidence intervals using robust standard errors.

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 p.p. year-on-year to April, as shown in panel C), whereas the highest-paying industries (Public Administration, Professional Services, and Financial Activities) saw much smaller increases in exit rates.[8]

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 detectable not only when considering the immediate aftermath 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.

Note that these patterns differ from what has typically been observed during recent recession and recovery periods. As Jaimovich and 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. 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 onward (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 and Siu (2020) evidence, the figure shows that the job losses during the Great Recession were disproportionately concentrated among middle-wage occupations and industries, both at the point of the employment trough, in December 2009, and also in the recovery period, in December 2014.

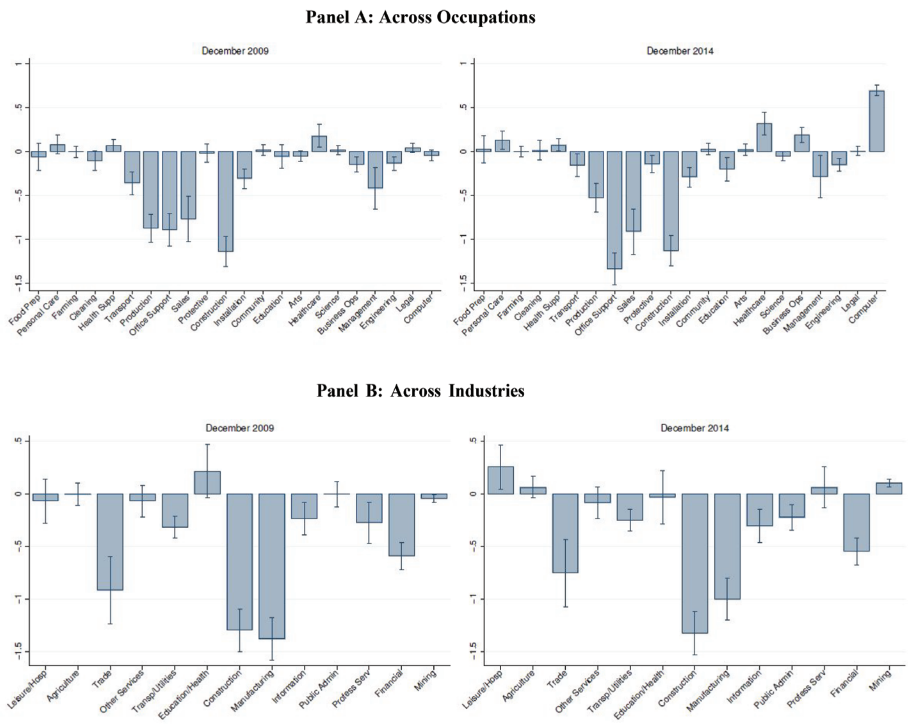
Heterogeneous Impacts across Demographic Subgroups

Research has long established 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 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

[8]Panel B of 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.

Figure 5. Differential Changes in Employment Rates across Occupations and Industries during and after the Great Recession



Notes: 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 vertical lines represent 95% confidence intervals using robust standard errors.

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.

Beginning with gender, overall we see that the growth rate of the employment to population ratio fell by 22 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.

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

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

	Feb 2020	Stocks: Emp rate change (%)		Flows: Exits		Flows: Hires	
	Emp rate (1)	April 2020 (2)	Feb 2021 (3)	April 2020 (4)	Feb 2021 (5)	April 2020 (6)	Feb 2021 (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 degree	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 graduate	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 college	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)
College graduate	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)
Age 16–25	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)
26–35	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)
36–55	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)
56–85	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)

Notes: 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.
$*p < 0.05$; $**p < 0.01$; $***p < 0.001$.

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 in April for workers under 25 compared to older workers, 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 finding is consistent with previous evidence that employment of Hispanic and non-White groups is notably hard-hit during recessions, likely attributable to hiring discrimination (Forsythe and 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 especially 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 1 to 4 p.p. in most cases. Workers younger than age 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 (2021), which showed 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 finding 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, some deviations occur between the patterns based on stocks and the patterns based on flows. In 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

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

flow-based results in Columns (4) through (7) of Table 1, we find that Black workers have suffered more severe employment losses than did White workers during the pandemic period.

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. Since the Great Recession lasted more than a year, we cannot use our year-over-year estimation strategy. Instead, we estimate the impact of each recession on the percentage change in the employment rate compared to the last pre-recession month (February 2020 and December 2007, respectively). As before, for the COVID period, 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). For the Great Recession period, we use data from 2003 to 2014, and we consider the impacts as of December 2009, which is near the employment trough in the aftermath of the Great Recession, and as of December 2014, which is several years after the end of the recession, and is at a point in time at which the aggregate employment rate had experienced a recovery that is roughly similar to what has been observed in the aftermath of the COVID shock.

Table 2 shows the results of this analysis. 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]

Columns (6) and (7) show that the Great Recession generated larger employment declines for men than for 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 at a similar point in the respective recoveries (i.e., employment has recovered by a

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

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 change*			*Dec 2007*	*Relative emp change*	
	Emp rate (1)	*April 2020* (2)	*Feb 2021* (3)	*June 2021* (4)	*Emp rate* (5)	*Dec 2009* (6)	*Dec 2014* (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 degree	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 graduate	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 college	0.60	−0.22***	−0.06***	−0.06***	0.68	−0.08***	−0.10***
		(0.00)	(0.00)	(0.01)		(0.01)	(0.01)
College graduate	0.71	−0.11***	−0.05***	−0.06***	0.77	−0.05***	−0.06***
		(0.01)	(0.00)	(0.01)		(0.01)	(0.01)
Age 16–25	0.53	−0.34***	−0.07***	−0.05***	0.54	−0.16***	−0.11**
		(0.01)	(0.01)	(0.01)		(0.03)	(0.03)
26–35	0.81	−0.18***	−0.06***	−0.06***	0.80	−0.06***	−0.02
		(0.00)	(0.00)	(0.00)		(0.01)	(0.01)
36–55	0.80	−0.16***	−0.04***	−0.04***	0.82	−0.06***	−0.03***
		(0.00)	(0.00)	(0.00)		(0.01)	(0.01)
56–85	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)

Notes: The 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 onward; 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.
$^*p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

similar proportion relative to the respective troughs), we see that in December 2014 young workers' employment rates had fallen by 9 p.p. more than employment rates of 26- to 35-year-old workers, whereas in June 2021 the employment rate impacts are statistically indistinguishable across these two groups. By contrast, while workers over 55 saw an initial employment rate decline that was larger than the 26- to 55-year-olds in April 2020, during the Great Recession these workers saw little employment decline. By June

2021, employment rates for workers older than 55 remain depressed by 8 p.p.

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 to 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, Miller, and Schaller (2012), with the major exceptions being the results for men (which are consistent with the findings of Alon et al. [2021]) and the results for older workers (which are 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 as compared to Black and Hispanic workers, which is a pattern that was not observed in the aftermath of the Great Recession.

Explaining Heterogeneous Impacts across Demographic Subgroups: Occupation, Industry, and Geography

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 first investigate whether the disproportionate employment losses experienced by disadvantaged demographic groups are because they are over-represented in the jobs that contracted most sharply (as shown in Figures A.4 and A.5), or if these workers experienced worse losses also *within* job categories. We then turn to the role of local density and state of residence.

We focus on outflows from employment, which allow us to consider the pre-displacement occupation and industry for all workers switching out of employment, including those who transition out of the labor force. 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:

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

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. The indicator variable Y_{it} is equal to 1 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, β, 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. These additional fixed effects control 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 occupation or industry affiliation, the estimated coefficient $\hat{\beta}$ should be driven to zero once these controls are introduced. An estimate of $\hat{\beta}$ that differs from zero even after controlling for occupations or industries would indicate differential exit rates across demographic groups occurring *within* job types.

In Figures A.11 and A.12 we plot the estimated coefficients and 95% confidence intervals for each demographic group. Table 3 summarizes the results from these regressions translated into the share of the gap in employment exit rates for each demographic group that can be accounted for by pre-displacement occupation and industry affiliation. In other words, we determine the fraction by which the baseline coefficient (i.e., the coefficient obtained without occupation or industry controls) is reduced when including occupation and/or industry controls.[11] In the top panel of Table 3, we focus on April 2020. The first column shows the raw estimated gap in employment exit rates (relative to males, Whites, 36- to 55-year-olds, and college graduates, respectively). The following three columns show the fraction of the gap that is accounted for when introducing fixed effects for 2-digit occupations, major industry groups, and when including both (always included directly, and interacted with the pandemic month indicators). The next three columns show results from specifications that include 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.

[11]In some cases, the share explained is negative. This occurs when the estimated coefficient becomes *larger* after introducing occupation and/or industry controls (i.e., the gap in exit rates within job categories is larger than the raw gap).

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

		Percentage 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 (%)*
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*
April 2020									
Female	3.6	2.8	−2.8	2.8	55.6	25.0	66.7	65.7	67.6
Black	2.8	53.6	14.3	3.6	53.6	28.6	46.4	7.9	35.7
Hispanic	5.2	55.8	25.0	63.5	63.5	44.2	73.1	86.5	78.8
Other	4.5	2.2	6.7	4.4	17.8	20.0	15.6	26.7	31.1
Age 16–25	10.1	63.4	50.5	76.2	76.2	53.5	82.2	80.9	76.5
26–35	1.8	22.2	50.0	55.6	50.0	50.0	66.7	58.3	57.3
56–85	1.8	22.2	5.6	16.7	33.3	16.7	33.3	52.1	50.0
No HS degree	11.5	70.4	28.7	79.1	77.4	37.4	80.9	83.2	83.2
HS degree	10.3	53.4	18.4	57.3	61.2	25.2	62.1	72.2	77.8
Some college	9.4	42.6	21.3	47.9	55.3	22.3	55.3	33.3	33.3
February 2021									
Female	0.7	−85.7	−100.0	−128.6	0.0	−85.7	−28.6	−42.9	−42.9
Black	3.5	17.1	0.0	14.3	25.7	20.0	22.9	31.4	11.4
Hispanic	3.5	28.6	14.3	31.4	31.4	17.1	28.6	40.0	51.4
Other	−0.9	0.0	−11.1	−11.1	11.1	−22.2	11.1	−22.2	−55.6
Age 16–25	−1.8	−72.2	−77.8	−105.6	−116.7	−88.9	−133.3	−127.8	−133.3
26–35	−0.1	−200.0	−200.0	−400.0	−400.0	−100.0	−400.0	−500.0	−500.0
56–85	2.2	9.1	0.0	9.1	9.1	9.1	9.1	9.1	9.1
No HS degree	2.7	111.1	40.7	122.2	122.2	66.7	133.3	133.3	140.7
HS degree	3.8	52.6	23.7	60.5	65.8	36.8	71.1	65.8	63.2
Some college	1.4	85.7	28.6	85.7	107.1	64.3	121.4	114.3	107.1

Notes: Column (1) 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- to 55-year-olds, and college graduates, respectively) based on the regression results from Equation (2). Columns (2) to (4) and columns (5) to (7) display the fraction of this gap that can be accounted for by workers' pre-displacement occupation and/or industry (at a broad and a detailed level, respectively). Columns (8) and (9) display the fraction that can be accounted for after controlling for whether the individual lives in a metropolitan area as well as the state of residence, in addition to detailed occupation and industry fixed effects. Ind., industry; Occ., occupation; SOC, Standard Occupational Classification.

The results show that two-thirds of the female–male gap in exit rates can be explained by detailed industry and occupation. For non-White groups, detailed industry and occupation can explain half of the gap for Black workers, three-quarters of the gap for Hispanic workers, and only 16% of the gap for other non-White workers. For workers younger than age 25, 80% of the gap is removed by controlling for detailed industry and occupation, while for workers age 26 to 35, these controls explain two-thirds of the gap. For workers older than age 55, only one-third of the gap can be accounted for by these controls. Finally, detailed industry and occupation can account for 81% of the gap for workers without high school degrees, 62% for those with a high school degree, and 55% for those with some college. Thus, for most groups, an important fraction of the gap in exit rates is because of differences in pre-displacement job affiliations, but substantial residual gaps are observed even within detailed industries and occupations.

In the bottom panel of Table 3 we show that, while most of the gaps in exit rates between demographic groups narrowed as of February 2021, the gap increased for Black workers, and for both Black and Hispanic workers more than 70% of the gap is within detailed industry and occupational categories. This finding implies that, on average, Black and Hispanic workers have benefited much less from the employment recovery observed between April 2020 and February 2021, even when compared to non-Hispanic White workers with the same occupation and industry background. In addition, the gap for older workers widened.[12] This result is consistent with disproportionate retirement rates among older workers, as documented by Coibion et al. (2020), and may be caused by the age profile of COVID-19, which is particularly dangerous for older individuals. The finding that very little of the gap for older workers is explained by pre-displacement occupation and industry suggests that these 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.

So far we have focused on nationwide 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 higher population density are more at risk from the direct effect of the virus.[13] Second, since mitigation policies such as lockdowns 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.

Given large differences in demographic composition across geographic areas, we analyze whether the residual gaps in employment exit rates across demographic groups (for workers with the same occupation and industry background) can be explained by differences in the impact of the pandemic across local areas. We do so by running an additional set of regressions, once again as in Equation (2), now adding metro status fixed effects interacted with a full set of pandemic month dummies (in addition to the detailed occupation and industry controls). We then also include a full set of state fixed effects, again interacted with the pandemic month dummies. These fixed effects would account for any differences at the state

[12]By February 2021, exit rates for individuals under 35 fell below exit rates for those 36 to 55, leading to negative exit rate gaps. Similarly, we find negative gaps for other non-Hispanic non-White individuals compared with White workers. For consistency, we maintain the same base comparison group in both time periods.

[13]Table A.3 shows that employment losses are modestly larger in urban areas compared to non-metro areas. Thus, consistent with the viral risk, we see a greater impact on employment for individuals living in closer proximity to others.

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 explain only 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, perhaps, 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 diverse lockdown policies and waves of the virus, employment responses appear to be mostly driven by national trends. This result is consistent with other work finding modest labor market differentials across lockdown policies and virus spread (e.g., Forsythe, Kahn, Lange, and Wiczer 2020).

When we consider the gaps between race and ethnicity groups, we find the results to be quite interesting. The findings for Black workers show that metro status increases the percentage explained in April by 20 p.p.; however, including state fixed effects reduces the percentage explained by 32 p.p. Thus, while some of the employment exit gap between Black and White workers is because Black workers are more likely to live in urban areas that were more affected by the pandemic employment shock, Black workers were disproportionately likely to lose their jobs in April compared with others in their same state of residence (and with the same metro status and same pre-displacement occupation and industry). 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%.

Conclusion

The economic fallout from the COVID-19 pandemic has been widespread. The magnitude of the employment losses, however, has differed substantially across types of jobs and groups of workers. This article shows that the pandemic has exacerbated pre-existing inequalities: Workers employed in lower-paying occupations and industries have been disproportionately affected, 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 and Neiman 2020; Ruiz-Euler et al. 2020; Mongey et al. 2021), as well as differences in the economic impacts of the pandemic across sectors.

Note, however, that the differential impact on disadvantaged groups extends well beyond their exposure linked 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 2020 and February 2021, even when compared to workers with the same occupation and industry background and in the same state of residence.

Going forward, policymakers must pay careful 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 the pandemic and to benefit less from the initial recovery.

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