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Determinants of Disparities in Early COVID-19 Job Losses

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ABSTRACT This study examines the sociodemographic divide in early labor market responses to the U.S. COVID-19 epidemic and associated policies, benchmarked against two previous recessions. Monthly Current Population Survey (CPS) data show greater declines in employment in April and May 2020 (relative to February) for Hispanic individuals, younger workers, and those with a high school diploma or some college. Between April and May, the demographic subgroups considered regained some employment. Reemployment in May was broadly proportional to the employment drop that occurred through April, except for Black individuals, who experienced a smaller rebound. Compared to the 2001 recession and the Great Recession, employment losses in the early COVID-19 recession were smaller for groups with low or high (vs. medium) education. We show that job loss was greater in occupations that require more interpersonal contact and that cannot be performed remotely, and that pre-COVID-19 sorting of workers into occupations and industries along demographic lines can explain a sizable portion of the demographic gaps in new unemployment. For example, while women suffered more job losses than men, their disproportionate pre-epidemic sorting into occupations compatible with remote work shielded them from even larger employment losses. However, substantial gaps in employment losses across groups cannot be explained by socioeconomic differences. We consider policy lessons and future research needs regarding the early labor market implications of the COVID-19 crisis.

KEYWORDS Stratification • Economic recession • Job loss • Discrimination • Work features decomposition

Introduction

The COVID-19 pandemic introduced new risks into economic, social, familial, and cultural activities that are otherwise commonplace, leading to disruptions that levied disparate impacts across demographic and socioeconomic groups. Job characteristics have emerged as particularly important moderators. For example, employment losses have been greater among people in jobs that involve face-to-face contact, and fewer losses occurred in jobs that can be performed remotely or are in essential industries.

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On the labor supply side, the COVID-19 transmission mechanism also raises the health risks of work tasks that require face-to-face contact with customers or coworkers, with risk varying along individual characteristics (Guerrieri et al. 2020). Labor supply might decline through other channels as well. For example, people's ability and willingness to work may have declined because the epidemic has compromised childcare services, schooling options, and other types of home and family health care availability (Dingel et al. 2020).

This study focuses on the labor market disruptions and job losses during the early months of the COVID-19 recession in the United States. We document substantial disparities in early epidemic unemployment patterns across demographic subpopulations defined by age, gender, race and ethnicity, marital status, parental status, and education. We develop simple measures of job attributes that may be relevant to the epidemic and show that these measures are associated with employment disruptions. Specifically, people working in jobs with more remote work capacity and less dependence on face-to-face interaction were more secure. Similarly, people working in essential industries were much less likely to become unemployed in the early months of the epidemic. In general, major demographic subpopulations are not evenly distributed across occupations and industries, and these differences are an important reason why some demographic groups have fared better than others.

We use decomposition techniques to quantify the share of employment disparities that is rooted in pre-epidemic sorting across occupations and industries. Such sorting explains a substantial share of many of the disparities in employment outcomes. Further, some of the job and industry factors that protected jobs during the early months of the epidemic are often associated with higher income and job security in normal times. This suggests that the epidemic aggravated many existing disparities. Our research complements prior work focused on inequality and the mechanisms that contribute to the persistence of disparities. Research on social stratification takes on "understanding and investigating the sources" of social inequality (Sakamoto and Powers 2005) through the study of population composition. Our article examines the distribution of job losses during the early epidemic in a social stratification framework that exploits population subgroups sorting across different jobs. We use information on how subgroups allocate themselves in different occupations and industries to explain the labor market shocks they experience during COVID-19 and the changes in inequality dynamics they will experience as a consequence.

We present four broad analyses to investigate disparate impacts in labor markets. First, we use data from the monthly Current Population Survey (CPS) to document and compare disparities in early COVID-19 era unemployment across groups. We find large declines in employment and increases in new unemployment among women, Hispanics, and younger workers. There is also polarization by education, with fewer job losses among college graduates (and those with more education), who can often work remotely, and high school dropouts, who tend to be in essential jobs. Hence, while both groups are somewhat shielded from job loss, highly educated workers are insulated from infection, while less educated workers likely face greater exposure, consistent with findings of Angelucci et al. (2020). We contrast these changes in employment losses with those during the Great Recession and the 2001 recession.

Second, we explore disparities in COVID-19 job losses across occupations and industries. We use O*NET data to develop indices of the extent to which each occupation allows remote work and requires face-to-face interaction.[1] Employment declined more in occupations requiring greater face-to-face interactions. Workers in jobs that could be performed remotely were less likely to experience new unemployment compared with historical trends. We further classify jobs as essential based on the "Guidance on the essential critical infrastructure workforce" issued by the U.S. Department of Homeland Security (2020) using the interpretation in Blau et al. (2020). We show that workers in essential jobs were less likely to lose a job in the early epidemic and were less likely to have been absent from work. All these patterns are stronger in April than in May.

Third, we assess the importance of caring for dependents as a factor in labor supply, estimating changes in employment and work absence for parents and for mothers. Relative to their experience in February, women were more likely to be absent from work in March 2020 (at four times the rate of March 2019) and be unemployed in April and May. Women with young children experienced particularly high rates of absence from work, which is concerning given the widespread closures of schools and childcare and the gendered nature of dependent care (Goldin 2022). Moreover, single parents, who are disproportionately female, were more likely to have lost jobs. Similarly, Alon et al. (2020) found that social-distancing policies have a larger effect on women than men, unlike in a more "typical" recession; Albanesi and Kim (2021) also found a sizable decline in labor force participation and in employment for women, unlike in previous recessions. Alon et al. (2020) and Albanesi and Kim (2021) suggest that the impact of the epidemic on working mothers could be persistent.

Our fourth contribution is to measure whether differences in job losses across demographic groups were due to pre-epidemic sorting across occupations and industries. We do so using a Oaxaca–Blinder decomposition, which allows us to simultaneously control for pre-pandemic socioeconomic traits associated with labor market opportunities and behavior. We show that a significant share of differences in employment loss across demographic groups is explained by differences in pre-epidemic sorting across occupations. However, for most groups, we also find that a nonnegligible share of the difference in job loss remains unexplained by either occupation sorting or other observable traits, in keeping with Busch (2020). Strikingly, we find that the Black–White gap in new unemployment grew between April and May 2020, at a time when one might have naturally expected it to decline. The presence of a large unexplained gap suggests that disparities in job loss in the pandemic are not reducible to differences in job characteristics and could possibly reflect disparate treatment by employers.

Related Research

The epidemic greatly reduced social and economic activity in 2020, with large sectors of the economy—transportation, hospitality, and tourism—essentially shutting down their normal operations between February and April, as state governments implemented a range of social-distancing mandates (Bartik et al. 2020; Coibion et al. 2020; Goolsbee

[1] Others have used O*NET to define occupations with the ability to work from home (Dingel and Neiman 2020; Mongey and Weinberg 2020) and high interpersonal contact (Leibovici et al. 2020).

and Syverson 2020; Gupta et al. 2020). In May, both the public and private sectors began to take steps to reopen some economic activities. Mobility measured using cell signals declined in all states, but was larger in those with early and information-focused policies (Gupta et al. 2020). The historically unprecedented increase in initial unemployment claims in March 2020 was largely across-the-board, in all states regardless of local epidemiological conditions or policy responses (Lozano-Rojas et al. 2020). Forsythe et al. (2020) showed a large drop in job vacancy postings as an indicator of labor demand across states regardless of state policies or infection rates. Adams-Prassl et al. (2020) and Dasgupta and Murali (2020) studied disparities in labor market impacts in other countries and found that the ability to work remotely shielded some workers from job loss. There is mounting evidence that layoff statistics may severely underestimate the extent of labor market adjustments. Coibion et al. (2020) estimated that unemployment greatly exceeded the level of unemployment insurance claims in early April.

A large literature illustrates how existing patterns of social stratification shape socioeconomic outcomes during crises. Dudel and Myrskylä (2017), Cheng et al. (2019), and Killewald and Zhuo (2019) found disparities in occupational wage gaps and other labor market outcomes on the basis of age, gender, and ethnicity in both the United States and abroad. Dudel and Myrskylä (2017) showed that the Great Recession shortened the life expectancy of older workers, especially of White men. Zissimopoulos and Karoly (2010) examined the short-term and longer term effects of Hurricane Katrina on labor market outcomes by subgroup of evacuees. Beyond labor market outcomes, large economic and social events also influence fertility (Grossman and Slusky 2019; Seltzer 2019), marriage (Schneider and Hastings 2015), migration (Sastry and Gregory 2014), and children's well-being (Cools et al. 2017; Schenck-Fontaine and Panico 2019). Given the peculiarities of the COVID-19 economic crisis, it is important to understand which population strata were most affected, why, and how these effects may lead to longer term disparities in well-being.

Data

Current Population Survey

Our main analysis uses data from the Basic Monthly CPS from February to May 2020. The analytic sample used in all regressions consists of all labor force participants aged 18–65 with complete information on gender, children under six years old, race and ethnicity, education, state, metropolitan residence, recent unemployment status, occupation and industry codes, and CPS sample weight. To focus on job losses related to the epidemic, we use a measure of recent (new) unemployment, which defines a worker as recently unemployed if they are coded as being unemployed in the focal week of the survey month and have been in that status for at most five weeks as of March 2020, 10 weeks in April 2020, and 14 weeks in May 2020.[2]

Focusing on recent unemployment allows us to study new job losses using only cross-sectional models. To verify that recent unemployment does indeed track job loss, we checked that the measure behaves like the change in employment rate. That

[2] These surveys use a reference week that includes the 12th of the month (U.S. Census Bureau 2019).

is, we check whether the incidence of recent unemployment across demographic groups in April and in May tracks month-over-month changes from February to April and from February to May, respectively, in the employment-to-population ratio. Evidence reported in panel A of the online appendix Figure A2.1 compares recent unemployment in April 2020 with the February-to-April change in employment rates by subpopulation; panel B shows the comparison for February and May. Our recent unemployment measure behaves like the change in the employment rate.

The CPS defines as "absent from job" all workers who were "temporarily absent from their regular jobs because of illness, vacation, bad weather, labor dispute, or various personal reasons, whether or not they were paid for the time off" (U.S. Census Bureau 2019). There was a massive increase in the share of workers coded as employed-but-absent from work between February and April, as well as in May. During the epidemic, these employed-but-absent workers deserve particular attention as some furloughed employees might have been recorded as short-term absent instead of unemployed, among other reasons. Therefore, we perform most of our analysis separately on measures of recent unemployment and employed-but-absent.

Further details on our recent unemployment variable, the definition of the analysis sample, and the employed-but-absent category during April and May 2020 are in the online Appendix A.1.

O*NET

We also use data from the 2019 Occupational Information Network (O*NET) Work Context module, which reports summary measures of the tasks used in 968 occupations (National Center for O*NET Development 2020). These data are gathered through surveys asking workers how often they perform particular tasks and about the importance of different activities in their jobs. Some of the questions relate to the need for face-to-face interaction with clients, customers, and coworkers, and other questions assess how easily work could be done remotely. For details on how this information is collected in O*NET, refer to the online Appendix A.3. We use such questions to build two occupation indices: Face-to-Face (questions on face-to-face discussions and physical proximity) and Remote Work (questions on use of electronic mail, written letters, and phone conversation).[3]

It is important to note that these occupational characteristics in the O*NET are measured prior to the epidemic. This means that they do not capture "work practice innovations" that may have been induced by the epidemic, such as the fact that many teachers and professors transitioned from face-to-face to online instruction during the epidemic. To check how well our two indices perform, we rank the occupations by their corresponding indices and create a list of the top and bottom 5% Face-to-Face and Remote Work occupations. We realize that, unsurprisingly, most of the top 5% Face-to-Face occupations are in the medical sector, which may be affected differently during the epidemic. Hence, we also show a list of the top nonmedical occupations. The rankings (reported in online appendix Tables A4.2 and A4.3 for Face-to-Face

[3] The complete list of the specific questions used to build each of the two indexes is in the online appendix Table A4.1.

and Remote Work, respectively) are reassuring, indicating that these indices measure what we expected.

We also compare our Remote Work and Face-to-Face indices with Dingel and Neiman's (2020) Teleworkability classification, which might be viewed as an alternative to our Remote Work index. The correlation between our indices is only .03, suggesting that they capture different features of an occupation. The correlation between the Face-to-Face index and Dingel and Neiman's (2020) Teleworkability variable is –.36. The occupations that score high in our Face-to-Face index tend to rank low in Teleworkability. Finally, the correlation between our Remote Work index and the Teleworkability variable is .51, suggesting that the two measures are indeed broadly similar.

Homeland Security Data on Essential Work

The U.S. Department of Homeland Security (DHS) issued guidance that describes 14 essential critical infrastructure sectors during the COVID-19 epidemic.[4] We follow Blau et al.'s (2020) definition of essential industries, which matches the text descriptions to the NAICS 2017 four-digit industry classification from the U.S. Census Bureau[5] and to the CPS industry classification system. From the 287 industry categories at the four-digit level, 194 are identified as essential in 17 out of 20 NAICS sectors. Online appendix Table A4.4 gives an abbreviated list of essential industries to clarify the classification scheme.

Employment Disruptions in Three Recessions

Figures 1 and 2 show the change in employment for the COVID-19 recession compared with the peak-to-trough change in employment for the 2001 recession (March 2001 to November 2001) and the Great Recession (December 2007 to June 2009). We seasonally adjust the change in employment for the two earlier recessions using calendar month fixed effects from January 2015 to December 2019. For COVID-19, we focus on two time periods that cover the initial "closing" phase of the pandemic (i.e., from February to April) and also a longer period (i.e., from February to May) that adds the ensuing "reopening" phase. All estimates use CPS sampling weights.

The light blue and light green bars in the figures show that employment losses during the first months of the COVID-19 epidemic dwarfed the declines for the other two recessions, which spanned nine and 19 months, respectively. This was true even after the COVID-19 reopening phase, during which employment rebounded substantially. The size and speed of the COVID-19 recession are reinforced in online appendix Figure A5.1, which shows seasonally adjusted nonfarm employment from March 2000 and May 2020. The bars in Figure 1 show the change in the employment rate for subpopulations defined by gender, having young children, race, ethnicity, age, and education. Figure 2 shows employment changes by marital and parental status

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

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

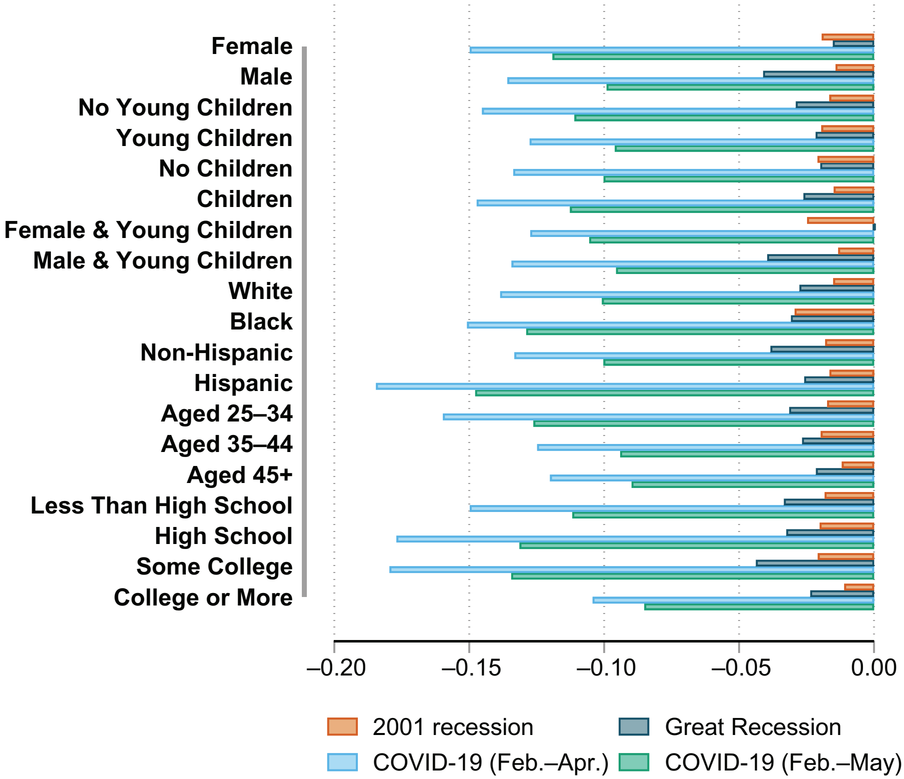

Fig. 1 Employment change in three recent recessions: 2001 recession, Great Recession, and COVID-19 recession (April and May 2020), by demographic characteristics. The sample consists of CPS respondents aged 18–65. For each bar, we compute the difference in the percentage of the demographic group that reports being employed and at work, between the start and end months of each recession, and between pre-COVID-19 and during COVID-19 (National Bureau of Economic Research 2012). For the COVID-19 recession, we compare both April 2020 and May 2020 to February 2020. The estimates are weighted using the CPS composited final weights. We seasonally adjust the estimates, including monthly fixed effects, in the computation of the average subgroups' employment change for the 2001 recession and the Great Recession.

interacted. Almost no group was spared from employment loss during any of the three recessions. However, the pattern of employment disruption is noticeably different in the early months of the COVID-19 recession.

Young (aged 18–24) and Hispanic workers fared the worst during the COVID-19 pandemic when compared to older and non-Hispanic workers and to the previous recessions. Black individuals also fared poorly, but by a smaller margin. Our conjecture is that these groups disproportionately work in industries that are particularly hit by social-distancing measures, such as food service, personal care services, or non-essential retail industries. Further, employment declined more for women than for men. Parents with their own children under 18 living in the household fared worse than those without, while workers without young children (under six) experienced larger job losses than those with children under six in their household. This trend is likely explained by differences in the impact of school closures on parents' job loss depending on their child's age.

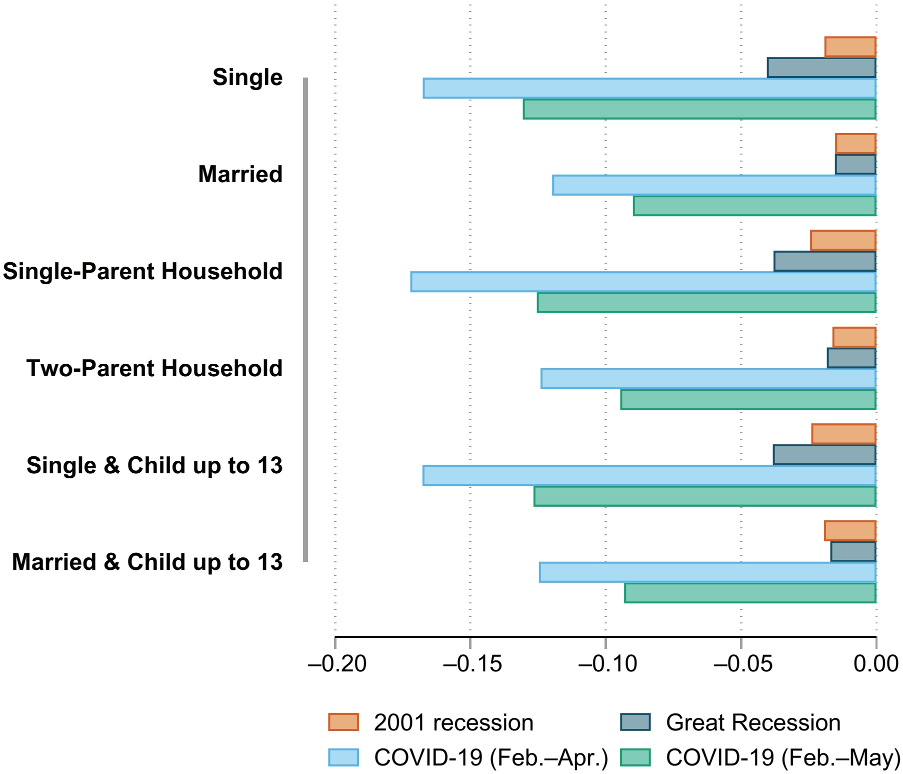

Fig. 2 Employment change in three recent recessions: 2001 recession, Great Recession, and COVID-19 recession (April and May 2020), by marital and parental status interacted. See note in Figure 1.

Employment effects were polarized by education: employment declined less for high school dropouts and those with at least a college degree compared with the intermediate education groups. As we show later, highly educated workers have better options to work remotely, limiting in-person interactions; in contrast, less educated workers are more likely to be in essential positions. While polarization is consistent with recent trends in the labor market, this kind of pattern was not a feature of the two previous recessions (Autor et al. 2006).[6]

Comparison of the decrease in employment between February and April (light blue) to that between February and May (light green) indicates that there were gains

[6] We formally check for polarization in two ways. First, for each of the three recessions, we create a graph showing the employment change for each of the four education categories: less than high school, high school graduate, some college, and college graduate or more (on the x-axis, in increasing order). We observe a very marked U shape across the education groups during the COVID recession, but not for the other two recessions. Second, using a regression on data from the COVID-19 recession, we reject the hypothesis that workers with less than a high school diploma and those with at least a college degree jointly experience a drop in employment equal to that of the intermediate education groups. In other words, our p value (equal to 0) for the F test rejects the hypothesis of nonpolarization. Those with a college degree or more and those with less than a high school education experience a drop in employment that is statistically lower than the one suffered by the intermediate education groups.

in employment between April and May as states began reopening. The recovery in employment that the groups experienced between April and May was broadly proportional to the employment losses that occurred between February and April. Thus, the distributional incidence of job loss and recovery was largely symmetric, with the notable exception of Black workers, who did not recover in May as much as would have been expected given their decline in employment in April.

Figure 2 shows that married individuals whose spouse was present experienced a smaller decrease in employment than single individuals (defined as those who were unmarried or had an absent spouse), regardless of whether we compare April or May to February. Single parents, who are disproportionately female (72%), experienced the largest decrease in employment; when comparing parents of children younger than 13 versus 18 years old, the age of children was weakly related to the change in employment during these months. In fact, single parents of children younger than 18 experience similar job losses to single parents of children under 13, and the same holds for two-parent households. This could also be explained by the interaction between childcare needs and school closure patterns.

Overall, this analysis highlights that Hispanic individuals, young workers (aged 18–24), and single parents were the most vulnerable workers early in the epidemic and those most in need of policy attention.

Job Tasks and Recent Unemployment

Job Tasks and the Labor Market: Descriptive Analysis

Figure 3 shows the mean of the Remote Work and Face-to-Face indices across subpopulations in the February 2020 CPS, providing insight into pre-epidemic worker sorting across occupations. Compared with men, women tended to work in jobs that both allow more remote work and involve more face-to-face activities. Hispanic individuals disproportionately worked in jobs that largely cannot be conducted remotely. Younger workers were in jobs with fewer remote work prospects and more face-to-face interaction, although the differentials are not as large. Remote work scores increased substantially with education level.

To examine employment disruptions in the early epidemic, we use data from the March, April, and May waves of the 2020 CPS. The March CPS data were collected largely before the major responses were observed and hence we view March as a hybrid period. As indicated, we classified people as recently unemployed if they were currently unemployed and had become unemployed within the past five weeks (March), 10 weeks (April), or 14 weeks (May). Ignoring reemployment, this measure captures employment disruptions since February in each subsequent monthly CPS. Figures 4 and 5 compare recent unemployment rates with Remote Work scores and Face-to-Face scores at the occupation level in the April and May CPS. In both figures, the left panel shows that recent unemployment rates tended to be lower in occupations with higher scores on the Remote Work index, suggesting that remote work capacity helped protect employment. In contrast, the right panel shows that recent unemployment rates were typically higher in occupations that involve more face-to-face tasks.

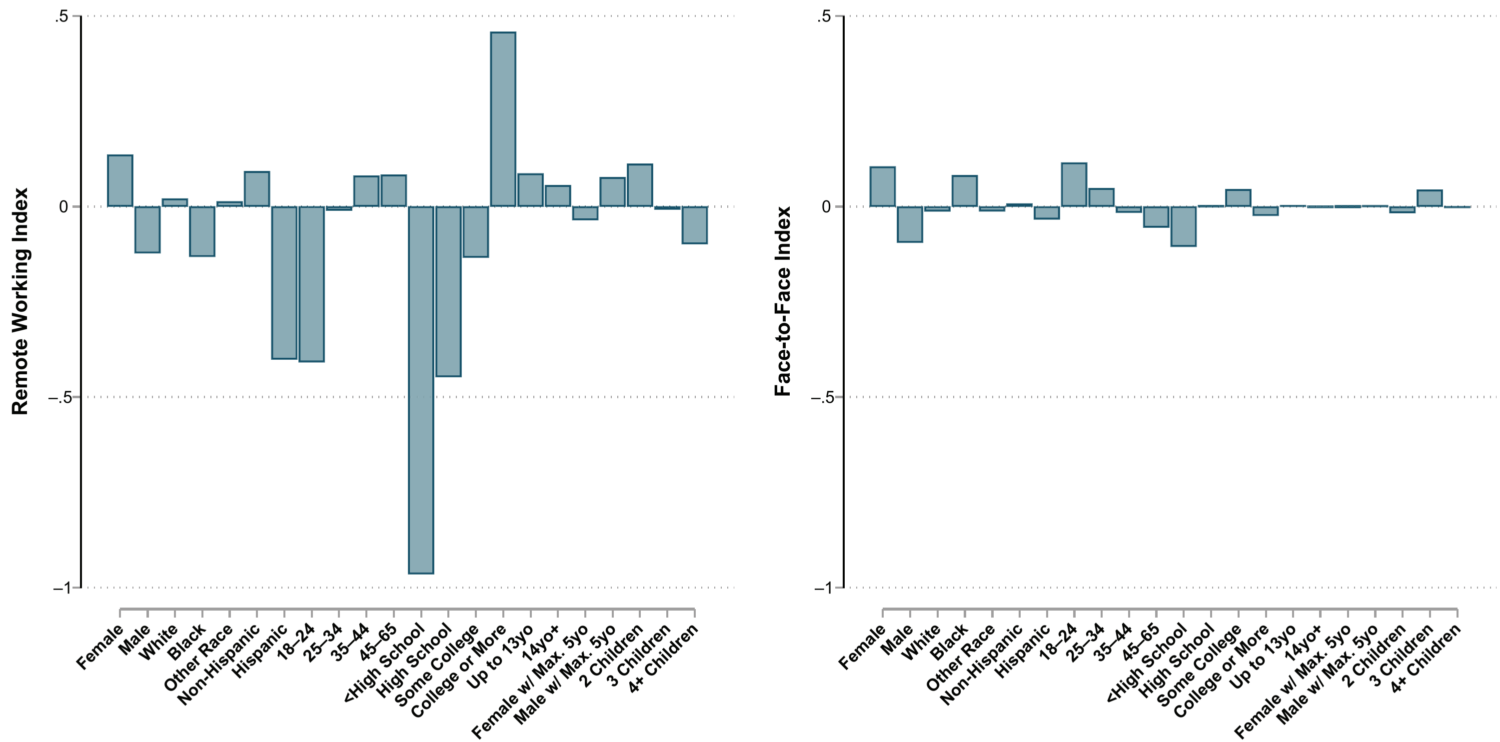

Fig. 3 Remote Work and Face-to-Face indices by demographic group in February 2020. The sample consists of CPS February 2020 respondents aged 18–65 in the labor force. To make the sample uniform, we drop observations with missing values for any of the covariates in any model for the month in consideration. Each index has been standardized to average mean 0 and standard deviation 1. We compute the average of each occupation index by subgroup. Negative numbers indicate lack of that characteristic in the jobs of that group.

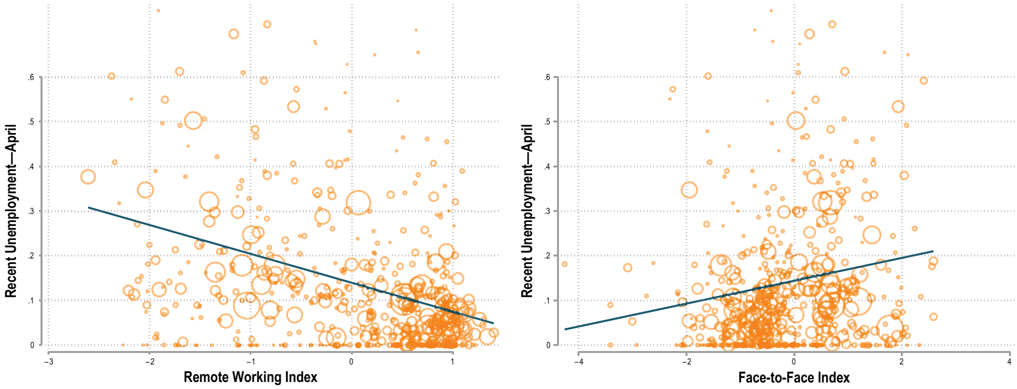

Fig. 4 Recent unemployment rate in April 2020 by occupation index for Remote Work and Face-to-Face. The sample consists of April CPS 2020 respondents aged 18–65 in the labor force. We produce the figure using the sample of observations in the regression in column 3 of Table 1, our most detailed model, for the month considered. We compute the average percentage recently unemployed in each occupation and plot that against the occupation's index value. Each occupational index has been standardized to have mean 0 and standard deviation 1. Each bubble represents a census occupation, with area proportional to the size of the workforce that holds that occupation in our sample. To improve readability, when plotting the bubbles we excluded from the sample the five occupations that, in April 2020, have recent unemployment rates above 78%. However, to reproduce the line plotting the linear prediction of recently unemployed on each occupation index, we do not drop these "extreme" occupations. The slope of the regression line in the left panel is –0.067 (constant = 0.139), while the slope in the right panel is 0.026 (constant = 0.140).

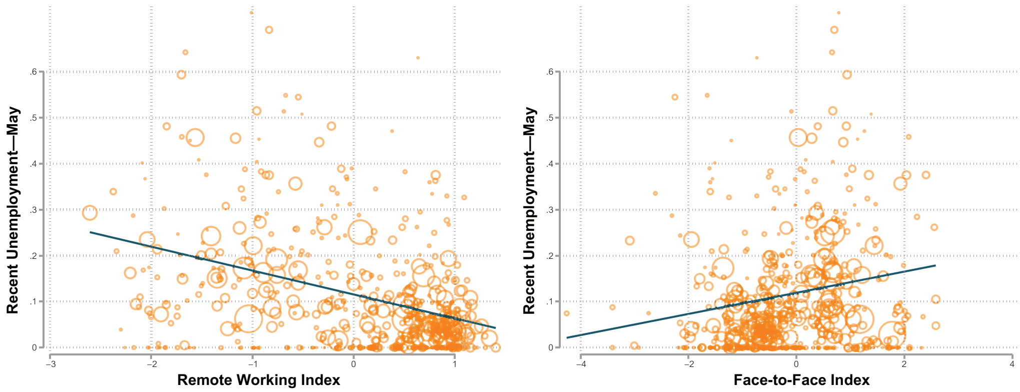

Fig. 5 Recent unemployment rate in May 2020 by occupation index for Remote Work and Face-to-Face. See note in Figure 4.

Job Tasks and the Labor Market: Regression Analysis

To assess the connection between worker and job characteristics and recent job losses, we fit regressions with the following form:

$$y_{ijks} = Face_j\beta_1 + Remote_j\beta_2 + Essential_k\beta_3 + Female_i\beta_4 + Child_i\beta_5 + \left(Child_i \times Female_i\right)\beta_6 + \boldsymbol{X_i}\delta + \boldsymbol{\varphi_s} + \epsilon_{ijks}. \quad (1)$$

Here y_{ijks} is an indicator that person i with occupation j, industry k, in state s is recently unemployed (Table 1) or temporarily absent from work (Table 2). $Face_j$ and $Remote_j$ are the indices of Face-to-Face and Remote Work. $Essential_k$ indicates that the person is in an essential industry. $Female_i$ indicates that the person is female, $Child_i$ indicates that the person has a child under age six, and $\boldsymbol{X_i}$ is a vector of covariates, including a quadratic in age, race/ethnicity indicators, and education indicators. All models include state fixed effects, denoted by $\boldsymbol{\varphi}_s$, and in some specifications they include state-specific epidemiological conditions as measured by the log of COVID cases, which are interacted with occupation characteristics. Occupation fixed effects are included in some but not all specifications because they subsume the occupation characteristics (i.e., $Face_j$, $Remote_j$, and $Essential_k$).

Table 1 reports estimates from March, April, and May. Column 1 in all three panels shows estimates from models that control for occupation and individual characteristics, but not for the number of COVID-19 cases in the state. Column 2 includes the log of state COVID cases (The New York Times 2020). Column 3 replaces the job task indices with occupation and industry fixed effects to account for any additional time-invariant job characteristics. Table 2 reports parallel estimates for temporary absence from work.

The coefficients on the Remote Work and the Face-to-Face indices reinforce the pattern in Figures 4 and 5. In the analysis of the April CPS, the model in column 1 implies that recent unemployment rates were 1.6 percentage points higher for people working in jobs that score 1 standard deviation (SD) higher on the Face-to-Face index. The recent unemployment rate in our April sample was 12.6%, which means that a 1-SD increase in the Face-to-Face score was associated with a 13% higher risk of being recently unemployed. The relationship is almost identical in the analysis based on the May CPS. In contrast, there was no association between the Face-to-Face index and recent unemployment in the March CPS, implying that the connection between employment instability and the Face-to-Face index was not a preexisting feature of the labor market. The coefficient on the Remote Work index is negative and significant in March, suggesting that there was a small pre-epidemic connection between remote work and employment disruption. However, the magnitude of the coefficient on Remote Work is seven times larger in April and almost six times larger in May than in March. Working in a job that scored 1 SD higher on Remote Work was associated with a 5.6-percentage-point lower risk of recent job loss, which is 44% of the recent unemployment rate in April. Likewise, the coefficient on "Essential" (−8.9 percentage points) indicates that working in an essential industry was associated with a 71% lower probability of recent unemployment and the magnitude in April is almost 13 times higher than in March. Column 2 includes interactions between state-level COVID-19 cases and job characteristics. The essential industry and Face-to-Face variables do not have strong interactions with COVID-19 cases, but Remote Work has a strong negative interaction with COVID-19 cases, indicating that remote work potential is particularly important in high-case environments.

The regressions show that recent unemployment rates vary with individual characteristics. Recent unemployment rates are about three percentage points higher for women in April and May; however, when occupation and industry fixed effects are included, the difference falls to one percentage point. The coefficient on the interaction term between female and children under age six is small and not statistically significant, suggesting that childcare responsibilities did not explain much of the gender gap

Table 1 Cross-sectional models: Characteristics of recently unemployed workers

	March—Mean = 0.018				April—Mean = 0.126				May—Mean = 0.112			
	Mean	(1)	(2)	(3)	Mean	(1)	(2)	(3)	Mean	(1)	(2)	(3)
Face-to-Face	–0.0219	–0.001	0.001		–0.0166	0.016**	0.017		–0.0119	0.016**	–0.003	
	(0.988)	(0.001)	(0.002)		(0.988)	(0.006)	(0.012)		(0.984)	(0.005)	(0.015)	
Remote Work	0.0761	–0.008**	–0.005**		0.074	–0.056**	–0.006		0.0648	–0.045**	0.020	
	(0.959)	(0.002)	(0.002)		(0.953)	(0.009)	(0.021)		(0.955)	(0.008)	(0.017)	
Essential	0.707	–0.007**	–0.012**		0.709	–0.089**	–0.078†		0.709	–0.073**	–0.058†	
	(0.455)	(0.002)	(0.003)		(0.454)	(0.014)	(0.045)		(0.454)	(0.011)	(0.029)	
Ln(cases)×Face-to-Face	–0.098		0.000	0.000	–0.167		0.000	0.000	–0.133		0.002	0.002
	(3.541)		(0.000)	(0.000)	(9.365)		(0.001)	(0.001)	(10.220)		(0.002)	(0.001)
Ln(cases)×Remote	0.263		–0.001†	0.0000	0.743		–0.005**	–0.005*	0.705		–0.006**	–0.005**
	(3.421)		(0.0000)	(0.001)	(8.988)		(0.002)	(0.002)	(9.906)		(0.002)	(0.001)
Ln(cases)×Essential	2.288		0.002**	0.001*	6.629		–0.001	–0.001	7.301		–0.002	–0.003
	(1.921)		(0.001)	(0.001)	(4.381)		(0.005)	(0.005)	(4.781)		(0.003)	(0.003)
Female×Child Under Six	0.0684	0.004	0.004	0.002	0.0651	–0.003	–0.003	–0.013	0.0627	0.001	0.001	–0.005
	(0.252)	(0.004)	(0.005)	(0.004)	(0.247)	(0.010)	(0.011)	(0.010)	(0.242)	(0.015)	(0.015)	(0.013)
Child Under Six	0.150	0.002	0.002	0.004	0.144	–0.009	–0.009	0.002	0.141	0.000	0.000	0.009
	(0.357)	(0.002)	(0.002)	(0.002)	(0.351)	(0.006)	(0.006)	(0.006)	(0.348)	(0.008)	(0.008)	(0.006)
Female	0.471	0.003†	0.003†	0.001	0.469	0.035**	0.034**	0.011*	0.469	0.030**	0.030**	0.009
	(0.499)	(0.002)	(0.002)	(0.002)	(0.499)	(0.008)	(0.009)	(0.005)	(0.499)	(0.008)	(0.008)	(0.005)
Black	0.129	0.007*	0.007*	0.006*	0.128	0.001	0.001	0.010	0.128	0.018†	0.018†	0.023**
	(0.335)	(0.003)	(0.003)	(0.003)	(0.334)	(0.009)	(0.009)	(0.009)	(0.334)	(0.009)	(0.009)	(0.008)
Hispanic	0.184	0.007**	0.007**	0.005*	0.184	0.012	0.012	0.011	0.185	0.015†	0.014	0.012†
	(0.388)	(0.002)	(0.002)	(0.002)	(0.387)	(0.008)	(0.008)	(0.008)	(0.388)	(0.008)	(0.009)	(0.007)
Age	0.418	–0.226**	–0.227**	–0.183**	0.411	–1.185**	–1.192**	–0.777**	0.410	–1.091**	–1.098**	–0.661**
	(0.124)	(0.072)	(0.073)	(0.060)	(0.128)	(0.167)	(0.166)	(0.095)	(0.129)	(0.185)	(0.185)	(0.125)
Age Squared	0.190	0.241**	0.241**	0.196**	0.185	1.273**	1.280**	0.856**	0.185	1.162**	1.168**	0.721**
	(0.106)	(0.082)	(0.082)	(0.070)	(0.108)	(0.181)	(0.180)	(0.112)	(0.108)	(0.206)	(0.206)	(0.140)
High School	0.249	–0.004	–0.004	–0.001	0.249	–0.003	–0.002	0.001	0.254	–0.008	–0.007	–0.013
	(0.433)	(0.004)	(0.003)	(0.004)	(0.433)	(0.013)	(0.013)	(0.011)	(0.435)	(0.012)	(0.012)	(0.009)

Table 1 (continued)

	March—Mean = 0.018				April—Mean = 0.126				May—Mean = 0.112			
	Mean	(1)	(2)	(3)	Mean	(1)	(2)	(3)	Mean	(1)	(2)	(3)
Some College	0.274	−0.002	−0.002	0.001	0.275	0.000	0.000	0.002	0.275	−0.005	−0.004	−0.010
	(0.446)	(0.003)	(0.003)	(0.003)	(0.447)	(0.013)	(0.013)	(0.010)	(0.447)	(0.012)	(0.012)	(0.009)
College Degree	0.266	−0.008**	−0.007**	−0.004	0.261	−0.044**	−0.044**	−0.021*	0.257	−0.046**	−0.045**	−0.035**
	(0.442)	(0.003)	(0.003)	(0.003)	(0.439)	(0.014)	(0.014)	(0.010)	(0.437)	(0.014)	(0.014)	(0.011)
Postgraduate Degree	0.148	−0.009*	−0.008*	−0.004	0.147	−0.079**	−0.078**	−0.031*	0.149	−0.079**	−0.078**	−0.046**
	(0.355)	(0.003)	(0.003)	(0.004)	(0.354)	(0.016)	(0.016)	(0.013)	(0.356)	(0.015)	(0.015)	(0.011)
Metropolitan	1.110	−0.006*	−0.006*	−0.006*	1.113	−0.030**	−0.029**	−0.012†	1.114	−0.029**	−0.028**	−0.013†
	(0.312)	(0.003)	(0.003)	(0.003)	(0.316)	(0.007)	(0.008)	(0.006)	(0.318)	(0.007)	(0.007)	(0.006)
Constant		0.079**	0.079**	0.059**		0.484**	0.485**	0.313**		0.439**	0.440**	0.300**
		(0.015)	(0.015)	(0.014)		(0.043)	(0.043)	(0.045)		(0.045)	(0.045)	(0.039)
State Fixed Effects		X	X	X		X	X	X		X	X	X
Occupation and Industries Fixed Effects				X				X				X
Number of Observations	44,474	44,474	44,474	44,474	43,754	43,754	43,754	43,754	42,432	42,432	42,432	42,432
R^2		.010	.010	.043		.079	.079	.196		.067	.068	.173

Notes: Coefficients for Eq. (1) using March, April, and May 2020 CPS data are for individuals on the labor force and with recent unemployment as the dependent variable. Column 1 includes sociodemographic and job task characteristics. Column 2 adds the states' epidemiological conditions as measured by their COVID-19 log exposure, interacted with occupation characteristics. Column 3 adds occupation and industries fixed effects. All models include state fixed effects. Standard deviations for means, and standard errors from multiway clustering at the state and occupation levels for regression estimates, are given in parentheses.

†$p < .10$; *$p < .05$; **$p < .01$

Table 2 Cross-sectional models: Characteristics of temporary absent workers

	March—Mean = 0.037			April—Mean = 0.071			May—Mean = 0.050		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Face-to-Face	0.009**	0.009**		0.014**	0.001		0.009**	0.002	
	(0.002)	(0.003)		(0.004)	(0.014)		(0.003)	(0.008)	
Remote Work	–0.007**	–0.005*		–0.014**	0.017†		–0.011**	0.016	
	(0.001)	(0.002)		(0.004)	(0.010)		(0.003)	(0.020)	
Essential	–0.017**	–0.019**		–0.034**	–0.034		–0.019**	–0.053**	
	(0.005)	(0.007)		(0.007)	(0.025)		(0.006)	(0.016)	
Ln(cases) × Face-to-Face		–0.000	–0.000		0.001	0.002		0.001	0.001
		(0.001)	(0.001)		(0.002)	(0.002)		(0.001)	(0.001)
Ln(cases) × Remote		–0.001	–0.001		–0.003**	–0.002*		–0.003	–0.002
		(0.000)	(0.001)		(0.001)	(0.001)		(0.002)	(0.002)
Ln(cases) × Essential		0.001	0.000		0.000	–0.001		0.003†	0.003
		(0.001)	(0.002)		(0.003)	(0.003)		(0.002)	(0.002)
Female × Child Under Six	0.030**	0.030**	0.029**	0.039**	0.039**	0.037**	0.035**	0.035**	0.034**
	(0.005)	(0.005)	(0.005)	(0.008)	(0.008)	(0.008)	(0.005)	(0.005)	(0.006)
Child Under Six	0.003	0.003	0.003	0.000	0.000	0.001	–0.001	–0.001	–0.000
	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)	(0.003)	(0.003)	(0.003)
Female	0.008**	0.008**	0.006**	0.009*	0.008†	0.001	0.010**	0.010**	0.007*
	(0.003)	(0.003)	(0.002)	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)
Black	–0.000	–0.000	0.000	0.004	0.004	0.006	0.004	0.004	0.006
	(0.004)	(0.004)	(0.004)	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)
Hispanic	0.001	0.001	0.000	–0.007	–0.007	–0.008	–0.004	–0.004	–0.003
	(0.004)	(0.004)	(0.004)	(0.010)	(0.010)	(0.009)	(0.005)	(0.005)	(0.004)
Age	–0.086	–0.086	–0.102	0.025	0.020	0.040	–0.012	–0.015	–0.053
	(0.069)	(0.069)	(0.065)	(0.092)	(0.093)	(0.080)	(0.074)	(0.073)	(0.068)
Age Squared	0.144†	0.144†	0.163*	0.039	0.043	0.028	0.070	0.073	0.119†
	(0.075)	(0.075)	(0.072)	(0.107)	(0.108)	(0.092)	(0.078)	(0.078)	(0.070)
High School	0.005	0.005	0.005	0.005	0.005	0.009	–0.005	–0.004	–0.004
	(0.004)	(0.004)	(0.004)	(0.008)	(0.008)	(0.009)	(0.008)	(0.008)	(0.008)

Table 2 (continued)

	March—Mean = 0.037			April—Mean = 0.071			May—Mean = 0.050		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Some College	0.008*	0.009*	0.007*	–0.006	–0.006	0.001	0.004	0.005	0.004
	(0.004)	(0.004)	(0.003)	(0.010)	(0.010)	(0.010)	(0.008)	(0.009)	(0.008)
College Degree	0.010*	0.010*	0.009*	–0.030**	–0.030**	–0.015	–0.013	–0.013	–0.008
	(0.005)	(0.005)	(0.004)	(0.010)	(0.010)	(0.011)	(0.008)	(0.008)	(0.007)
Postgraduate Degree	0.000	0.001	–0.003	–0.050**	–0.050**	–0.026*	–0.029**	–0.028**	–0.015*
	(0.005)	(0.005)	(0.006)	(0.011)	(0.011)	(0.012)	(0.009)	(0.009)	(0.006)
Metropolitan	–0.005†	–0.005†	–0.005*	–0.009	–0.008	–0.003	–0.003	–0.003	0.002
	(0.003)	(0.003)	(0.002)	(0.008)	(0.008)	(0.008)	(0.005)	(0.005)	(0.005)
Constant	0.051**	0.051**	0.043**	0.098**	0.099**	0.061*	0.061**	0.061**	0.028†
	(0.014)	(0.014)	(0.013)	(0.020)	(0.020)	(0.029)	(0.015)	(0.015)	(0.016)
State Fixed Effects	X	X	X	X	X	X	X	X	X
Occupation and Industries Fixed Effects			X			X			X
Number of Observations	44,474	44,474	44,474	43,754	43,754	43,754	42,432	42,432	42,432
R^2	.012	.012	.042	.023	.023	.074	.016	.016	.062

Notes: Coefficients for Eq. (1) using March, April, and May 2020 CPS data are for individuals on the labor force and with temporary absence from work as the dependent variable. Column 1 includes sociodemographic and job task characteristics. Column 2 adds the states' epidemiological conditions as measured by their log exposure, interacted with occupation characteristics. Column 3 adds occupation and industries fixed effects. All models include state fixed effects. Standard errors from multiway clustering at the state and occupation levels are shown in parentheses.

†$p < .10$; *$p < .05$; **$p < .01$

in unemployment early in the epidemic; however, we later show that presence of young children is a factor in absence from work. Recent unemployment rates are substantially higher for younger workers and decline with age at a decreasing rate. Recent unemployment was lower among college-educated workers: graduate degree holders were about 7.9 percentage points less likely to have become unemployed in the 10 weeks leading up to the April CPS, and college graduates were about 4.4 percentage points less likely to be recently unemployed. This relationship is much weaker in March, but on the same level during May. Including occupation and industry fixed effects attenuates the education gradient somewhat, but it remains strong and significant. Recent unemployment rates were about three percentage points lower among workers living in metropolitan areas for both April and May. Again, including occupation and industry fixed effects lessens but does not eliminate this relationship. Overall, occupation and industry characteristics were far more important in April and May than in March. We attribute this increase, and the slight decrease from April to May, to the spread of the pandemic, the policy responses, and their subsequent easing during the first part of May.

Table 2 shows results from models with "employed but absent" as the outcome. Our estimates show that workers in jobs relying heavily on face-to-face interactions were more likely to experience absence from work, while those who could work remotely more easily, and those in essential industries, were less likely to be absent from work. The coefficients on job attributes have similar signs in March and April, but the magnitude of the coefficients is much larger in April. The magnitude declines somewhat in May, which may indicate that absences precede dismissals. However, the data classification issues we discussed earlier make this a tentative conclusion.

The education gradient is very similar to the one found for recent unemployment, with education protecting against work absence. Women with young children were particularly likely to be temporarily absent in all months, suggesting that childcare responsibilities likely played an early and lasting role in absence rates. To probe the timing of effects, we plotted the coefficients from columns 3 of Tables 1 and 2 over time during the pandemic (March through May 2020) and for the same months in 2019. In several cases, we can spot a striking change in coefficient in both graphs starting in March 2020, the onset of the epidemic; the 2019 coefficients are more centered around 0. These graphs are shown in online appendix Figures A7.1 and A7.2.

Further Analyses and Robustness Checks

We conducted a series of sensitivity analyses to assess the robustness of our results. We report these results in the online appendix and discuss them briefly here.

First, we explored whether mortality risk[7] from COVID-19 affected labor supply among high-risk groups by estimating regressions that include a measure of COVID-19

[7] We use Bayes' theorem to infer mortality rates by age and gender from the Chinese Center for Disease Control and Prevention (2020). Specifically, we calculated

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

where $Gender = \{Female,\ Male\}$ *and* $Age = \{20-29, \ldots, 70-79, 80+\}$. We normalize the variable to have a mean of 0 and a standard deviation of 1 on the entire CPS sample.

mortality risk as a covariate. The results are presented in online Table A8.1 for recent unemployment and in Table A8.2 for absent from work. Overall, they suggest that among people working in nonessential jobs with average face-to-face and remote work capacity, workers with higher COVID-19 mortality risk were actually less likely to experience a recent unemployment spell in April and May. In April, the coefficient on the mortality index implies that a 1-SD increase in mortality risk reduced the recent unemployment rate by about 1.3 percentage points. Since our mortality risk measure is mainly driven by age and gender, this likely reflects that older workers had more job security than younger workers. However, the coefficient on the interaction term between mortality risk and the Remote Work index is positive, implying that this pattern was partly offset for people working in jobs that were more suitable for remote work. In contrast, mortality risk does not appear to be a factor in temporary absences during April or May.

In our main analysis, we consider recent unemployment and recent absence as separate outcomes. In supplementary work, we combine the two outcome variables into a single dependent variable indicating either recent unemployment or recent absence. The regression results are qualitatively unchanged, but the magnitudes are, as expected, frequently larger because both outcomes behave similarly. These estimates are reported in online Appendix A.9 and Table A9.1.

Next, we examine the possibility that the relationship between job characteristics and recent unemployment reflects preexisting patterns of employment instability not related to the epidemic. A consistent and comparably strong relationship between job characteristics and employment even before the COVID-19 epidemic would throw into question our finding that such characteristics determined labor outcomes during April and May 2020. As a check, we run the same models on April and May 2019 data. We find no clear relationship between either job Face-to-Face Index or being in an essential industry and recent unemployment. There appears to be a negative correlation between Remote Work and recent unemployment in April and May 2019, but the strength of this relationship is an order of magnitude larger in 2020 than in 2019. For temporary work absence, we find a positive and significant coefficient on Face-to-Face, but of a much smaller magnitude in 2019 (between half as small to seven times as small in 2019 compared to 2020, depending on the specification). Tables A10.1 and A10.2 in online Appendix A.10 show the full results, which suggest that while there may have been some preexisting relationships between the various job characteristics we study and labor market outcomes, these characteristics became considerably more important during the epidemic.

We further probe the robustness of our results to the number of weeks used to define the recently unemployed variable. In the robustness check, we vary the number of such weeks. The model coefficients are not sensitive to the cutoff used to define "recent" unemployment. Online Appendix A.11 includes the graphs we used for this exercise (Figures A11.1 and A11.2).

Finally, we replicated Figure 3 and our regression specifications using the definition of Teleworkability as defined by Dingel and Neiman (2020). We find the same sociodemographic groups scoring high (or low) in both telework and remote work, showing the similarity of these two measures. In the regression models with the Teleworkability variable in place of our Remote Work index, we find that the estimates are very similar to our results, and our main analysis is robust to this alternative measure. The graph appears in Figure A6.1 and the regressions in Tables A12.1 and A12.2 in online Appendix A.12.

Decomposing Group Differences in Recent Unemployment

The analysis so far shows that recent unemployment rates in April and May varied substantially across subpopulations. Differences in the kinds of jobs workers held at the onset of the epidemic likely contributed to this variation. In this section, we use a version of the Oaxaca–Blinder decomposition to quantify the role of pre-epidemic sorting more formally (Blinder 1973; Oaxaca 1973). We find robust evidence that pre-epidemic group differences in job characteristics explain the majority of the recent unemployment gap for most comparisons. However, we also show that significant disparities in unemployment are not explained by observable characteristics. Rather, they reflect differences in the rates at which different groups became unemployed at the start of the pandemic, holding job sorting and other characteristics fixed.

Decomposition Model

We examine six aggregate gaps in recent unemployment rates: White versus Black, high school graduate versus high school dropout, female versus male, non-Hispanic versus Hispanic, college graduate versus high school graduate, and older versus younger workers. For each pair, we specify regression models linking recent unemployment with observed characteristics in each of the groups:

$$y_i^A = \alpha_0^A + \boldsymbol{X_i^A\beta^A} + \epsilon_i^A$$

$$y_i^B = \alpha_0^B + \boldsymbol{X_i^B\beta^B} + \epsilon_i^B.$$

In these models, y_i^g is a binary measure of recent unemployment for person i who is a member of subpopulation $g \in [A,B]$[8]; $\boldsymbol{X_i^g}$ is a vector of covariates; α_0^g is a group-specific intercept; and $\boldsymbol{\beta^g}$ is a group-specific vector of coefficients. Let $\bar{y}^g$ and $\boldsymbol{\bar{X}^g}$ represent the average value of the recent unemployment measure and the covariates among group g. The average difference in the shares of workers reporting recent unemployment between A and B is

$$\bar{y}^A - \bar{y}^B = \boldsymbol{\bar{X}^A\beta^A} - \boldsymbol{\bar{X}^B\beta^B} + (\alpha_0^A - \alpha_0^B)].$$

In the standard Oaxaca–Blinder decomposition, the difference in the share recently unemployed between the two groups can be expressed as

$$\bar{y}^A - \bar{y}^B = (\boldsymbol{\bar{X}^A} - \boldsymbol{\bar{X}^B})\boldsymbol{\beta^A} + \left[\boldsymbol{\bar{X}^B}(\boldsymbol{\beta^A} - \boldsymbol{\beta^B}) + (\alpha_0^A - \alpha_0^B)\right].$$

In this form of the decomposition, the first term, $(\boldsymbol{\bar{X}^A} - \boldsymbol{\bar{X}^B})\boldsymbol{\beta^A}$, is called the "endowment effect" and represents the part of the aggregate gap that is explained by differences in average value of observed covariates between the two groups. The second term, $\left[\boldsymbol{\bar{X}^B}\left(\boldsymbol{\beta^A} - \boldsymbol{\beta^B}\right) + \left(\alpha_0^A - \alpha_0^B\right)\right]$, is called the "coefficient effect" and reflects the gap that arises because workers in the two groups have different unemployment outcomes even given the same observed endowments. Oaxaca and Ransom (1994)

8 In each decomposition, group B is the relatively disadvantaged group in terms of employment.

pointed out that the relative size of the endowment and coefficient effects depends on which group's coefficients are treated as "correct" or "nondiscriminatory." The foregoing equation treats group A coefficients as the benchmark, but the decomposition could just as easily be written with group B as the benchmark, leading to a different result. To circumvent this ambiguity, we follow the recommendation in Fortin (2006) to use coefficients from a pooled regression as the benchmark. In the pooled regression, groups A and B are allowed to have different intercepts but are restricted to have the same coefficients on the observed covariates.[9] Using $\boldsymbol{\beta}^{\boldsymbol{P}}$ and α_0^P to represent coefficients from the pooled model, the aggregate gap in recent unemployment rates is

$$\bar{y}^A - \bar{y}^B = \left[(\bar{\boldsymbol{X}}^A - \bar{\boldsymbol{X}}^B)\boldsymbol{\beta}^{\boldsymbol{P}}\right] + \left[(\bar{\boldsymbol{X}}^A(\boldsymbol{\beta}^A - \boldsymbol{\beta}^{\boldsymbol{P}}) + (\alpha_0^A - \alpha_0^P)) - (\bar{\boldsymbol{X}}^B(\boldsymbol{\beta}^A - \boldsymbol{\beta}^{\boldsymbol{P}}) + (\alpha_0^A - \alpha_0^P))\right],$$

where $\left[(\bar{\boldsymbol{X}}^A - \bar{\boldsymbol{X}}^B)\boldsymbol{\beta}^{\boldsymbol{P}}\right]$ represents the part of the aggregate recent unemployment gap that can be attributed to differences in pre-epidemic endowments, using the coefficients from the pooled model as the benchmark. The coefficient effect is characterized by the deviation between the pooled coefficients and each group's unrestricted coefficients. Using this framework, we say that $E = \dfrac{(\bar{\boldsymbol{X}}^A - \bar{\boldsymbol{X}}^B)\boldsymbol{\beta}^{\boldsymbol{P}}}{\bar{y}^A - \bar{y}^B}$ is the share of the aggregate gap coming from the endowment effect.[10] The overall explained share can itself be decomposed to determine the share of the gap explained by specific groups of variables.

Specifically, we can write

$$\left(\bar{\boldsymbol{X}}^A - \bar{\boldsymbol{X}}^B\right)\boldsymbol{\beta}^{\boldsymbol{P}} = \left(\bar{\boldsymbol{X}}^{A,Dem} - \bar{\boldsymbol{X}}^{B,Dem}\right)\boldsymbol{\beta}^{\boldsymbol{P},Dem} + \left(\bar{\boldsymbol{X}}^{A,Job} - \bar{\boldsymbol{X}}^{B,Job}\right)\boldsymbol{\beta}^{\boldsymbol{P},job},$$

where $\bar{\boldsymbol{X}}^{g,Dem}$ and $\bar{\boldsymbol{X}}^{g,job}$ are g-specific averages of demography and job-specific characteristics, and $\boldsymbol{\beta}^{\boldsymbol{P},Dem}$ and $\boldsymbol{\beta}^{\boldsymbol{P},job}$ are conformable parameter vectors. It follows that the overall explained share can be decomposed into a share associated with demographic and job factors so that $E = E^{Dem} + E^{Job}$. In practice, we break the explained share into several categories, including demographic-, industry-, and occupation-specific characteristics.[11]

Decomposition Results

Figure 6 summarizes the most significant gaps in our data. For ease of visualization, they appear ordered from smallest to largest for: White versus Black, high school graduate versus high school dropout, female versus male, non-Hispanic versus

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[9] Our notation $\boldsymbol{\beta}^{\boldsymbol{P}}$ (and α^P) corresponds to $\boldsymbol{\beta}^*$ in Jann (2008), the nondiscriminatory coefficient vectors. We implement the twofold Oaxaca decomposition using the pooled option in Stata.

[10] This decomposition requires a normalization that specifies how much of the unexplained gap comes from positive deviations from the pooled outcome for the advantaged group and how much from negative deviations for the disadvantaged group. Our estimates assume the deviations are symmetric, that is, $(\bar{\boldsymbol{X}}^A(\boldsymbol{\beta}^A - \boldsymbol{\beta}^{\boldsymbol{P}}) + (\alpha_0^A - \alpha_0^P)) + (\bar{\boldsymbol{X}}^B(\boldsymbol{\beta}^B - \boldsymbol{\beta}^{\boldsymbol{P}}) + (\alpha_0^B - \alpha_0^P)) = 0.$

[11] A similar exercise can be conducted to break the coefficient effect across categories. However, the differences in coefficient effects are generally not statistically significant when we focus on the same groups

Hispanic, college graduate versus high school graduate, and older versus younger workers. Figure 7 shows the same decompositions but applied to the May data for recent unemployment. The full results of the decompositions appear in online appendix Tables A13.1 and A13.3 for April and May 2020, respectively.

For each gap, we estimate three versions of the pooled decomposition model. Each model includes basic demographic characteristics (age, gender, race, ethnicity, education, and presence of young children) and state controls. The three models are differentiated by how much detail we include regarding job characteristics. Model A includes the Face-to-Face, Remote Work, and Essential Job indices. Model B adds a full set of 523 occupation dummy variables, which, of course, absorb the variation from the Face-to-Face and Remote Work indices.[12] Finally, Model C adds a full set of 261 industry dummy variables, which absorb the variation from the Essential index. Hence, Model C is the most general specification and nests Model B, which nests Model A.

Focusing first on Model A for the April data, the explanatory contributions of task-based sorting and essential industry sorting operate in different directions across groups. For example, the non-Hispanic–Hispanic gap is quite large at –4.45 percentage points, relative to a baseline recent unemployment rate of 12.1%. About 52.18% of the raw gap arises because Hispanic workers are overrepresented in jobs with little opportunity for remote work. However, these relative losses are partially offset by the fact the Hispanic workers are overrepresented in essential jobs, accounting for −12.24% of the raw gap. This pattern is similar for the Black–White gap. The gender gap displays a different pattern; continuing with the April data, most of the gender gap is unexplained, and in fact sorting on the basis of remote work predicts a smaller gap than actually appears in the data because women are more likely to be in jobs that permit remote work. Moving to Models B and C, we see that sorting by occupation and industry explains a sizable portion of the gender, race, and ethnicity gaps in recent unemployment. However, there remain substantial unexplained differences in employment losses across groups even in these more detailed decompositions.

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

All of the patterns we observe are consistent from April to May except one: the gap in recent unemployment between Black and White workers (see Figure 7). In May, the raw gap is –0.0345 percentage points, double the –0.0171 gap from April.

of demographic and job characteristics. As a result, we cannot say with confidence whether certain types of jobs are differentially protective against job loss.

12 For Model B, Table A13.2 in online Appendix A.13 reports the share of variation in April explained by sorting across five top-level categories in the census occupational classification system: Management, Business, Science, and Arts; Service; Sales and Office; Natural Resources, Construction, and Maintenance; and Production, Transportation, and Material Moving. A sixth category, Military Specific Operations, does not appear because the CPS is a survey of the civilian noninstitutional population. Table A13.4 shows the same results using May data.

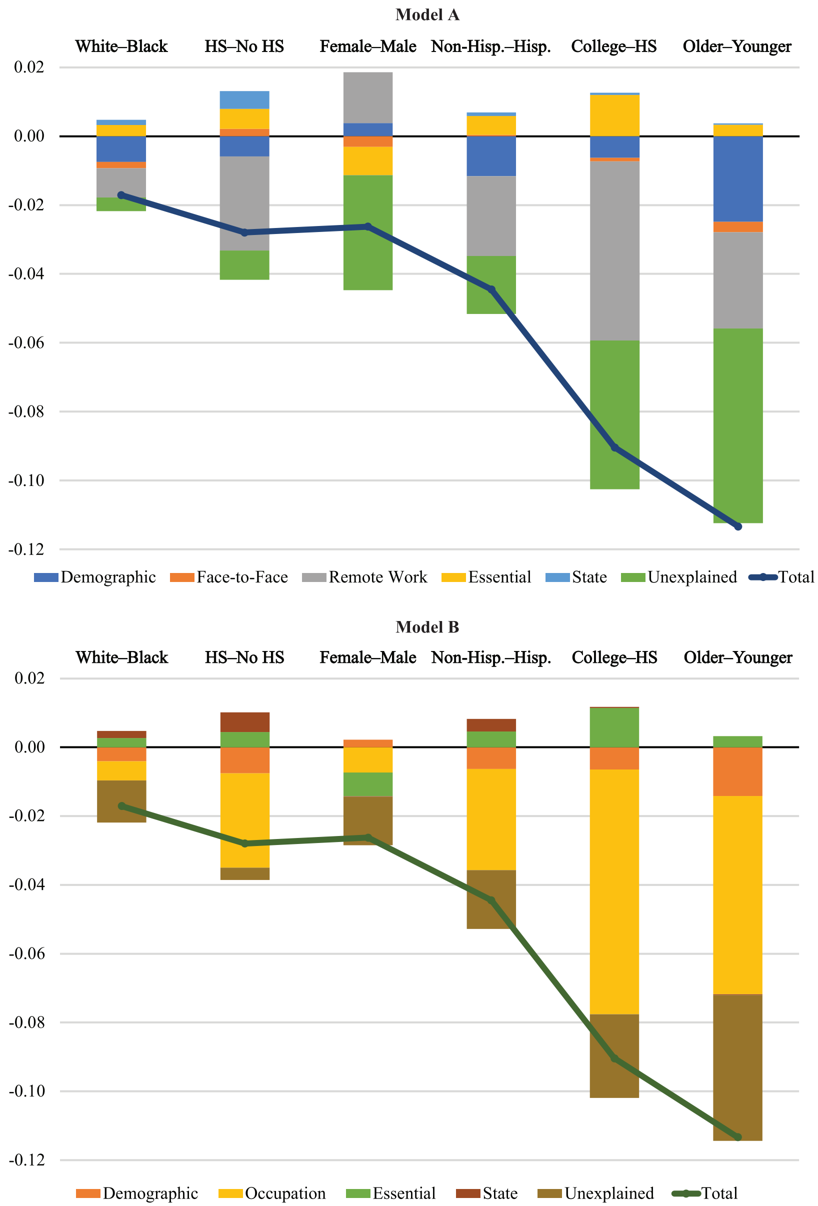

Fig. 6 Oaxaca–Blinder decomposition for April 2020: A graphical representation. The three panels are a graphical representation of the Oaxaca decomposition estimates shown in online appendix Table A13.1. These are obtained through three different models, all of which include sociodemographic controls (i.e., age, gender, race, ethnicity, and education), state fixed effects, and a dummy variable for the presence of children under six. Model A includes the Face-to-Face, Remote Work, and Essential Job indices. Model B adds a full set of 523 occupation dummy variables. Model C includes a full set of 261 industry dummy variables and reports the share of each gap explained by sorting into industries classified as Essential versus Nonessential. Each shaded area represents the share that is, depending on the color, explained by the different sets of variables reported in the legend. The line total shows the raw gap between each comparison pair. (Figure 6 is continued on next page.)

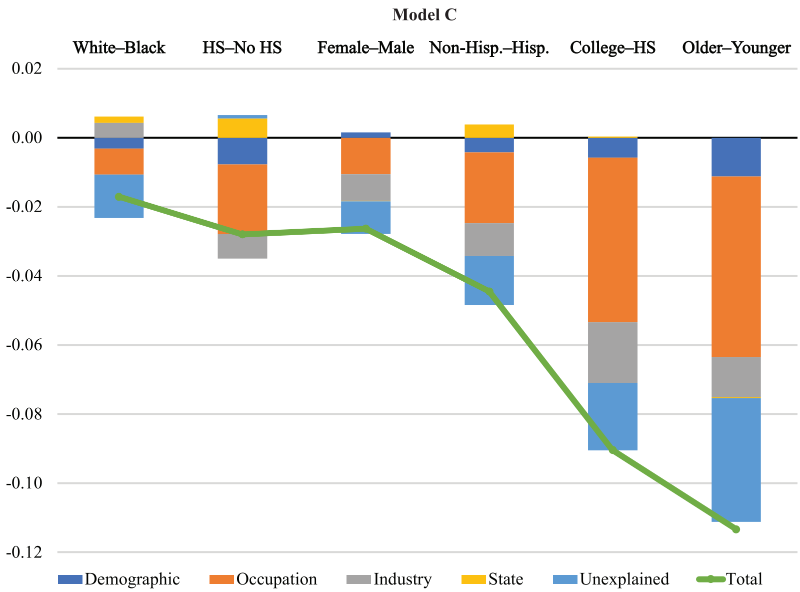

Fig. 6 (continued)

Curiously, all of the growth in the gap is from sources that are not explained by the individual or job characteristics included in the model. Overall, recent unemployment rates fell in May relative to April, as they did for headline unemployment. Consistent with this trend, recent unemployment also fell for White workers. However, recent unemployment rates increased slightly for Black workers. Our decomposition indicates that whatever prevented recent unemployment rates from falling for Black workers was unrelated to any of the individual or job characteristics included in our model. One explanation relates to how the CPS classifies workers as unemployed versus employed-but-absent across months. On the other hand, this result may indicate that even given the same characteristics, White workers are more likely to be reemployed than Black workers in a recovery.

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

We ran these models on data from the same months in 2019 as well (Tables A13.1 and A13.3 in the online appendix) to investigate the role that occupation sorting played in explaining differences in job loss prior to the pandemic. We find that the magnitude of most raw gaps for the groups we consider is much smaller in 2019 than in 2020. Even before the pandemic, for some groups the Remote Work index does explain a statistically significant but economically small share of differences in job loss. Nevertheless, the size and the significance of our 2020 results, compared to

Fig. 7 Oaxaca–Blinder decomposition for May 2020: A graphical representation. See note in Figure 6. (Figure 7 is continued on next page.)

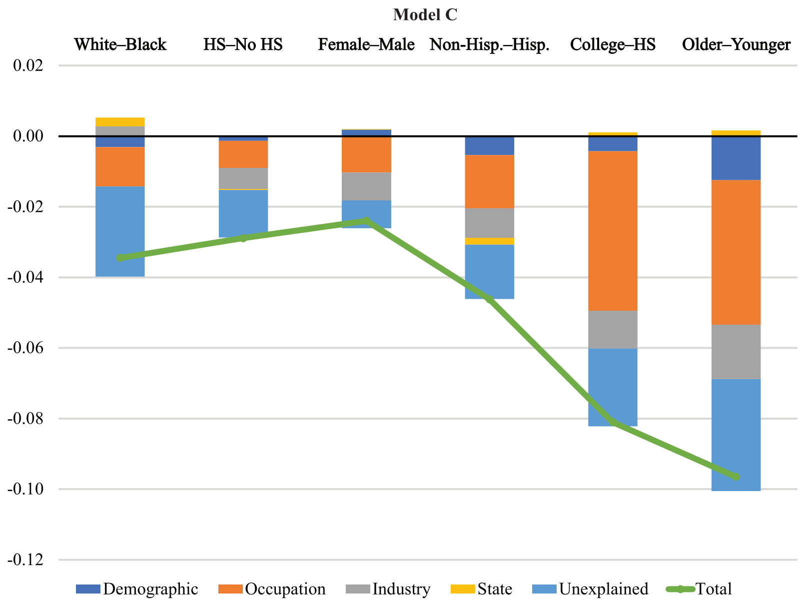

Fig. 7 (continued)

2019, establish that occupational sorting in jobs characterized by high remote work and low face-to-face interaction did contribute substantially more to disparities in job loss during the epidemic than in normal times. Two examples are particularly meaningful. The first is the White–Black raw gap, which in 2019 was significant, but was about half the size of the 2020 raw gap. Furthermore, while remote work explained only 3.64% of the 2019 gap, that increased to 23.31% in 2020. Another example is the gap between high school graduates and high school dropouts. While in 2019 remote work explained more than 57% of the raw gap, the estimated gap was statistically insignificant and approximately zero. However, in 2020, that percentage increased to almost 72% and the raw gap was more than six times as large as in the previous year, and this time it was statistically significant.

Conclusions

After only a few months in 2020, the COVID-19 job losses were larger than the total multiyear effect of the Great Recession. Moreover, there were large disparities in job losses across demographic groups and people with different levels of education. Much of the overall variation in recent unemployment stemmed from differences across different types of jobs. For example, in the April CPS, we found that recent unemployment rates were about 44% lower among workers in jobs that are more compatible with remote work. In contrast, workers in jobs that require more face-to-face contact were at higher risk of recent unemployment.

Formal decomposition analysis shows that a substantial share of the disparity in recent unemployment across racial, ethnic, age, and education subpopulations can be explained by differences in pre-epidemic sorting across occupations and industries that were more versus less sensitive to the COVID-19 shock. However, in almost all cases, a large share of the gaps in job losses between social strata cannot be explained by either occupation sorting or other observable traits. There are at least three possible sources for the unexplained share. First, workers may have different labor supply responses to the epidemic. Second, variation in exposure to labor demand shocks may not be fully reflected in the occupational or demographic differences we considered. Third, workers may face disparate treatment when employers make layoff and recall decisions. The available data do not allow us to distinguish between these three channels.

These results raise concerns about the risks of workplace COVID-19 exposure and how that risk is distributed across the population. More highly educated workers had more job security during the epidemic because their work is often compatible with remote work. The least educated workers have also experienced less recent unemployment, largely owing to their concentration in essential industries, but these workers likely face greater exposure to COVID-19 itself. Thus, the higher job security available to workers with high or low education potentially masks a disparity in the health risks. New government policies or private-sector innovations that increase the viability of remote work for a larger share of the economy could be extremely valuable.

The analysis of May CPS data showed an uptick in employment that likely derived from the business reopenings implemented in most states during that month. Although rates of recent unemployment and absence from work were still high in the May data, the data do suggest that reopening policies reduced the negative impact of the epidemic on the labor market. The improvements in labor market outcomes are consistent with cell signal data, which show a rise in physical mobility starting in mid-April and continuing through May (Nguyen et al. 2020). Of course, future potential waves of the virus make the return to full normalcy and its duration quite uncertain.

In the meantime, our results highlight that there are large disparities in the current labor market crisis, and they suggest a role for targeted public policies. Although women with young children did not have statistically larger increases in recent unemployment compared to men with young children, despite the disruptions in school and childcare, their higher rate of "employed-but-absent" is worrying and could indicate larger losses in future employment. Moreover, single parents, who are overwhelmingly women, experienced a larger decrease in employment between February and April, as well as between February and May, than their married counterparts. Efforts to support new childcare options are important in this context. In May 2020, during the reopening phase, we found some evidence of racial disparities in reemployment. For example, Black workers became employed at a proportionately lower rate than did other groups. Further, the decomposition analysis shows that while for most groups recent unemployment decreased in May, it increased slightly for Blacks, and this gap is not related to any of the individual or job characteristics we considered.

Our results point at deeper structural damage to the economy than may initially meet the eye. Previous research has documented large scarring effects of graduating from high school or college during a recession, and the longer term effects of early career setbacks may be even larger than the near-term effects (Rothstein 2019). Our work shows that recent unemployment rates are very high among the youngest workers overall and in comparison to earlier recessions. Finding workers whose employment match with their employer is highly productive is costly. Hence, efforts to support early career workers, as well as older displaced workers, may need to be a particular target of policy in the near future. Another important policy consideration that arises from our study regards access to health care. In the United States, workers receive health care and other benefits through employers. Assuming economic conditions in the post-epidemic years improve but remain unstable as a result of future waves of the virus, policymakers should make it a priority to help workers maintain their occupation with their original employers. However, if economic conditions do not return to normal rapidly, then the smooth reallocation of workers into different types of jobs may also be needed. ■

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