Employment Transitions Among Older Americans During the Initial Lockdown and Early Reopening Months of the COVID-19 Recession

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This study examines the employment status of older Americans in the months immediately before and after the peak COVID-19 lockdown in April 2020. We construct longitudinal employment data from 2019–2020 Current Population Surveys. To account for seasonal fluctuations in employment and retirement patterns that are not unique to the COVID-19 recession, we implement a difference-in-differences analysis using multinomial logistic regressions. We find that the onset of the pandemic immediately and adversely affected all workers, but the extent of the employment disruptions varied by age group, sex, and whether the worker has a college degree. Reemployment patterns after the peak lockdown month also varied but did not simply reverse the earlier patterns. Our findings imply that the employment effects of the COVID-19 recession are substantially different from those of previous recessions.

Introduction

Employment disruptions during economic downturns can have lasting consequences, particularly for older adults. In the early stages of the COVID-19 pandemic, U.S. unemployment rose sharply and work hours decreased. The effects, however, were not uniform across worker subgroups. For example, employment loss was higher among workers with less education (Bartik and others 2020) and minorities (Andrea and others 2022; Fairlie, Couch, and Xu 2020; Kim and others 2021; Moen, Pedtke, and Flood 2020).

In this article, we investigate how the onset of the COVID-19 pandemic and the resulting recession affected the employment dynamics of older Americans. Although there has been a surge of interest in studying the pandemic's employment effects, few studies have focused on older adults and even fewer have assessed their employment patterns by following individual subjects over time. Moreover, heterogeneity in pandemic employment patterns among older adults is not well established, despite studies (such as Kim and others 2021) showing disparate effects among other subgroups in the working-age population.

The employment dynamics of older Americans during the COVID-19 recession are important to document and understand given the rising median age of the population and the significance of employment for older adults' income and preparation for retirement (Goda and others 2022; Munnell and Rutledge 2013). In addition, the COVID-19 recession could affect older Americans in unexpected ways (Resnick, Zimmerman, and the Gerontological Society of America COVID-19 Task Force 2021). State government–mandated business closures; social distancing policies; and occupational differences between essential and nonessential workers and the ability to work from home, among other factors, may affect groups differently. Further, because the risk of serious health

Selected Abbreviations

CPS	Current Population Survey
DID	difference-in-differences
IPUMS	Integrated Public Use Microdata Series
MORG	Merged Outgoing Rotation Group

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complications from the virus increases sharply with age (Polyakova and others 2020; Verdery and others 2021), the COVID-19 recession may affect older adults differently than prior downturns. We explore the employment dynamics of older adults during the early months of the COVID-19 recession using monthly data from the Current Population Survey—Merged Outgoing Rotation Group (CPS-MORG), available from the Integrated Public Use Microdata Series (IPUMS) database (Flood and others 2020). We construct two longitudinal data sets that track individuals' monthly employment status before and after the peak lockdown in April 2020. We track whether workers had continuous work, transitioned from employment to non-employment, or resumed work, and compare the experiences of older and younger workers. A unique challenge in studying changes in older adults' employment over time is controlling for events unrelated to COVID-19, especially involving retirement. To circumvent this issue, we use difference-in-differences (DID) regressions, which adjust for observed differences in employment across age groups over the same months in 2019.

Our results shed new light on the labor market experiences of older adults during the COVID-19 recession. We find that the onset of the pandemic had a large and immediate adverse effect on employment for older Americans, yet older men and women were less likely to transition from employment to nonemployment than younger workers were. However, there was considerable heterogeneity across education levels. During the early reopening months of the summer of 2020, older Americans were less likely to resume employment than younger adults were because they were also less likely, on average, to have experienced employment disruptions during the lockdown, which mitigates their seeming disadvantage in reemployment.

Background: Older Adults' Employment During Hard Economic Times

We situate our study within the rapidly growing literature on the employment effects of the economic downturn caused by the COVID-19 pandemic. Studies find evidence of a range of adverse employment outcomes related to state-mandated lockdowns, business closures, and social distancing policies. The outcomes include surging unemployment, unprecedented temporary layoff rates, a spike in labor force nonparticipation, and declining work hours (Bartik and others 2020).

Yet the employment effects have not been felt uniformly across groups. For example, work-hour reductions related to increased caregiving requirements affected mothers far more than fathers (Collins and others 2020). Additionally, unemployment at the onset of the recession was concentrated among the less-educated (Bartik and others 2020; Moen, Pedtke, and Flood 2020), although workers without a high school diploma appear to be less negatively affected because they tend to be employed in "essential" occupations (Montenovo and others 2020). Minorities also were hard hit by the economic fallout of COVID-19 (Andrea and others 2022; Fairlie, Couch, and Xu 2020; Kim and others 2021).

Comparatively little attention has focused on older Americans' employment over the pandemic. A body of literature indicates that older and younger adults often fare differently in terms of employment disruptions during recessions (Redbird and Grusky 2016). Regarding job loss, studies have consistently found that older adults are less negatively affected, in large part because of their seniority and job experience (Couch and others 2018). If this pattern continued during the pandemic, we would find evidence that older adults' employment was more stable than that of their younger counterparts during the COVID-19 recession. On the other hand, older workers who are displaced during recessions tend to experience greater wage losses and reductions in income (Couch and others 2018; Couch, Jolly, and Placzek 2009). They also tend to experience longer unemployment spells between jobs (Johnson and Butrica 2012; Neumark and Button 2013; Wanberg and others 2016).

A complication in studying the employment effects of economic downturns on older adults is accounting for retirement transitions. A strand of research shows that economic downturns, such as the Great Recession, are associated with increased probabilities of retirement and early Social Security benefit claiming (Coile and Levine 2011; Fichtner, Phillips, and Smith 2012). Research also finds evidence that some older adults postpone retirement or take "bridge jobs" (for example, positions taken to maintain income or health insurance coverage while searching for permanent work or until becoming eligible to claim retirement benefits) during economic contractions (Munnell and Rutledge 2013). Job loss during recessions may also increase the long-run probability of Social Security disability benefit uptake (Couch and others 2013).

Research on past recessions provides insights, but the COVID-19 recession has notable distinctions.

Many state governments responded to the public health and safety emergency by abruptly mandating business closures, issuing stay-at-home orders, and instituting social distancing policies, which resulted in more rapid employment loss than occurred in past recessions. Job losses also were concentrated in industry sectors differing from those in past recessions, such as retail sales and hospitality rather than construction and manufacturing (Cajner and others 2020; Montenovo and others 2020). Yet many job losses related to COVID-19 might be temporary, as evidenced by a rebound in employment in May and June of 2020 that was fueled in large part by workers returning to their same jobs (Cheng and others 2020; Sanzenbacher 2021).

There are various reasons why the COVID-19 economic downturn could affect employment differently for older and younger adults. As noted earlier, older adults tend to have longer job tenure and work experience, which increase employment stability. Yet older workers also face greater risk of severe complications from the virus than their younger counterparts do. Consequently, older workers who fear the virus or who face greater exposure may be more likely to leave the labor force or retire earlier than expected to minimize the risk of infection. This may be particularly evident among persons who cannot work remotely or are aged 62—Social Security's early eligibility age for retirement benefits—or older. Vulnerability to the virus may also reduce older workers' propensity to take bridge jobs, as such jobs often entail more face-to-face contact (Bui, Button, and Picciotti 2020).

There are also demand-side reasons why the employment dynamics of older adults may have differed from those of younger persons during the pandemic. One aspect is age discrimination. Employers may hold negative stereotypes about older workers, which can reduce their employment stability or reemployment opportunities during an economic downturn (Neumark, Burn, and Button 2019). Further, to the extent that employers view older workers as more expensive or vulnerable than younger workers during the COVID-19 recession (Ayalon and others 2020), older workers could be more susceptible to layoffs or displacement.

Disparate employment outcomes can also result from the types of occupations and industries that employ older adults (Carr 2021). Some industries were more negatively affected by the COVID-19 outbreak than others (Adams-Prassl and others 2020; Angelucci and others 2020; Fairlie, Couch, and Xu 2020). Older workers are less likely than younger workers to be employed in industries such as eating and drinking establishments, where job losses related to COVID-19 were higher.

To date, the few studies that focused on older workers have shown mixed evidence. Bui, Button, and Picciotti (2020) document larger relative increases in unemployment at the onset of the COVID-19 recession among adults aged 65 or older, particularly among women. Moen, Pedtke, and Flood (2020) report marked increases in unemployment among men and women in their 50s without a college degree. Another study shows increased probabilities of early work-to-retirement transitions in April 2020 (Coibion, Gorodnichenko, and Weber 2020). Heterogeneity by sex also may emerge (Couch, Fairlie, and Xu 2022). Bui, Button, and Picciotti (2020) find greater relative drops in employment for female workers aged 65 or older than for similarly aged men. Goda and others (2022) show that older workers' employment dropped sharply, and their unemployment rate increased, in the early months of the COVID-19 pandemic. Like Sanzenbacher (2021), we build on these works by tracking changes in employment status for individuals longitudinally while controlling for general economic trends over time.

The employment effects induced by the COVID-19 pandemic also differ across time. April 2020 is commonly described as the most stringent lockdown month as indicated by job losses, business closures, reduced operations, and stay-at-home policies (Bureau of Labor Statistics 2021; Fairlie, Couch, and Xu 2020). The sharp drop in economic activity in April led to large increases in unemployment and dramatic employment loss. Reopenings in the late spring and summer of 2020 led to modest rebounds in employment levels in many states, largely involving individuals who resumed working at their previous job (Cheng and others 2020; Kim and others 2021). To our knowledge, no prior studies have examined how older adults' employment dynamics differed from those of the prime working-age population between these two phases.

Research Design

We use data from the January–July 2019 and 2020 surveys of the CPS-MORG, a nationally representative monthly employment survey. The CPS-MORG uses a unique 4-8-4 outgoing-rotation design, which means that households are interviewed for 4 consecutive months, then unobserved for 8 months, then reinterviewed for 4 additional months. Using an identification key to link responses for individual respondents, we can construct two longitudinal data sets that contain monthly information for those individuals over multiple months. The first data set allows us to track changes in individuals' employment status from the prelockdown phase (January–March 2020) to the peak lockdown month (April 2020). The second data set enables us to track employment status from April to the early "reopening" months (May–July). Each data set includes some individuals who are not included in the other, but the demographic characteristics of both panels are very similar.

For each data set, we select two observations per respondent to detect any changes in their employment status. For the first data set, which we call the "lockdown panel," we link the April observation to that for the latest prelockdown month (that is, March, if available; if the March interview is absent, then February; if not February, then January). For the second data set, the "reopening panel," we link the April observation to the latest postlockdown month in our observation period (that is, July, if available; if the July interview is absent, then June; if not, then May). We use the CPS-MORG data covering the same months in 2019 for comparison.

Our analytic sample consists of men and women aged 18–69 who are not enrolled in school or institutionalized. To examine employment transitions, we use a DID design with multiple time periods using multinomial logistic (logit) regression models. DID is a quasiexperimental approach that allows us to better isolate a specific effect from general trends over time (Gangl 2010), making it suitable for analyzing the COVID-19 downturn.

Of particular interest are differences by age; specifically, comparisons of older workers' employment-status changes with those of individuals of the prime working ages of 30–49 over the same period. However, comparing employment changes among older and prime-age workers poses the unique challenge of distinguishing between the types of employment transitions more typical of one age group or the other. For example, older adults who stop working are likely to include some who retire voluntarily. To disentangle the increases in nonemployment that are due to COVID-19 from retirement transitions in a "normal" year, we introduce a second difference—that is, the difference between 2019 and 2020. Applying the DID approach thus allows us to account for employment trends across age groups that occurred prior to the COVID-19 recession as we estimate the differentials that occurred during the pandemic.

In nonlinear DID models such as binary or multinomial logits, one cannot assume that the time effect is constant across groups and the group effects are constant across time (Puhani 2012). Thus, we cannot assume common trends for the expected potential outcomes. However, we can assume common trends for a nonlinear transformation of the expected outcomes (Lechner 2011). That is, we estimate the treatment effect (COVID-19) on older workers by comparing the difference across age groups of the conditional expectation of the observed outcomes (or the observed change in work status) to the difference across age groups in the conditional expectation of the counterfactual outcomes (or the counterfactual change in work status without interaction effects between time and groups). Throughout the article, we interpret the estimated DID effects for older workers relative to the prime working-age population.

The main dependent variable is employment status. The variable consists of four mutually exclusive employment-status categories that may occur over two points in time: (1) continuously employed; (2) employed to not employed; (3) not employed to employed; and (4) continuously not employed. For example, in the lockdown panel, respondents who were employed in March and not employed in April are classified as "employed to nonemployed." This dependent variable offers a reliable estimate about employment status during the COVID-19 recession. "Nonemployed workers" include those who had a job but were not at work, as well as those who were unemployed or not in the labor force. Workers who are temporarily laid off are ordinarily classified as unemployed. However, during the COVID-19 lockdown, a substantial portion of such individuals were miscategorized as "employed but not at work" because of the abruptness of the layoffs (Bureau of Labor Statistics 2021). As a result, unemployment rates among labor force participants in that period may be biased. We focus on an individual's probability of being at work because that metric is not affected by the COVID-19–related misclassification and thus is the most stable measure of employment.

The analysis and the dependent variable for both the lockdown and reopening data panels are consistent. Note that we elected not to restrict the analysis sample for our logit models to those who were employed in January–March for the lockdown panel, and to those who were not at work in April for the reopening panel. This is because restricting the analysis sample to individuals who were not at work in April for the reopening panel could lead to a serious selection bias.

Put briefly, those who were not at work in April 2020, following the onset of the pandemic, would not be comparable to those who were not at work in April in 2019. That is, we cannot assume the common trends if we limit the analysis sample in such a way. Our strategy can avoid this problem. Using this dependent variable, we calculate a series of sex-specific multinomial logit regression estimates as follows:

$$\ln\left(\frac{P(Y_k)}{P(Y_c)}\right) = \sum \beta_{jk} G_j + \gamma_k T + \sum \delta_{jk}(G_j \times T) + \sum \theta_{lk} X_l + \alpha_s + M_\mu ,$$

where $P(Y_c)$ is the probability of the employment status of the reference group (continuous work) and $P(Y_k)$ is the probability of the employment status of the comparison group. G_j is a set of dummy variables indicating age group *j*. Workers of prime working ages (30–49) are the reference group. Older adults are broken out into narrower age ranges (50–54; 55–59; 60–64; 65–69). β_{jk} measures the relative odds of outcome *k* for age group *j* compared with the reference group at time *T* (a dummy variable for year 2020). Thus, γ_k quantifies the change in the logarithm of the odds ratio (log odds) of outcome *k* in 2020 compared to 2019 for the prime working-age group. Our main interest is the coefficient of $(G_j \times T)$, δ_{jk}, which measures the change in the relative odds of the outcome *k* for the age group *j* in 2020 over the same months in 2019 relative to the change for the reference group (prime-age workers).

Control variables, X_l, include race/ethnicity (non-Hispanic White, non-Hispanic Black, Asian, Hispanic, other), race/ethnicity interacted with year, education (less than high school diploma, high school graduate, some college, bachelor's degree, and graduate degree), education interacted with year, marital status, nativity, citizenship status, family size, and number of children. Fixed effects, α_s, control for state-level variation in lockdown severity and other unobserved state-level heterogeneity. CPS panel months, M_μ, are also controlled. To assess the role of job characteristics in driving differences in employment transitions by age group, some sets of models include labor-market covariates. All models generate estimates separately for men and women with survey weights. We report robust standard errors.

Although the National Bureau of Economic Research (2022) defines the COVID-19 recession as occurring from February to April 2020, we use "COVID-19 recession" to refer to the April 2020 peak lockdown month and the May–July 2020 observation period. We use "reopening" to refer to our May–July 2020 observation period.

Results

We find sharp drops in employment in all age groups at the onset of the pandemic (that is, in April 2020 relative to April 2019), but the reduction was proportionally larger for younger workers, particularly for those aged 18–29 (Table 1). For example, the share of employed (and currently working) adults aged 18–29 dropped by 20.4 percentage points from April 2019 to April 2020 (from 77.5 percent to 57.1 percent). In comparison, the drop was 13.8 percentage points among workers aged 30–49 and 9.9 percentage points among workers aged 60–64.

Chart 1 presents the monthly employment rates for men and women from January to July in both 2019 and 2020, by age group. In 2020 (panels C and D), employment rates declined substantially and immediately at the start of the pandemic, particularly from March to April, the month of the most stringent lockdowns. For example, among persons aged 60–64, the employment rate declined from 58 percent to 52 percent for men and from 49 percent to 40 percent for women. The employment rate rebounded modestly after April but remained lower than in the prepandemic months.

Chart 1 also shows variations by age in how steeply employment declined in the early months of the pandemic. Overall, the extent of employment loss was deeper among younger age groups. For example, panel C shows that the share of currently working men aged 18–29 dropped by 17.1 percentage points from March to April 2020 (from 77.4 percent to 60.3 percent). In comparison, the drop was 11.6 percentage points among men aged 30–49 and 6.5 percentage points among men aged 60–64. Panel D shows similar trends for women: The employment rate of those aged 18–29 decreased 18.0 percentage points from March to April 2020, while the decline was 8.7 percentage points for women aged 60–64.

Table 2 presents the regression-adjusted DID results for the lockdown panel, which show the change in the probability of each of the four employment statuses (two continuations and two transitions) between the prepandemic months (January–March 2020) and the peak lockdown month (April 2020) relative to the same period in 2019, by age and sex. For ease of interpretation, we report the predicted values based on the estimated log odds. Separate panels present results for men and women. Both panels also present DID estimates for each age group relative to the reference group (the prime working ages of 30–49). The DID estimates therefore quantify the extent to which

Table 1.
Employment status before and during the COVID-19 pandemic and other descriptive statistics for adults aged 18–69, by age group (in percent)

Characteristic	18–29	30–49	50–54	55–59	60–64	65–69
Employment status, April 2019						
Employed, currently—						
Working	77.5	79.6	75.8	68.5	55.5	32.1
Not working	1.6	1.9	2.2	2.1	1.9	1.3
Unemployed	4.8	2.2	2.1	1.6	1.4	0.9
Not in labor force	15.6	15.4	16.4	18.7	16.4	8.9
Retired	0.6	0.9	3.5	9.1	24.8	56.7
Employment status, April 2020						
Employed, currently—						
Working	57.1	65.8	63.2	57.3	45.6	24.8
Not working	5.3	5.6	4.9	5.4	4.7	3.7
Unemployed	15.7	9.7	9.8	8.9	7.0	4.8
Not in labor force	21.2	18.1	18.8	20.2	18.0	9.4
Retired	0.6	0.9	3.3	8.2	24.7	57.2
Educational attainment						
Less than high school diploma or equivalent	8.5	8.8	9.7	9.9	9.5	9.1
High school diploma or equivalent	35.3	25.2	27.9	30.3	31.2	28.5
Some college, no bachelor's degree	27.4	24.8	25.3	26.6	27.0	27.9
Bachelor's degree	23.0	25.5	23.0	21.1	19.9	20.4
Postgraduate degree	5.7	15.8	14.1	12.1	12.3	14.2
Sex						
Men	51.3	49.6	49.1	48.6	47.6	46.8
Women	48.7	50.4	50.9	51.4	52.4	53.2
Race/ethnicity						
Non-Hispanic White	53.8	57.1	63.5	68.1	70.6	73.4
Non-Hispanic Black	14.3	12.3	12.0	11.5	11.6	10.3
Asian American	5.5	7.5	6.0	5.1	5.1	4.9
Hispanic	22.7	20.5	16.4	13.3	10.9	9.8
Other	3.8	2.7	2.0	2.0	1.8	1.6
Nativity						
Foreign-born	13.3	23.7	22.5	19.2	16.2	14.9
U.S.-born	86.7	76.3	77.5	80.8	83.8	85.1
Marital status						
Married	21.8	62.3	66.1	65.4	64.9	64.4
Separated, divorced, or widowed	3.1	12.8	20.8	22.8	24.9	27.6
Never married	75.1	24.9	13.1	11.8	10.2	8.0
Average number of children in home	0.344	1.294	0.916	0.561	0.339	0.229
Sample size [a]	152,178	376,523	97,493	109,480	109,998	96,657
Unique respondents [a]	60,875	126,214	33,523	36,787	36,459	31,696

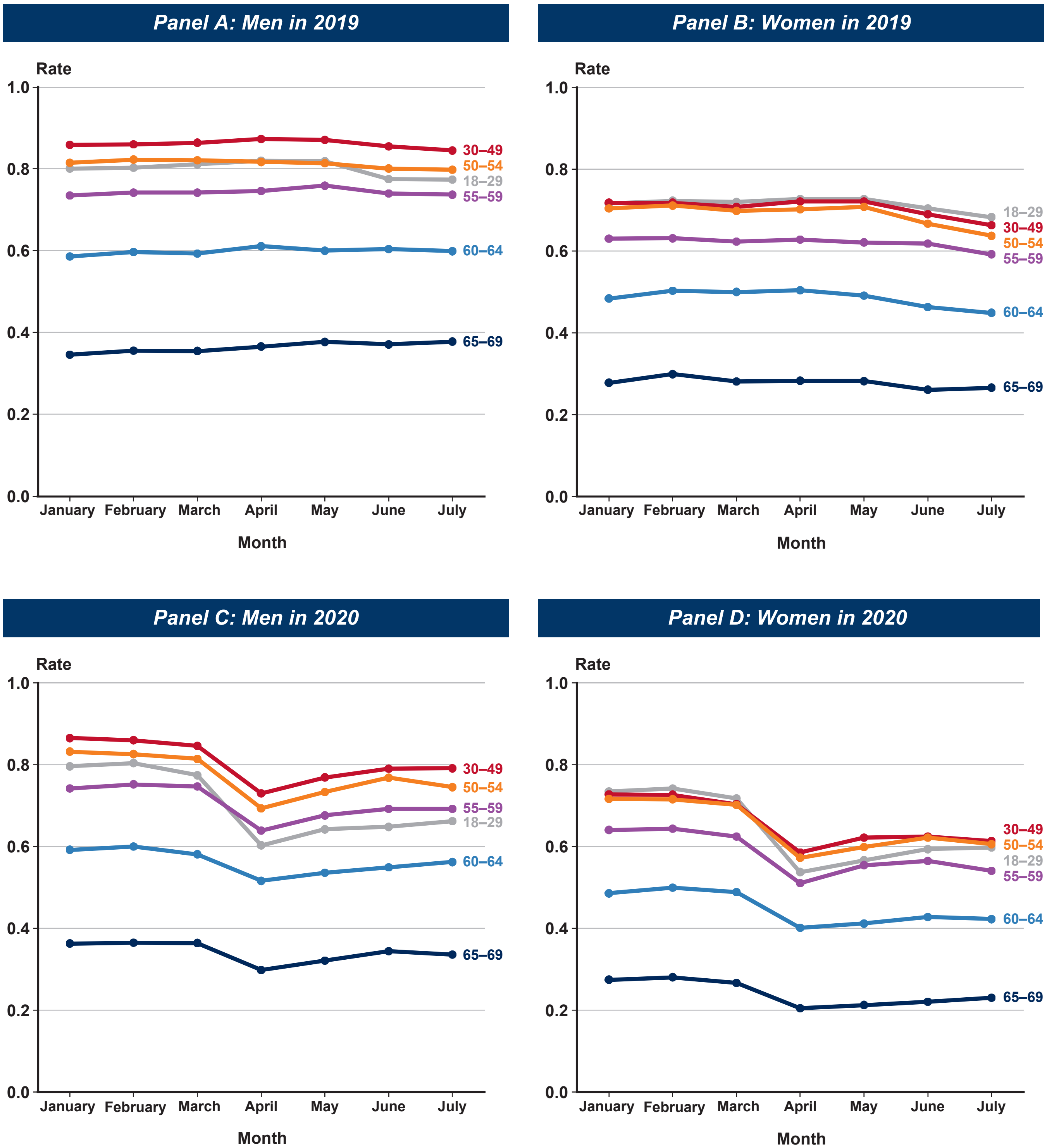
SOURCE: Authors' calculations using CPS-MORG data available from the IPUMS database.

NOTES: Rounded components of percentage distributions do not necessarily sum to 100.0.

Demographic characteristics are as of April 2020.

a. Because the CPS uses a rotating sampling scheme, a single respondent can be interviewed multiple times.

Chart 1.
Monthly employment rates by age group and sex: January–July 2019 and 2020



SOURCE: Authors' calculations using CPS-MORG data available from the IPUMS database.

Table 2.
Lockdown panel: Predicted probability of each employment status between January–March and April, 2019 and 2020, by age group; and DID estimates between age groups; all by sex

Variable and age group	Working in January–March and— Working in April (continuously employed)	Working in January–March and— Not working in April (employed to nonemployed)	Not working in January–March and— Working in April (nonemployed to employed)	Not working in January–March and— Not working in April (continuously nonemployed)
		Men		
Probability in 2019				
18–29	0.866	0.028	0.041	0.064
30–49	0.849	0.023	0.035	0.092
50–54	0.804	0.028	0.029	0.138
55–59	0.732	0.031	0.029	0.208
60–64	0.580	0.031	0.034	0.355
65–69	0.296	0.033	0.023	0.648
Probability in 2020				
18–29	0.714	0.155	0.036	0.096
30–49	0.712	0.139	0.028	0.121
50–54	0.678	0.139	0.026	0.158
55–59	0.615	0.144	0.023	0.217
60–64	0.471	0.120	0.023	0.385
65–69	0.228	0.108	0.018	0.646
Difference from 2019 to 2020				
18–29	-0.152***	0.126***	-0.005	0.032***
30–49	-0.137***	0.116***	-0.007*	0.028***
50–54	-0.127***	0.110***	-0.003	0.020
55–59	-0.117***	0.114***	-0.006	0.009
60–64	-0.109***	0.090***	-0.011*	0.030
65–69	-0.068***	0.075***	-0.006	-0.001
DID between age groups				
18–29	-0.015	0.011	0.001	0.003
30–49 (reference group)	. . .	. . .	. . .	. . .
50–54	0.010	-0.005	0.004	-0.009
55–59	0.021	-0.002	0.001	-0.020
60–64	0.029	-0.026*†	-0.004	0.002
65–69	0.070***	-0.041***‡	0.001	-0.030
Number		45,722		
Pseudo R^2		0.1518		

(Continued)

Table 2.
Lockdown panel: Predicted probability of each employment status between January–March and April, 2019 and 2020, by age group; and DID estimates between age groups; all by sex—*Continued*

Variable and age group	Working in January–March and—		Not working in January–March and—	
	Working in April (continuously employed)	Not working in April (employed to nonemployed)	Working in April (nonemployed to employed)	Not working in April (continuously nonemployed)
	Women			
Probability in 2019				
18–29	0.690	0.036	0.040	0.234
30–49	0.698	0.034	0.037	0.232
50–54	0.696	0.035	0.034	0.235
55–59	0.606	0.031	0.028	0.336
60–64	0.473	0.036	0.031	0.459
65–69	0.239	0.028	0.024	0.709
Probability in 2020				
18–29	0.535	0.187	0.027	0.250
30–49	0.568	0.155	0.027	0.250
50–54	0.566	0.153	0.027	0.254
55–59	0.499	0.149	0.019	0.333
60–64	0.369	0.121	0.022	0.488
65–69	0.165	0.079	0.015	0.740
Difference from 2019 to 2020				
18–29	-0.155***	0.151***	-0.013*	0.016
30–49	-0.130***	0.122***	-0.010***	0.018**
50–54	-0.129***	0.118***	-0.007	0.019
55–59	-0.107***	0.118***	-0.009*	-0.003
60–64	-0.104***	0.085***	-0.009*	0.029
65–69	-0.074***	0.051***	-0.008	0.031*
DID between age groups				
18–29	-0.025	0.030**	-0.002	-0.002
30–49 (reference group)	. . .	. . .	. . .	. . .
50–54	0.000	-0.004	0.003	0.000
55–59	0.023	-0.004	0.001	-0.021
60–64	0.026	-0.037***†	0.001	0.010
65–69	0.056***	-0.070***	0.002	0.012
Number	48,565			
Pseudo R^2	0.1106			

SOURCE: Authors' calculations using CPS-MORG data available from the IPUMS database and DID regression analysis.

NOTES: Control variables are fixed at the means.

Control variables are race/ethnicity, race/ethnicity interacted with year, education, education interacted with year, marital status, nativity, citizenship status, family size, number of children, state of residence, and CPS panel month.

. . . = not applicable.

* = $p < 0.05$; ** = $p < 0.01$; *** = $p < 0.001$ (marginal effects, two-tailed test).

† = $p < 0.05$; ‡ = $p < 0.01$ (logit DID estimates for which the sample is limited to those who worked in January–March, two-tailed test).

employment transitions experienced by older workers during the lockdown differed from those of the prime-age population, adjusting for general economic trends and the control variables in the models. Of key interest for this lockdown panel is the employed-to-nonemployed category from 2019 to 2020 by age.

Not surprisingly, the onset of the pandemic was significantly associated with higher employed-to-nonemployed transition rates for men than occurred in 2019 for all age groups (indicated by positive figures for differences between 2019 and 2020). However, the magnitude of the increases varied substantially by age. Younger workers were more likely to transition from employment to nonemployment during the pandemic: That likelihood increased by 11.6 percentage points for men aged 30–49, but by only 9.0 percentage points for men aged 60–64 and 7.5 percentage points for men aged 65–69. Interestingly, the increase from 2019 to 2020 in the likelihood of moving from employed to not employed for men in their late 50s was nearly the same as that for prime-age men.

Among women, workers in their 60s were significantly less likely than their younger counterparts to transition from employed to not employed at the onset of the COVID-19 recession. Those aged 18–29 experienced the highest increase from 2019 to 2020 in the likelihood of such a transition (15.1 percentage points), while women aged 65–69 experienced the lowest percentage-point increase (5.1).

Some observers might wonder whether workers in their 60s had lower increases in employed-to-nonemployed transitions because their baseline at-work rates (that is, before April) were lower than those of younger age groups. One way to address this concern is use logit models that limit the sample to those who were employed before the pandemic. This is possible because we can assume the common trend between 2019 and 2020 even with the restricted sample. In Table 2, statistically significant estimates from these limited-sample logit models are indicated by a dagger (or double dagger) symbol. The DID logit estimates generate significant negative coefficients for employed-to-nonemployed transitions for men and women in their 60s, which implies that their employed-to-nonemployed transition rates relative to those of prime-age workers were not simply a reflection of the lower baseline at-work rate before April. (With a p-value of 0.052, the estimate for women aged 65–69 is not marked with a dagger.)

Table 3 presents results for models like those used in Table 2 but also stratified by education. For brevity, we present only the final DID estimates, with prime-age workers as the reference group. Interestingly, the relative advantage for older workers over prime-age workers during the early months of the COVID-19 recession was experienced largely by those without a college degree. We know this because the probability of shifting from employment to nonemployment for men without a college degree was lower among the three oldest age groups (55–59, 60–64, and 65–69) than for prime-age men (ages 30–49). By contrast, the differences between workers in prime working ages and the other age groups in the odds of shifting to nonemployment is more compressed in the model comprising men with at least a bachelor's degree.

For older women, we also see significant differences by education. Among women without a college degree, those aged 55–69 had lower likelihoods of shifting from employment to nonemployment between January–March and April 2020 than did the prime-age group. By contrast, among those with a college degree, the likelihood of employment disruption—relative to prime-aged women—was slightly higher for those aged 55–59, was not significantly different for those aged 60–64, and was lower only for those aged 65–69.

Note that the lower likelihood of transitioning from employment to nonemployment for older nondegree-holding workers than for prime-age nondegree-holding workers does not also mean that those older nondegree-holding workers fared better than older workers with a college degree. Pandemic-related employment disruptions affected nondegree-holding workers more negatively than degree-holders regardless of age.

We designed additional models that included labor market covariates (industry, occupation, public/private sector) along with the control variables listed in Table 3 (results available upon request). Interestingly, when those models were stratified by education, we found that the lower likelihood of employed-to-nonemployed transition for older nondegree-holding workers than for prime-age nondegree-holders largely dissipated once we adjusted for labor market covariates, for both men and women. This implies that older nondegree-holding workers were less likely to experience employment disruptions than prime-age nondegree-holding workers during the lockdown phase because of the kinds of jobs they had. By contrast, among the models including only persons with a college degree, we found evidence that older workers were at least as likely as prime-age workers to experience disruption. These results cast doubt on the idea that older adults' labor market transitions during the COVID-19 lockdown were uniform.

Table 3.
Lockdown panel DID estimates of employment-status predicted probabilities between January–March and April, 2019 and 2020, by sex, age group, and education, with demographic and education control variables

Education and age group	Working in January–March and— Working in April (continuously employed)	Working in January–March and— Not working in April (employed to nonemployed)	Not working in January–March and— Working in April (nonemployed to employed)	Not working in January–March and— Not working in April (continuously nonemployed)
		Men		
Less than bachelor's degree				
18–29	-0.012	0.008	0.002	0.001
30–49 (reference group)	. . .	. . .	. . .	. . .
50–54	0.027	-0.014	0.006	-0.019
55–59	0.051*	-0.032*†	0.004	-0.023
60–64	0.055*	-0.064***†	0.002	0.006
65–69	0.132***	-0.085***‡	0.006	-0.053*
Number		30,201		
Pseudo R^2		0.1417		
Bachelor's degree or higher				
18–29	-0.023	0.015	-0.001	0.009
30–49 (reference group)	. . .	. . .	. . .	. . .
50–54	-0.009	0.001	0.001	0.006
55–59	-0.016	0.038*	-0.003	-0.019
60–64	0.005	0.028	-0.014	-0.019
65–69	-0.010	0.019	-0.004	-0.005
Number		15,521		
Pseudo R^2		0.1534		
		Women		
Less than bachelor's degree				
18–29	-0.037	0.034*	-0.002	0.005
30–49 (reference group)	. . .	. . .	. . .	. . .
50–54	-0.009	-0.014	0.006	0.017
55–59	0.051*	-0.027*	0.000	-0.024
60–64	0.037	-0.055***	0.010	0.008
65–69	0.094***	-0.101***†	0.007	-0.001
Number		30,103		
Pseudo R^2		0.0948		
Bachelor's degree or higher				
18–29	-0.011	0.025	-0.003	-0.011
30–49 (reference group)	. . .	. . .	. . .	. . .
50–54	0.015	0.004	0.001	-0.020
55–59	-0.025	0.033*	0.006	-0.013
60–64	0.022	-0.018	-0.015	0.012
65–69	0.003	-0.031*	-0.004	0.032
Number		18,462		
Pseudo R^2		0.1134		

SOURCE: Authors' calculations using CPS-MORG data available from the IPUMS database and DID regression analysis.

NOTES: Control variables are fixed at the means.

Control variables are race/ethnicity, race/ethnicity interacted with year, education, education interacted with year, marital status, nativity, citizenship status, family size, number of children, state of residence, and CPS panel month.

. . . = not applicable.

* = $p < 0.05$; ** = $p < 0.01$; *** = $p < 0.001$ (marginal effects, two-tailed test).

† = $p < 0.05$; ‡ = $p < 0.01$ (logit DID estimates for which the sample is limited to those who worked in January–March, two-tailed test).

Table 4 presents the results for employment patterns between April and the reopening months (May–July) for 2019 and 2020. The DID results show that men and women in their 60s were less likely to transition from nonemployed to employed during May–July 2020 than prime-age workers were, adjusting for general trends over time. Although this result suggests that older men were less likely than younger men to become reemployed in absolute terms, the pattern is mainly driven by the smaller baseline of older workers with employment disruptions in April, as implied by our results in Table 2. Table 4's DID results show that the proportion of adults continuously working from April through May–July 2020 is significantly higher for men aged 60–69 than for prime-aged men. The same is true for women.

We also investigated employment status during the reopening months by education (Table 5). When the models were limited to workers without a college degree, men and women aged 60–69 were less likely than prime-aged workers to transition from non-employed to employed in May–July 2020. However, relative to 2019, the likelihood of working continuously in 2020 for older men and women was higher than that of their prime working-age counterparts, and their relative likelihood of transitioning from employed to not employed was lower.

The experience of older degree-holders differed slightly. Like older nondegree-holders, their employment rate relative to prime-age workers was higher in 2020 than in 2019 (not shown). However, this occurred not because older degree-holders transitioned from not employed to employed more than their prime-aged counterparts (indicated by the absence of statistically significant coefficients), but because their likelihood of employment disruption was lower than that of prime-age degree-holders (illustrated by generally negative coefficients). This may indicate that degree-holding older workers who had a job were less likely to retire in 2020 than in 2019, perhaps in wariness of the unstable economic environment.

Discussion and Conclusions

We seek a better understanding of the labor market effects of the COVID-19 recession on older adults. Using longitudinally linked monthly CPS data, we present regression-adjusted DID estimates of older workers' employment dynamics during two early phases of the COVID-19 pandemic. Several findings are noteworthy.

First, the DID estimates confirm that the onset of the pandemic caused large and immediate employment disruptions for many workers aged 55–69. Employment instability in later life can negatively affect income and retirement savings. Yet relative to workers aged 30–49, older workers—particularly those in their 60s—were less likely to experience employment disruptions.

Our results also point to heterogeneity among older workers, with educational level being an important dimension. Among workers in their 60s, those without a college degree experienced more adverse employment effects from the COVID-19 recession than did degree-holders. However, among nondegree-holders, workers aged 60–69 experienced less employment disruption during the lockdown phase, and were more likely to remain continuously employed, than their peers aged 30–49. By contrast, among college graduates, employment patterns of older and prime-age workers were more similar. We found that in the summer of 2020, after the peak lockdown, older adults experienced less employment disruption than younger workers did. Older workers without a college degree generally fared better than their prime-age counterparts, whereas differences by age were smaller for degree-holders.

The consequences of the COVID-19 pandemic could affect older Americans in unexpected ways. Our findings suggest that the employment effects may differ from those of previous recessions, especially for older workers with a college degree. For example, older degree-holders may have more resources, which enabled some of them to withdraw funds or pause their labor force participation during the initial onset and lockdown and thereby mitigate exposure risks. This may in turn have led to greater employment-status changes relative to prime-age college graduates than were seen in previous economic downturns. Another possibility is that employers took the recession as an opportunity to lay off certain types of older workers.

Our study also adds to the literature by providing a framework for exploring the early effects of COVID-19 on the employment dynamics of older workers using a DID approach. Yet the medium- and long-term effects of the pandemic, and the implications of its employment disruptions on long-term outcomes, remain uncertain. For example, an important question for future research is how the pandemic affected retirement resource accumulation and financial planning among older adults (Li and Mutchler 2020).

Table 4.
Reopening panel: Predicted probability of each employment status between April and May–July, 2019 and 2020, by age group; and DID estimates between age groups; all by sex

Variable and age group	Working in April and— Working in May–July (continuously employed)	Working in April and— Not working in May–July (employed to nonemployed)	Not working in April and— Working in May–July (nonemployed to employed)	Not working in April and— Not working in May–July (continuously nonemployed)
		Men		
Probability in 2019				
18–29	0.859	0.043	0.036	0.062
30–49	0.843	0.040	0.028	0.089
50–54	0.779	0.038	0.034	0.149
55–59	0.708	0.049	0.031	0.212
60–64	0.565	0.059	0.034	0.342
65–69	0.301	0.043	0.028	0.627
Probability in 2020				
18–29	0.691	0.057	0.098	0.155
30–49	0.695	0.046	0.087	0.172
50–54	0.638	0.043	0.093	0.226
55–59	0.594	0.044	0.091	0.272
60–64	0.460	0.044	0.067	0.429
65–69	0.236	0.031	0.061	0.673
Difference from 2019 to 2020				
18–29	-0.169***	0.014*	0.062***	0.093***
30–49	-0.147***	0.006	0.059***	0.083***
50–54	-0.141***	0.005	0.059***	0.077***
55–59	-0.114***	-0.005	0.059***	0.060***
60–64	-0.105***	-0.015*	0.033***	0.087***
65–69	-0.066***	-0.012	0.033***	0.045**
DID between age groups				
18–29	-0.021	0.009	0.003	0.010
30–49 (reference group)	. . .	. . .	. . .	. . .
50–54	0.006	-0.001	0.001	-0.006
55–59	0.034	-0.011	0.001	-0.023
60–64	0.042*	-0.021*	-0.025**	0.004
65–69	0.082***	-0.018*	-0.026**	-0.037
Number		44,242		
Pseudo R^2		0.1304		

(Continued)

Table 4.
Reopening panel: Predicted probability of each employment status between April and May–July, 2019 and 2020, by age group; and DID estimates between age groups; all by sex—*Continued*

Variable and age group	Working in April and— Working in May–July (continuously employed)	Working in April and— Not working in May–July (employed to nonemployed)	Not working in April and— Working in May–July (nonemployed to employed)	Not working in April and— Not working in May–July (continuously nonemployed)
		Women		
Probability in 2019				
18–29	0.688	0.063	0.044	0.204
30–49	0.688	0.058	0.034	0.220
50–54	0.663	0.056	0.032	0.248
55–59	0.575	0.059	0.030	0.336
60–64	0.442	0.058	0.025	0.475
65–69	0.227	0.042	0.026	0.706
Probability in 2020				
18–29	0.484	0.058	0.116	0.342
30–49	0.543	0.051	0.088	0.318
50–54	0.526	0.050	0.065	0.359
55–59	0.465	0.046	0.077	0.412
60–64	0.334	0.043	0.069	0.553
65–69	0.154	0.024	0.038	0.783
Difference from 2019 to 2020				
18–29	-0.204***	-0.005	0.072***	0.138***
30–49	-0.144***	-0.007	0.054***	0.097***
50–54	-0.138***	-0.007	0.033***	0.111***
55–59	-0.110***	-0.013	0.047***	0.076***
60–64	-0.107***	-0.015*	0.045***	0.078***
65–69	-0.072***	-0.017**	0.013*	0.077***
DID between age groups				
18–29	-0.060***	0.002	0.018*	0.040**
30–49 (reference group)	. . .	. . .	. . .	. . .
50–54	0.007	0.000	-0.020*	0.014
55–59	0.035	-0.006	-0.007	-0.022†
60–64	0.037*	-0.009	-0.009	-0.019†
65–69	0.072***	-0.011	-0.041***	-0.020
Number		46,978		
Pseudo R^2		0.1002		

SOURCE: Authors' calculations using CPS-MORG data available from the IPUMS database and DID regression analysis.

NOTES: Control variables are fixed at the means.

Control variables are race/ethnicity, race/ethnicity interacted with year, education, education interacted with year, marital status, nativity, citizenship status, family size, number of children, state of residence, and CPS panel month.

. . . = not applicable.

* = $p < 0.05$; ** = $p < 0.01$; *** = $p < 0.001$ (marginal effects, two-tailed test).

† = $p < 0.05$; ‡ = $p < 0.01$ (logit DID estimates for which the sample is limited to those who worked in January–March, two-tailed test).

Table 5.
Reopening panel DID estimates of employment-status predicted probabilities between April and May–July, 2019 and 2020, by sex, age group, and education, with demographic and education control variables

Education and age group	Working in April and— Working in May–July (continuously employed)	Working in April and— Not working in May–July (employed to nonemployed)	Not working in April and— Working in May–July (nonemployed to employed)	Not working in April and— Not working in May–July (continuously nonemployed)
			Men	
Less than bachelor's degree				
18–29	-0.033	0.013	0.011†	0.009
30–49 (reference group)	. . .	. . .	. . .	. . .
50–54	0.027	0.002	-0.011	-0.018
55–59	0.050*	-0.007	-0.007	-0.036
60–64	0.058*	-0.019*	-0.040***	0.000
65–69	0.121***	-0.011	-0.042***	-0.069**
Number		29,273		
Pseudo R^2		0.1230		
Bachelor's degree or higher				
18–29	-0.002	-0.004	-0.006	0.012
30–49 (reference group)	. . .	. . .	. . .	. . .
50–54	-0.026	-0.005	0.021	0.010
55–59	0.019	-0.018	0.013	-0.014
60–64	0.036	-0.024	-0.004	-0.008
65–69	0.033	-0.030*	-0.005	0.001
Number		14,969		
Pseudo R^2		0.1253		
			Women	
Less than bachelor's degree				
18–29	-0.062**	-0.008	0.019	0.051*
30–49 (reference group)	. . .	. . .	. . .	. . .
50–54	0.013	0.003	-0.037**	0.021
55–59	0.058**	-0.009	-0.011	-0.037
60–64	0.073***	-0.002	-0.024*	-0.047*
65–69	0.120***	-0.007	-0.061***	-0.052**
Number		28,941		
Pseudo R^2		0.0856		
Bachelor's degree or higher				
18–29	-0.065**	0.021	0.018	0.026
30–49 (reference group)	. . .	. . .	. . .	. . .
50–54	0.001	-0.002	0.001	0.001
55–59	0.003	0.000	-0.004	0.001
60–64	-0.009	-0.021	0.012	0.017
65–69	0.009	-0.016	-0.013	0.020
Number		18,037		
Pseudo R^2		0.1039		

SOURCE: Authors' calculations using CPS-MORG data available from the IPUMS database and DID regression analysis.

NOTES: Control variables are fixed at the means.

Control variables are race/ethnicity, race/ethnicity interacted with year, education, education interacted with year, marital status, nativity, citizenship status, family size, number of children, state of residence, and CPS panel month.

. . . = not applicable.

* = $p < 0.05$; ** = $p < 0.01$; *** = $p < 0.001$ (marginal effects, two-tailed test).

† = $p < 0.05$; ‡ = $p < 0.01$ (logit DID estimates for which the sample is limited to those who worked in January–March, two-tailed test).

In closing, we note that we have conducted some preliminary follow-up work to the analysis reported here. To gain some initial insights into the longer-run employment effects of COVID-19, we used recently released CPS data for an outgoing rotation group, which contains employment information for some of the April 2020 respondents as of 1 year later. Focusing on workers who experienced employment disruptions during the lockdown in April 2020, we find that 73 percent of those in the prime-age group (ages 30–49) had resumed employment in April 2021, while only 53 percent of workers aged 60–69 were employed. Whether the pandemic recession accelerated shifts to retirement or disability benefit uptake among older workers requires future study. The effect of the widespread introduction of COVID vaccines around April 2021 on labor market outcomes also warrants future research. Another fruitful avenue of future research would be to address the long-term financial implications of the employment disruptions caused in the early months of the pandemic, including the potential impacts of unemployment insurance and stimulus payments.

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