THE NEW SCHOOL
SCHWARTZ CENTER FOR ECONOMIC POLICY ANALYSIS

Employment and Retirement Among Older Workers During the COVID-19 Pandemic

Owen Davis

Schwartz Center for Economic Policy Analysis (SCEPA)
Department of Economics
The New School for Social Research
6 East 16th Street, New York, NY 10003
economicpolicyresearch.org

Suggested Citation: Davis, O. (2021) "Employment and Retirement Among Older Workers During the COVID-19 Pandemic." Schwartz Center for Economic Policy Analysis and Department of Economics, The New School for Social Research, Working Paper Series 2021-6.

WORKING PAPER #6
2021
DEC

Employment and Retirement Among Older Workers During the Covid-19 Pandemic

Owen Davis*

December 7, 2021

Abstract

The Covid-19 pandemic dealt an unprecedented shock to older workers and led to a sharp increase in the share of U.S. adults who are retired. This paper uses Current Population Survey data to explore the distribution and determinants of employment loss and retirement among older workers during the pandemic. Employment declines among older workers were greatest for low earners, women, non-whites and non-college-educated workers. By contrast, increased transitions to retirement occurred across demographic groups and concentrated in both the lowest- and highest-earning quartiles. Job characteristics that best predicted increased pandemic retirement transitions were employment in high-contact occupations and part-time work schedules. I estimate that part-time workers made up roughly 70% of the increase in net year-to-year employment-to-retirement transitions during the first year of the pandemic. This finding has implications for recent Social Security claiming behavior and for the possible persistence of the pandemic retirement boom.

Keywords— older workers, retirement, labor supply, Covid-19

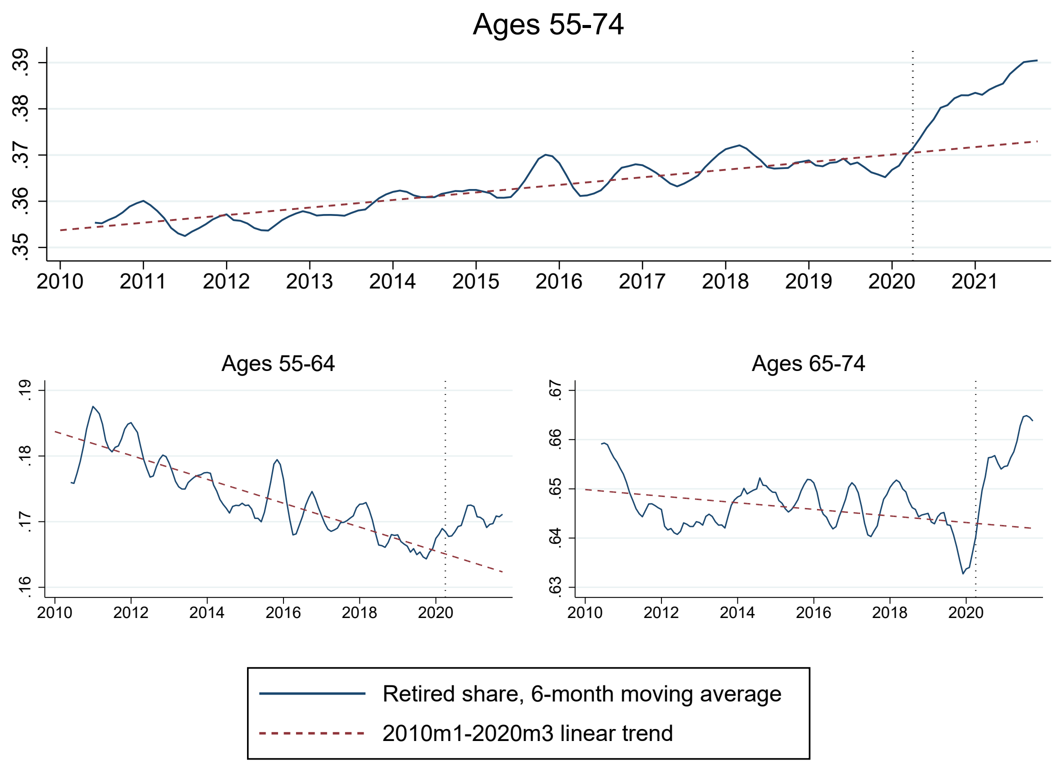
1 Introduction

The Covid-19 pandemic dealt a unique shock to older workers. Roughly 3.7 million workers ages 55 and older fell into unemployment between March and April 2020. Although many were soon recalled, 35% of the older unemployed were permanent job losers in the fourth quarter of 2020. By October 2021, the employment-population ratio of workers 55 and older was down 2.2 percentage points from February 2020. The decline in older workers' employment rate can be largely explained

*New School for Social Research and Schwartz Center for Economic Policy Analysis. Email: odavis@newschool.edu. I would like to thank Teresa Ghilarducci and Siavash Radpour for their support and feedback throughout the research process. Aida Farmand, Bridget Fisher, Barbara Schuster, and Tony Webb provided thoughtful comments.

by a nearly equivalent increase in the retired share of the older population. As Figure 1 shows, the retired share of older adults has diverged significantly from its pre-pandemic linear trend.

Figure 1: Retired share by age group, 2010-2021



Note: Predicted series are constructed using a linear time trend, January 2010–March 2020.

This paper examines trends in employment and retirement for older workers in the wake of Covid-19 using microdata from the Current Population Survey (CPS). The analysis explores the impact of demographic factors (age, sex, race, and education) as well as job characteristics (occupation, industry, and other measures) on employment and retirement trends.

In employment outcomes, older workers faced all the same forces that affected younger and mid-career workers, including severe disruptions in service industries and jobs with high levels of close personal contact. Yet older workers also faced magnified dangers from Covid-19, whose mortality risk is exponential in age (Bauer et al., 2021); likely age discrimination in job-finding; as well as potentially age-skewed impacts relating to the ability to work from home (Brynjolfsson et al., 2020). At the same time, older workers typically benefit from the relative job security afforded by seniority. The interaction of these and other factors led to distinct employment outcomes for older workers.

An additional set of overlapping and at times conflicting influences affected retirement during the pandemic. Potential push factors into retirement included job loss, health risks, heightened occupational stress and overwork, and age discrimination in hiring (Dahl and Knepper, 2020). A notable pull factor into retirement was the rapid recovery in asset prices that followed the initial

Covid shock, which stands in sharp contrast to the long slump that followed the Great Recession. Mitigating the trend toward increased retirement was heightened economic uncertainty, particularly at the start of the pandemic, which may have pushed some to delay retirement plans (Horowitz et al., 2021). Generous unemployment insurance may also have kept workers in the labor force who otherwise might have dropped out (Marmora and Ritter, 2015).

Using the year-to-year longitudinal structure of the CPS, I find that the relative declines in older workers' employment in the first 12 months of the pandemic exceeded those of mid-career workers (ages 35-54), a gap that was not driven by industry or occupational composition of the age groups. Segments of the older workforce that experienced larger employment declines included women, non-college and non-white workers, as well as part-time employees and workers in occupations characterized by high physical proximity to others. As has been documented previously for workers of all ages (e.g., Dalton et al., 2021), employment declines followed a strong earnings gradient, with the lowest-paid older workers seeing the largest employment declines.

Turning to retirement, I find statistically significant increases in the retired share following the onset of the pandemic. While these increases were greater for those 65 and older, I also find trend breaks in the retired share for subgroups in the 55-64 year-old range, especially non-college men. Turning to measures of year-to-year retirement transitions out of employment, I find that while some groups with high job loss early in the pandemic also experienced higher flows to retirement, the correspondence is weak. Pandemic retirement transitions did not follow the same earnings gradient as employment loss, but instead an inverted U-shape, with the highest- and lowest-paid quartiles exhibiting excess retirement in the first year of the pandemic. The occupation group with the greatest increase in retirement in the first 12 months of the Covid shock was protective services, a group that includes police officers.

In both descriptive data and regressions, I find that among those who were employed in the year before the pandemic, the factors most associated with increased pandemic retirement transitions were high physical proximity on the job and part-time status, while demographics played little role. Part-time status remains a relatively strong predictor of increased pandemic retirement even after controlling for industry, occupation, demographic characteristics and state-level Covid death rates as well as in samples restricted to workers younger than 70. By a rough estimate, part-time workers were responsible for 70% of the net increase in year-to-year transitions from employment to retirement in the first year of the pandemic, a finding with possible implications for the future path of the retired share.

The results presented here extend the early evidence on older workers' employment and retirement outcomes presented in Bui et al. (2020), who found older workers to be at greater risk of unemployment than younger groups early in the pandemic. This paper confirms the direction, if not the magnitude, of the estimates in Coibion et al. (2020), who found a sharply increased retired share in the first month of the pandemic according to proprietary survey data. Cortes and Forsythe (2021) found that retirement increased throughout the pandemic, not just in the initial months, and that retirements were widespread across industries and occupations, results which are broadly confirmed here. Goda et al. (2021) report the somewhat counterintuitive result that while labor force exits due to retirement increased for adults ages 62-70, Social Security Administration retirement applications did not. High rates of retirement among part-time workers may help reconcile these trends.

The paper most closely related to this one is Quinby et al. (2021), who also examine year-to-year employment and retirement transitions. They too find little role for demographics in retirement transitions, concluding that the increase in retirements was concentrated among those ages 70 and up. This paper extends these results by incorporating analysis of work schedules and physical proximity on the job, which predict retirement during the first year of the pandemic even when the sample is restricted to those under 70.

Section 2 describes the data used in this paper. Section 3 explores employment trends for older workers throughout the pandemic. Section 4 examines retirement trends. Section 5 discusses some ramifications stemming from the retirement findings, including the role of part-time work. Section 6 concludes.

2 Data

This paper uses monthly Current Population Survey (CPS) microdata via IPUMS-CPS (Flood et al., 2021). The CPS is a monthly survey of roughly 60,000 households conducted jointly by the U.S. Bureau of Labor Statistics and the U.S. Census.

In addition to performing time-series cross-sectional analysis of employment rates and retired shares, I use the longitudinal structure of the CPS to explore workers' labor market transitions from year to year. The CPS interviews households for four consecutive months, leaves them out for the next eight months, then interviews them again for four more months (e.g., a household could be interviewed Jul.-Oct. 2019 and Jul.-Oct 2020). The 4-8-4 structure allows researchers to link households from month to month or year to year. Both BLS and IPUMS provide appropriate population weights for conducting these analyses.[1]

To supplement the CPS data, I adopt measures of job-related work-from-home (WFH) difficulty and high physical proximity (HPP) from Mongey et al. (2021). Building on Dingel and Neiman (2020), these measures draw from O*NET job characteristics data to generate binary indicators reflecting WFH difficulty and physical proximity at the detailed occupation level.

In comparing older workers to other age groups, I adopt the following cutoffs: younger workers (18-34 years old), mid-career workers (35-54) and older workers (55-74).[2] The distinction between

[1]For year-to-year transitions, I use the IPUMS weighting variable *lnkfw1ywt*. In regressions in which the sample is limited to the Outgoing Rotation Group (ORG)—workers in their fourth and eighth interviews—I construct a weight following BLS weighting procedures that matches the linked ORG sample to race, sex, age and geographic composition of the initial month sample.

[2]The 35-54 year-old group has also been called "mature workers" (e.g. Levine and Mitchell, 1988)

mid-career and younger workers acknowledges significant differences within the below-55 group. Many of the youngest workers are employed in transitional and entry-level jobs and many are students. In comparison, most of those ages 35-54 have established careers, as do most older workers. Mid-career workers face a lower incidence of job separation, both voluntary and involuntary, than younger workers (Gittleman, 2019).[3] All of these characteristics make the mid-career group a more appropriate comparison for older workers than the entire under-55 group. In much of the descriptive analysis presented here, the older category excludes workers 75 and over, the vast majority of whom are already retired.

3 Employment

3.1 Older workers versus mid-career workers

In 2019, on average, 48.5% of older adults (ages 55-74) were employed.[4] In April 2020, the employment-population ratio (EPOP) fell to 42.0% as millions of workers experienced layoffs, furloughs, or other job separations amidst the Covid-19 outbreak and lockdowns. As Figure 2 shows, the 13% decline in the older worker EPOP relative to its 2019 average was comparable to the decline faced by mid-career workers, while both were eclipsed by the 20% decline in the younger worker EPOP.[5] Throughout the pandemic period, the older worker EPOP matched or slightly lagged that of mid-career workers relative to pre-pandemic. The older worker EPOP fell again in summer 2021 and as of October 2021, older workers remained the farthest behind among age groups in their employment recovery.

In previous recessions, older workers tended to face lower employment losses than mid-career workers, largely due to tenure (Johnson and Mommaerts, 2021). During the recovery from the Great Recession, the 55-74 EPOP, indexed to its 2007 average, remained well above that of mid-career workers. Likewise, the U3 unemployment rate of mid-career workers exceeded that of older workers during and after the Great Recession, while that pattern was reversed for the first 6 months of the Covid-19 recession (Davis et al., 2020).

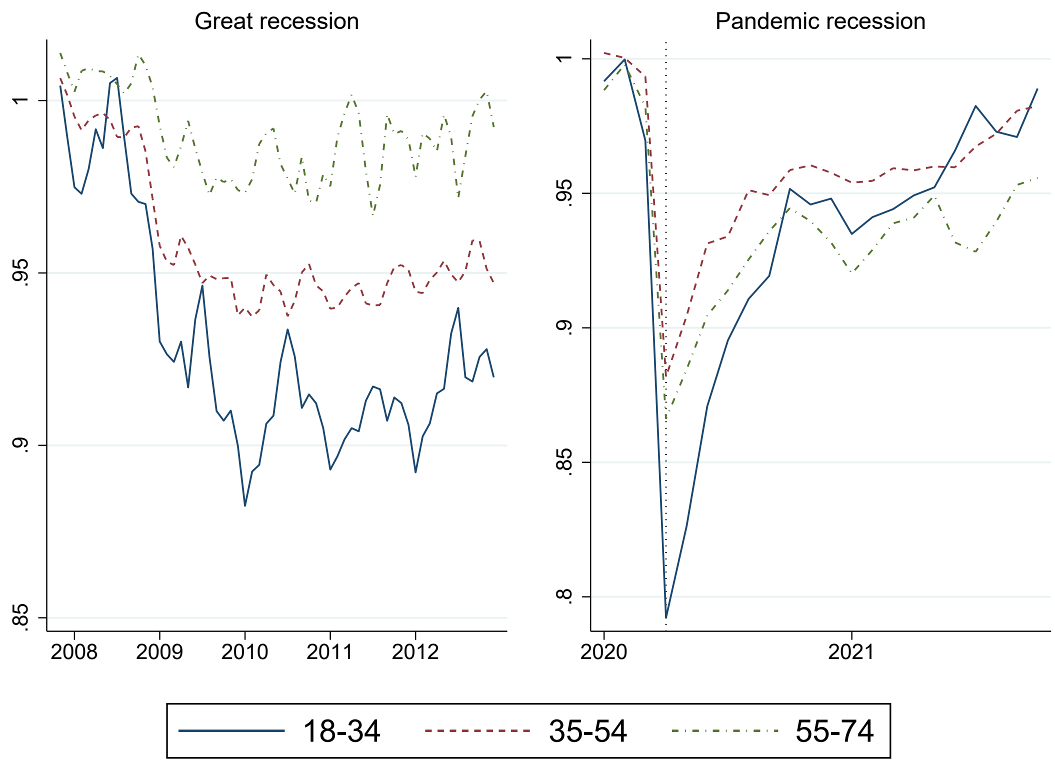
Since the pandemic had concentrated impacts on sectors like leisure and hospitality, as well as a steep age gradient in health risk, it is an open question to what extent pandemic employment declines for older workers driven by their industrial/occupational distribution or other, age-specific factors. To approach this question, I use a decomposition methodology that follows Dalton et al. (2021), detailed in Appendix B. The methodology differentiates between employment declines occurring for

[3]See, for instance, the age breakdowns in the Employee Tenure Summary produced by the BLS. A majority (54%) of wage and salary workers ages 35-44 have accrued at least 5 years of job tenure, while just 29% of those 25-34 have 5 years or more on the job (U.S. Bureau of Labor Statistics, 2020).

[4]These figures are constructed from public-use microdata and are not seasonally adjusted.

[5]Since different age groups have very different baseline employment rates, the series are indexed to pre-pandemic rates for ease of comparison. I use entire-year 2019 averages for baseline EPOPs rather than a single month to diminish the impact of group-specific seasonal effects.

Figure 2: Employment rates by age group, Great Recession versus Covid-19 Recession



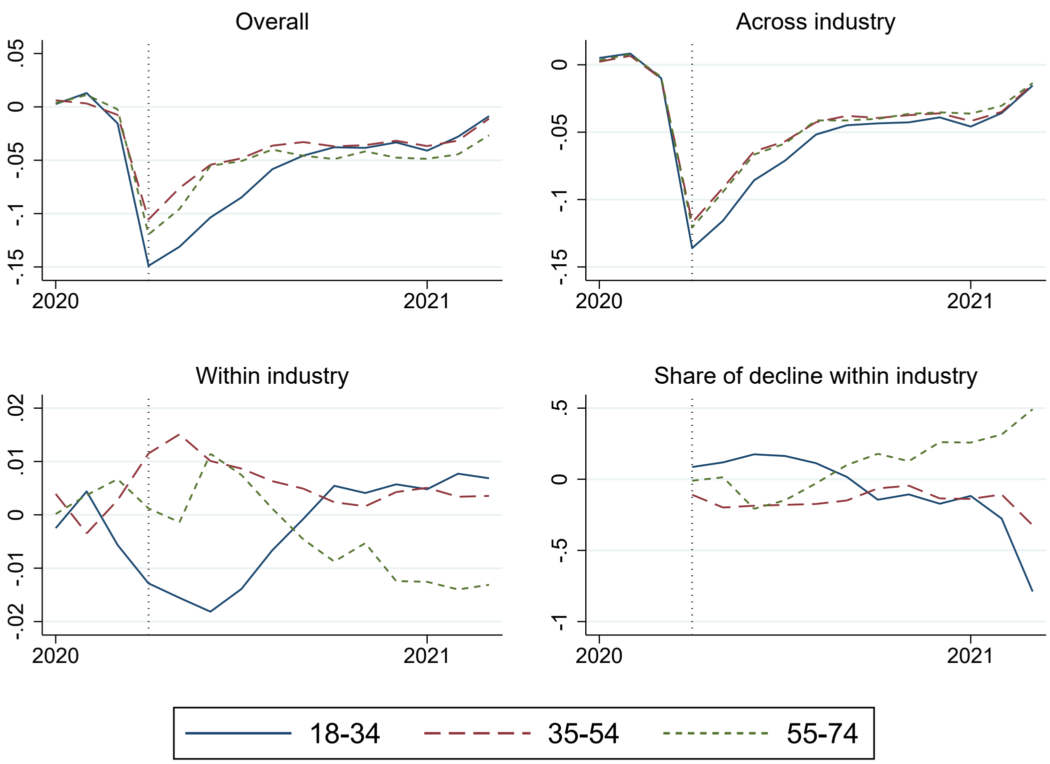
Note: Employment-population ratios for each age group and time period are indexed to their full-year average for the calendar year prior to the recession (2007 and 2019 for Great Recession and Covid-19 recession, respectively). Not seasonally adjusted.

specific age groups within sectors versus declines that occurred across sectors due to differential impacts of the recession on different industries. This decomposition technique makes use of the longitudinal aspect of the CPS, tracking employment transitions across 12-month spans. For this reason, the analysis can extend only to March 2021, after which the baseline periods (12 months prior) reflect pandemic impacts.

To begin, I explore the within- and across-sector components of employment decline after taking account of 14 major industry groups or sectors (definitions follow Census designations, with Wholesale Trade and Retail Trade split into separate categories). The overall decline in the upper-left panel of Figure 3 reflects the share of workers who are still employed in each age group 12 months after being initially employed (e.g., for older workers in reference month April 2020, the denominator is 55-74 year-olds employed in April 2019 and the numerator is the number of these workers who are still employed when observed again in April 2020). This transition rate is normalized to pre-pandemic trends.[6]

[6]Since different age groups have different underlying rates of annual employment change, this still-employed rate is normalized by subtracting the prior 5-year average of employment change by age group. Each of the components of employment decline, within and across, are similarly normalized using 5-year

Figure 3: Normalized change in employment by age group, decomposition results with respect to industry



Note: Plots reflect results of decomposition methodology described in Appendix B. The *overall* plot displays the share of those who were employed 12 months prior who are still employed in the reference month, normalized to shares still employed over 2015-2019. The *across* plot displays the change in employment for each group that is due to the distribution of that group's employment across industries. The *within* plot shows the change in employment specific to each age group within industries. The bottom-right plot shows the share of overall employment change due to within-industry changes.

The distribution of each of the three age groups across sectors plays only a small role in the disparate employment trends observed between them. The upper-right panel shows the across-industry component of employment declines for the three age groups—i.e., the extent to which an age group's disproportionate representation in harder-hit (or less affected) industries produced higher (lower) employment declines. Younger workers' larger employment decline was driven in part by the mix of sectors they worked in, while across-industry declines were largely comparable between older and mid-career workers.

The employment gap that opened between older and mid-career workers in mid-2020 was driven by employment declines for older workers *within* industry sectors, after taking account of their sectoral composition, as is evident in the two lower panels of Figure 3. In the bottom-left panel older workers' within-sector change in employment goes from positive in the early months of the

averages. "Still employed" means only that the respondent was observed employed at two points 12 months apart; it does not rule out non-employment at some point in between.

pandemic to consistently negative through March 2021. The lower-right panel plots the share of overall normalized employment decline that occurred within sectors. It was only older workers in late 2020 and early 2021 whose employment declines occurred within sectors.

Since these trends may be driven by occupational patterns within industries, I combine major occupations and major industries into $22 \times 14 = 308$ industry-occupation groups (some are excluded due to sample size). The results of the same decomposition strategy are plotted in Figure A.1 in Appendix A. Inclusion of initial occupational group mitigates the within component of employment declines among older workers, but only marginally. Older worker's employment declines during the pandemic were driven by age-specific factors not explained by industry or occupation.[7]

3.2 Employment trends among older workers

Employment rates among older workers varied significantly between different demographic groups in the pandemic period. Figure 4 plots indexed EPOPs for two older age groups (55-64 and 65-74), disaggregated by sex, education (defined by having a four-year college degree), race (white, Black, or Hispanic), and marital status. As before, EPOPs are indexed to the full-year 2019 average by group. Appendix Table A.2 presents unadjusted EPOPs for these demographic groups at three points in time: the 2019 average, the April 2020 nadir, and October 2021.

The largest and most persistent declines among older workers generally occurred among 65-74 year-olds. Women and non-college older workers experienced greater employment declines in the early months of the pandemic. Among women, 55-64 year-olds soon caught up with 55-64 year-old men, yet the older female group remained behind men 65-74. Non-college workers 55-64 have trailed college-educated workers of the same ages, the latter of whom regained their pre-pandemic EPOP in October 2021.

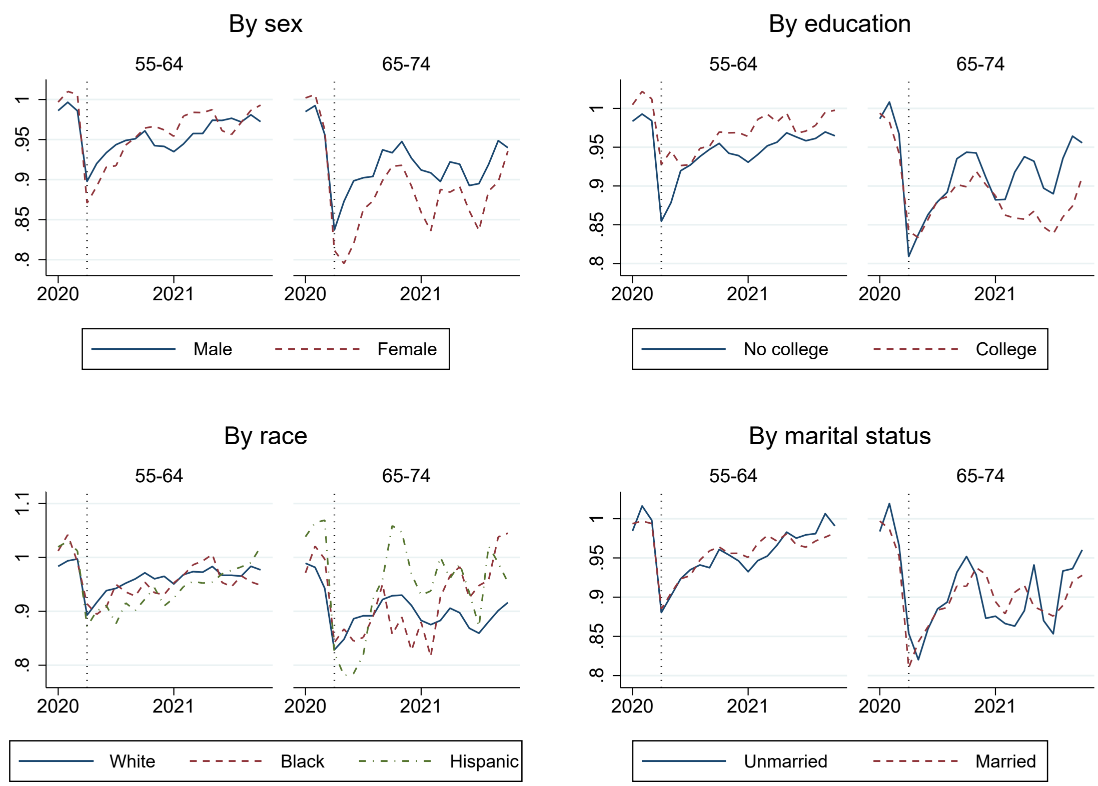
Surprisingly, at later ages (65-74), non-college workers have moved closer to their pre-pandemic EPOP than college-educated workers. Yet it is important to note that there was less "catching up" to do for the non-college population 65-74; the baseline 2019 EPOPs for non-college and college workers 65-74 were 23.7% and 35.2%, respectively. One way of looking at this is that non-college workers who remain employed after 65 are a more select group within their educational category than college-educated workers who remain employed after 65.

Looking at race, at ages 55-64 white workers recovered more quickly than Black or Hispanic workers, though by mid-2021 the groups had mostly converged.[8] Again, a surprising pattern emerges at ages 65-74: by late 2021, Black and Hispanic workers of this age group had essentially regained their pre-pandemic EPOPs, while white workers' EPOP was 10% below its pre-pandemic 2019 average, a fall from 28.5% to 25.6%. As in the case of college versus non-college workers, baseline

[7] The trends described here hold when the older age group is confined to workers 55-64 and industry-occupation combinations are used. In this case, the within-sector decline begins later and is roughly half the level of the full 55-74 group's within-sector decline. Results available upon request.

[8] The "other" category of race is omitted in the charts due to small sample size and a high amount of noise in the series.

Figure 4: Employment rates by age group and demographics



Note: Employment rates indexed to full-year 2019 averages. Not seasonally adjusted.

EPOPs among workers 65 to 74 were lower for Black and Hispanic workers than white workers. Differences in employment recovery by marital status are minimal.

The analysis up to here has focused on EPOP rather than unemployment rates, since labor force dropout can reduce the unemployment rate. Figure A.2 shows unemployment trajectories. As in the case of EPOP, the initial pandemic shock hit women, non-college, and non-white workers hardest.

Taken together, the demographic trends in older workers' pandemic-era employment reflect some existing patterns of vulnerabilities among demographic groups, but not at all ages. These trends provide an indication of the numerous and sometimes conflicting factors underlying the pandemic shock and recovery for older workers. These include Covid-19 health risks, ability to work from home, retirement preparedness, seniority, and shifting labor demand, as well as the perennial issue of age discrimination facing older job-seekers.

3.3 Employment transitions among older workers

Examining year-to-year transitions among older workers who were employed pre-pandemic and subsequently observed after March 2020 allows for an analysis of job-specific factors that drove employment changes during the pandemic. The measure of interest is the share of workers still employed in the reference month among all those who were employed a year earlier. To produce stable and comparable measures of longitudinal change among different groups, I first calculate monthly 5-year averages of the still-employed share in the years preceding the pandemic. These 5-year averages, calculated for each calendar month over the period 2015-2019, are then subtracted from each 2010-2021 series in order to produce normalized employment change measures.

Figure 5 shows these normalized measures of employment change for nine disaggregations of older workers. The top three are demographic (sex, race, and education), next is metropolitan area of residence, and the rest concern job characteristics: full-time job status, difficulty working from home (WFH), high physical proximity on the job (HPP), whether self-employed, and public versus private sector. The first dotted vertical line in the plots indicates the first month of Covid-19's major effects on CPS respondents in April 2020; the second, at March 2021, indicates the last month in which prior-year employment is (mostly) unaffected by the pandemic. After March 2021, the prior-year employed are those whose employment survived the pandemic shock, making them an inappropriate comparison with the pre-pandemic population. Caution is warranted in interpreting post-March-2021 trends.

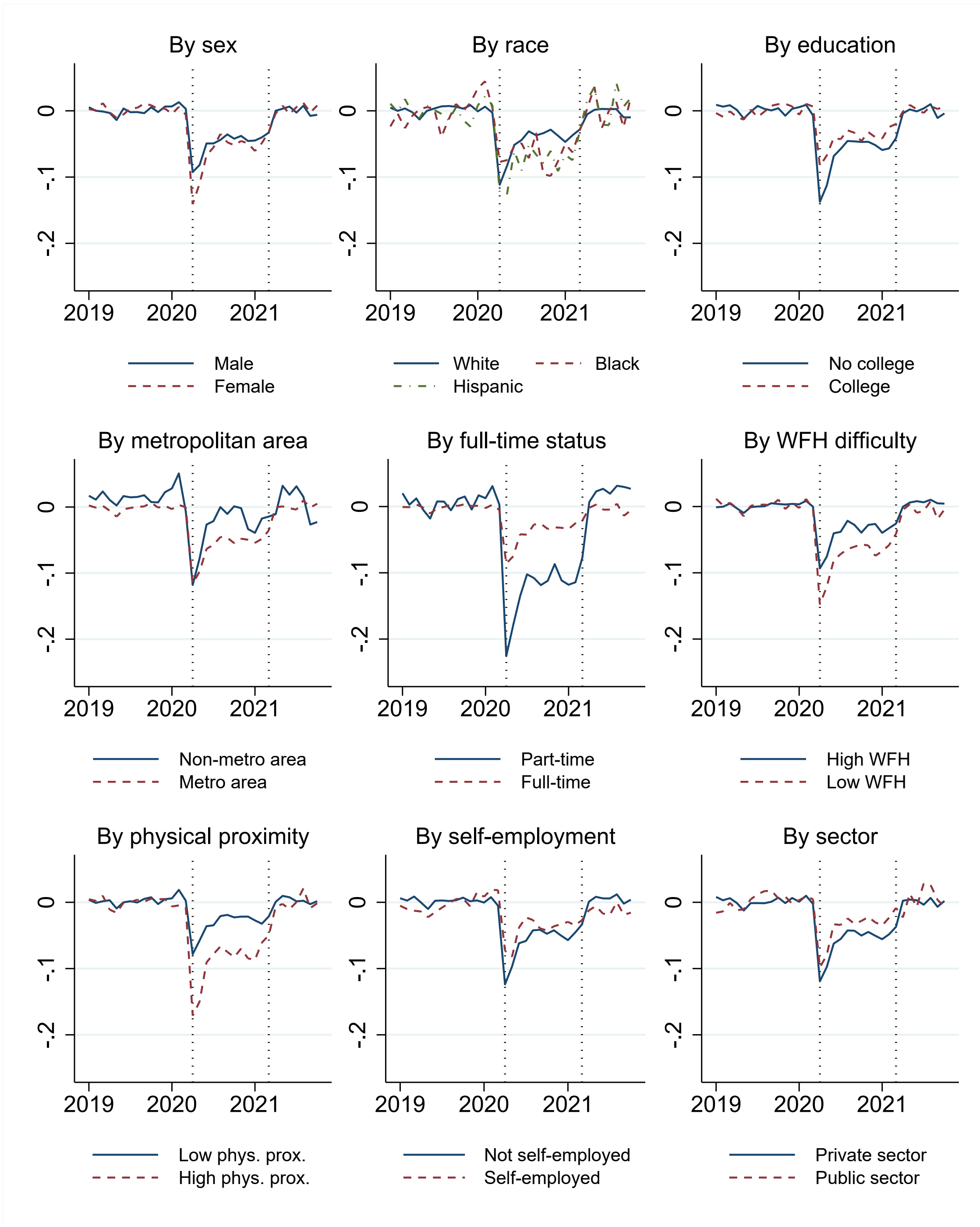
The demographic patterns in the still-employed share largely follow those seen in cross-sectional data. The normalized share of workers still employed fell further for women, non-white, and non-college workers than for male, white, and college-educated workers. Turning to job factors, by far the largest employment gap among any of the categories is that between part-time and full-time workers. The pandemic caused a decline in the normalized still-employed share that was roughly three times greater for part-time than for full-time older workers. A possible concern is that, since part-time employment is strongly correlated with age, this figure may simply reflect larger pandemic-driven changes in retirement probability by age. In regressions presented below, however, a strong effect for part-time workers persists even after controlling for age.

The larger and more persistent employment declines for low-WFH and HPP jobs confirm the importance to pandemic-era employment of the ability to work remotely and with sufficient distance from others. Older workers in non-metro areas experienced a more rapid employment recovery. Public sector workers and the self-employed also experienced smaller employment declines.

To examine the pandemic's employment effects by earnings, I compute weekly earnings quartiles for workers 55-74, both for all workers in this age range and for full-time workers only.[9] Given the

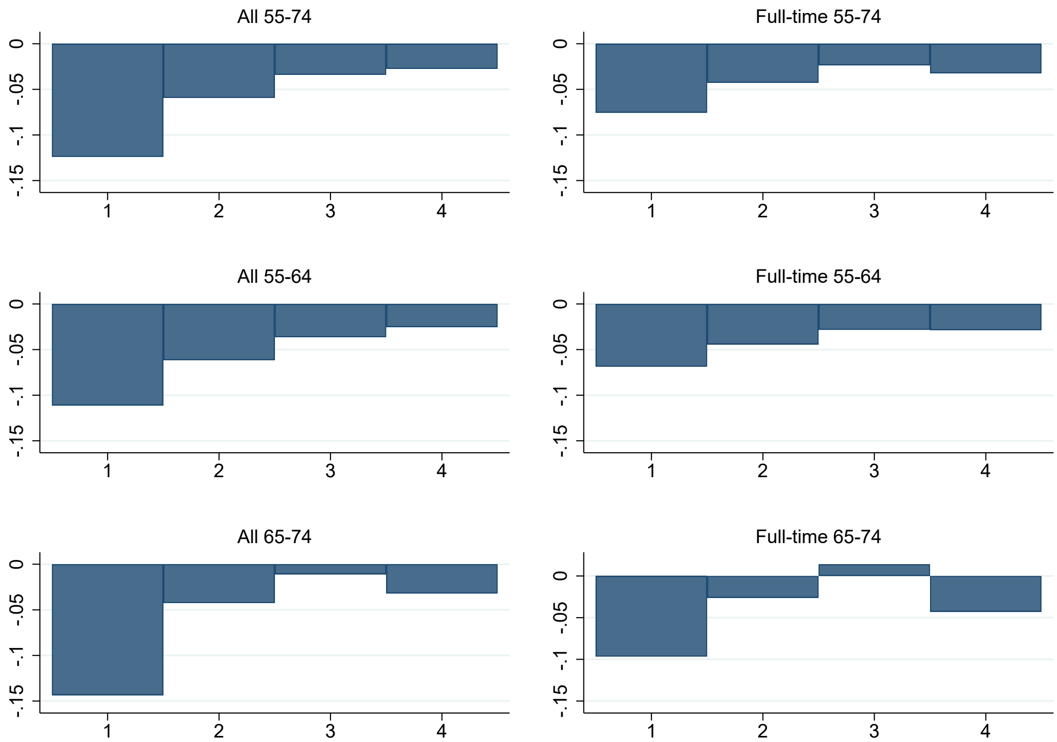
[9] For the preceding longitudinal analyses I use the 1-year forward-looking longitudinal weights provided by IPUMS. Since earnings questions are only asked in the fourth and eighth waves of each household's CPS rotation, however, I construct new weights for the individuals with earnings data linking across 12 months. Since households are asked about earnings in only the fourth and eighth months-in-sample, the sample size for these calculations is one-quarter the size of the previous longitudinal calculations.

Figure 5: Share still employed among those employed 12 months prior, normalized to pre-pandemic average, ages 55-74



Note: Series show the share of workers still employed among those employed 12 months prior, normalized by subtracting the 2015-2019 average still-employed share by calendar month for each group.

Figure 6: Normalized still-employed share by earnings group, 2020m4-2021m3 average



Note: Figures show the average normalized still-employed share, April 2020 through March 2021, for each earnings/age/hours category. Series are normalized by subtracting the 2015-2019 average still-employed share by calendar month for each earnings/age/hours group.

correlation of part-time work with age noted above, it is important to make this distinction in order not to mistake increases in retirement driven by age for those specific to earnings categories. I follow the same procedure as before to normalize still-employed shares according to different combinations of older age group, earnings quartile, and full-time status. Figure 6 summarizes the results. In order to condense information, the bars show the average of the still-employed share over the first 12 months of the pandemic (April 2020 through March 2021).

In every grouping of older workers' earnings categories, a clear gradient emerges, with the largest employment declines occurring in the lowest weekly earnings quartile. The gradient is less steep when the sample is restricted to full-time workers. Regardless of full-time status, the greatest normalized employment declines are seen for the bottom-quartile workers in the 65-74 group. The reversal of the gradient at the highest earnings quartile for the oldest workers, visible for both the complete sample and for the full-time-only group, likely reflects retirement among high earners , as will be seen below.

The longitudinal form of CPS also allows examination of employment transitions by industry and occupation. Figures A.3 and A.4 show the normalized still-employed share averaged over the first year of the pandemic for the 14 industry sectors and 22 major occupation groups, respectively.

Normalized year-to-year employment declines among industry sectors are led by leisure and hospitality; mining, other services, and transportation and utilities. Among occupations, the greatest declines were in food preparation and serving, personal care services, transportation, and protective services.

3.4 Decomposing employment trends

The same decomposition methodology introduced earlier can help disentangle the effects of demographic and job-specific factors from major industry- and occupation-wide trends. Now I restrict the age range of the decomposition to 55-74 years old and decompose by combined industry-occupation categories. Appendix Figures A.5-A.8 plot the resulting normalized changes in share still employed, along with across- and within-industry/occupation components.

The decompositions show larger employment declines in the early months of the pandemic for women and non-college workers within industry-occupation combinations, though in both cases the within share diminishes after several months. The decomposition by race (Figure A.6) shows white older workers enjoying a slight within-industry/occupation advantage throughout the pandemic, with Asian and other races being hardest hit initially, while Black and Hispanic employment declines within industry/occupation come after the first few months of the pandemic. Only Black workers faced consistent within-industry/occupation employment declines through the second half of 2020 and early 2021; the within component of these declines was responsible for 25-50% of Black workers' normalized employment declines during this period.

Decomposing normalized employment declines along full-time status clarifies the earlier results regarding the importance of part-time work in older workers' pandemic employment loss. According to these results, the large employment declines among part-time workers were not due to the prevalence of part-time work in sectors shut down by the pandemic, such as food service or retail sales. The within-industry/occupation component of part-time workers' employment decline was responsible for 7.8 percentage points of this group's initial April 2020 decline in normalized still-employed share, roughly a third of the overall 24 percentage point decline part-time workers experienced in that month (see Figure A.8). Throughout the first year of the pandemic, older part-time workers continued to face employment declines within industry/occupation categories accounting for an average 40% of this group's overall employment decline. These patterns hold when the sample is restricted to ages 55-64.

3.5 Employment of older workers in the pandemic: regression evidence

To extend the analysis provided above, I perform a probit regression on a sample of older workers observed between April 2018 and March 2021 who were employed in the year prior. The outcome variable is employment during the reference month. Demographic controls include five-year age groups, education, sex, race, and marital status. Local effects are controlled for using metro area, state fixed effects, and state Covid death rates calculated on the 10th of the month of the CPS survey. Job-related controls are self-employment status, full-time status, occupational WFH difficulty, HPP status, and major industry group and major occupation group (added in models 2 and 3, respectively). With the exception of state Covid death rates, the controls listed above are all interacted with a Covid dummy in order to estimate the extent to which the pandemic differentially affected different types of workers. National economic conditions are captured by month fixed effects.

One concern in using a binary outcome model such as probit is heteroskedasticity, which can lead to biased and inconsistent parameter estimates (Yatchew and Griliches, 1985). A natural assumption is that the variance of employment outcomes is increasing in age. To account for this possibility, I use a heteroskedastic probit model, with the variance of the error term specified as a linear function of respondent age.[10] Appendix Table A.3 presents the same set of models estimated as linear probability models. These yield the same qualitative conclusions as the results discussed below.

Results are reported in Table 1. Models 2 and 3 add in industry and industry and occupation controls, respectively, both interacted with the Covid indicator; model 4 excludes workers 70 and older. A somewhat surprising result is the positive and significant coefficient on the 60-64 age group (the 55-59 group serves as baseline). Broader negative employment effects of the pandemic are captured in the monthly fixed-effect terms (not shown here), especially in the initial months of the pandemic. Among demographic characteristics, other race (which is largely Asian American) weakly predicts greater employment declines (significant at the 10% level and only in model 1), while college education was associated with higher employment during the pandemic across all models (10% significance). Marital status and gender were not significant predictors of employment loss over the first year of the pandemic. The regressors most significantly associated with a higher rate of employment separation during the pandemic were working part-time and working in a high-contact occupation.

What explains the importance of part-time work in pandemic employment transitions, even after controlling for industry and occupation? Both labor supply and labor demand considerations might be at play. On the supply side, older part-time workers may be more willing to leave work in the face of Covid-related health risks and pandemic-related work disamenities if they are secondary earners or work part-time to supplement retirement income. Part-time workers may also have a higher rate of health issues. On the demand side, employers may have seen part-time workers (and specifically older part-time workers) as more expendable when making layoff and rehiring decisions. These issues are discussed further in Section 5.

[10]The Stata command `hetprobit` estimates this model as well as providing a likelihood ratio test of the null hypothesis of homoskedasticity. In all the results reported here, the null of homoskedasticity in age is strongly rejected ($p < 0.001$).

Table 1: Regression results for the effect of the pandemic on employment among those employed 1 year earlier, 2018-2021

	1	2	3	4
Covid	0.227	1.213	0.902	2.532
	(0.597)	(0.763)	(0.780)	(2.638)
ages 60-64	0.420**	0.395**	0.358**	0.796
	(0.179)	(0.171)	(0.166)	(0.489)
ages 65-69	0.325	0.293	0.288	0.320
	(0.207)	(0.198)	(0.196)	(0.631)
ages 70+	-0.144	-0.178	-0.185	
	(0.283)	(0.274)	(0.271)	
Black	-0.162	-0.215	-0.102	-0.179
	(0.260)	(0.254)	(0.249)	(0.783)
Hispanic	-0.202	-0.128	0.0438	0.159
	(0.260)	(0.247)	(0.244)	(0.758)
other race	-0.615*	-0.505	-0.421	-1.260
	(0.341)	(0.318)	(0.309)	(0.997)
female	0.103	0.0401	-0.0191	-0.0858
	(0.148)	(0.149)	(0.155)	(0.497)
college	0.407**	0.329*	0.295*	1.016*
	(0.185)	(0.173)	(0.176)	(0.590)
married	-0.0111	-0.0152	-0.0207	0.0729
	(0.154)	(0.148)	(0.146)	(0.469)
metro area	-0.194	-0.109	-0.121	0.0489
	(0.199)	(0.191)	(0.189)	(0.608)
part-time	-0.712***	-0.629***	-0.596***	-1.921**
	(0.244)	(0.224)	(0.218)	(0.776)
self-employed	0.406*	0.347	0.383*	1.309*
	(0.218)	(0.215)	(0.221)	(0.759)
low WFH	-0.0629	0.0511	0.359	0.983
	(0.159)	(0.162)	(0.252)	(0.816)
high phys. prox.	-0.944***	-0.817***	-0.729***	-1.859**
	(0.260)	(0.241)	(0.252)	(0.810)
state death rate	0.0572	0.0421	0.0362	0.0380
	(0.149)	(0.143)	(0.139)	(0.448)
Month FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Industry controls	No	Yes	Yes	Yes
Occupation controls	No	No	Yes	Yes
70+ included	Yes	Yes	Yes	No
N	56240	56240	55794	48889

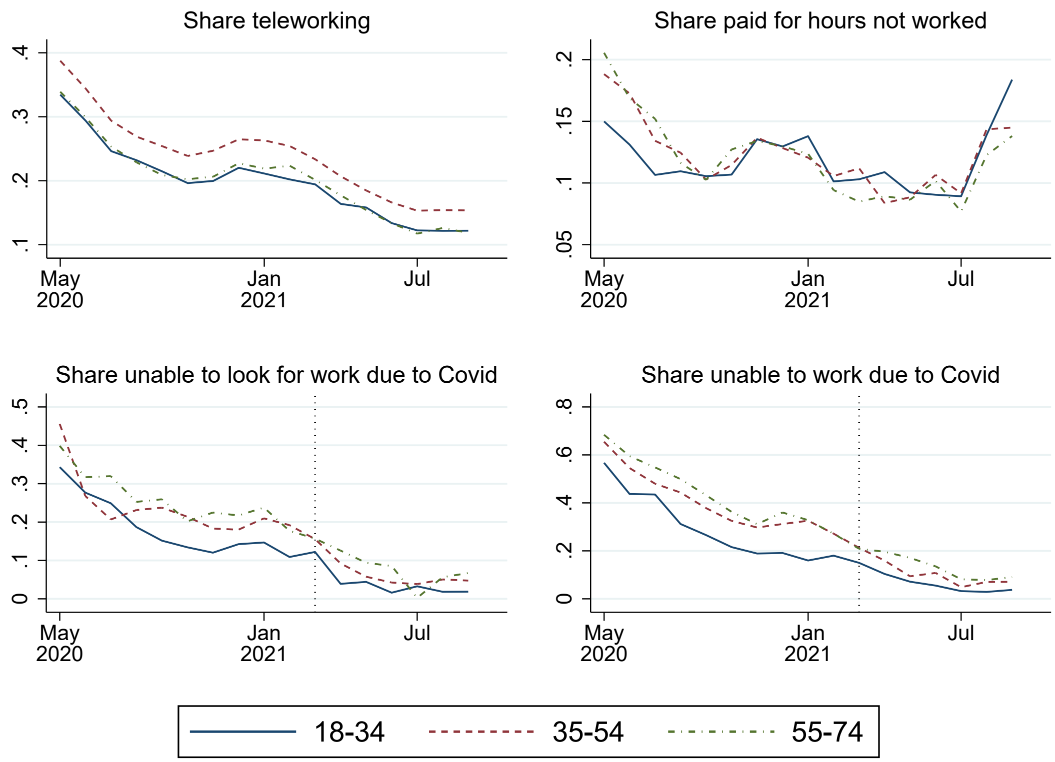
Standard errors in parentheses
* $p<0.1$, ** $p<0.05$, *** $p<0.01$

Note: Results of heteroskedastic probit regressions of employment status among workers who were employed 12 months prior to the reference month. Sample restricted to CPS ORG respondents ages 55 and older except where indicated. To reduce clutter, coefficient estimates for regressors not interacted with Covid dummy are left out of the table above. All listed coefficients are interacted with the pandemic dummy aside from the state Covid death rate variable (which equals zero pre-pandemic). Robust standard errors.

3.6 Covid-specific survey evidence

Beginning in May 2021, CPS surveys included a series of Covid-specific questions: whether the respondent engaged in telework, whether they received pay for hours not worked, inability to work due to Covid, and inability to look for work due to Covid. These questions help address potential ways in which older workers were differentially impacted by the pandemic.

Figure 7: Covid-related labor market impacts by age group



Note: Samples for top row are all employed workers. Samples for bottom row are all non-working, non-retired adults who were employed 12 months prior. Vertical dotted line at March 2021 in bottom-row charts reflects the final month in which prior employment is unaffected by pandemic.

Figure 7 shows the share of workers in each broader age group affected by each Covid labor market impact. The sample for the top two rows (telework and paid for work not performed) is all employed workers in each age group. Calculating the share of those unable to work or look for work poses sample definition problems due to the large share of retired workers in the older group. For the bottom row variables, then, I define the sample as workers who were employed in the prior year and were neither working nor retired in the reference month.[11]

The only Covid-specific labor market measure that exhibits a large and consistent age differential is the share teleworking. Throughout the pandemic, the share of employed mid-career workers

[11]There are three possible not-in-the-labor-force states: unable to work (disabled), retired, and a catchall "other" category.

teleworking was on average 3.7 percentage points higher than the share of employed older workers teleworking, despite the fact that roughly equal shares of older workers and mid-career workers held jobs that could be performed remotely pre-pandemic according to O*NET occupation characteristics (Chen and Munnell, 2020). The WFH differential holds when restricting the sample to high WFH occupations and/or to college-educated workers.

In a logit regression of telework on age group—controlling for sex, education, race, metro area, self-employment, major industry and occupation groups, and month fixed effects—I find that older workers were less likely to work from home during the pandemic than mid-career workers by a precisely estimated log-odds ratio of -0.13 ($p < 0.001$); see Appendix Table A.4 for full results. The WFH coefficient estimate is consistent with explanations having to do with human capital—older workers have less expertise with computer technology and are therefore less likely to work remotely—as well as age discrimination in the offer of training.

These results shed some light on the evidence presented above suggesting WFH difficulty was not as strong a predictor of older worker employment declines as high physical proximity or part-time status. Older workers were less likely to work from home than mid-career workers after controlling for education, occupation and industry. Even in high-WFH employment settings, older workers benefited less from WFH arrangements, diminishing the potential advantage older workers in high-WFH settings may have had over their peers in low-WFH jobs.

4 Retirement

Declines in employment among older workers in the pandemic were driven in part by changes in the retired share. Yet the two are not mirror images of each other. Older workers who are neither employed nor retired may be unemployed or not in the labor force for reasons other than retirement. Whether a decline in EPOP for a group of workers is matched by an increase in the retired share of that group depends on flows among these categories. The boundaries are porous, however, as CPS data show older workers frequently transition into and out of retirement or between different categories of not-in-labor force (NILF).[12]

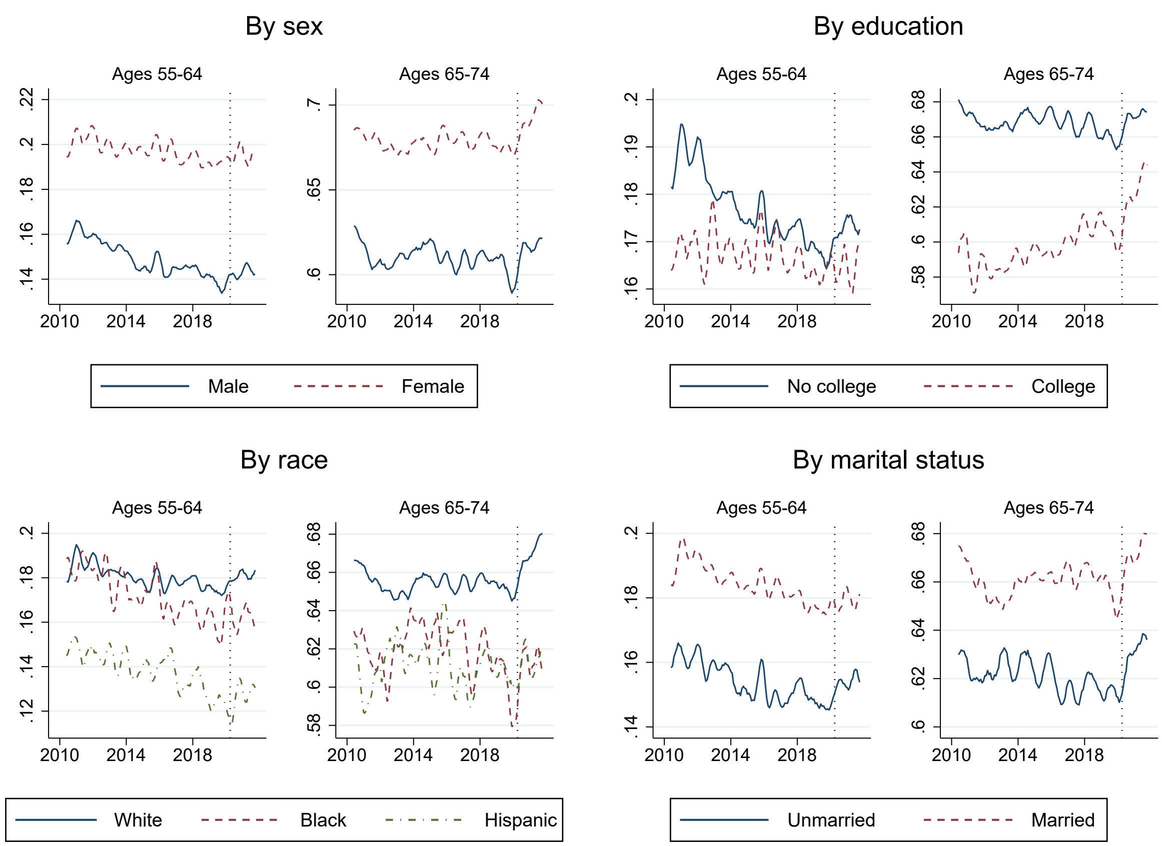
4.1 Time series cross-sectional analysis

As seen in Figure 1 above, the retired share of the older population grew significantly from the start of the pandemic, with the 6-month moving average exceeding a simple linear pre-Covid trend by 1.7 percentage points in October 2021. The trend break is present both for those ages 55-64 and for those 65-74, though more prominently for the older group. For the younger group of retirees, the change appears as a halt to a decade-long fall in the retired share.

[12] In the analysis that follows, I use the IPUMS-CPS employment status variable to define retirement (empstat = 36).

The rise in the retired share did not occur evenly across demographic groups. Figure 8 displays the retired share by sex, education, race and marital status for both of the older age groups, with series plotted in 6-month moving averages. Trend breaks around Covid are more apparent for the 65-74 group in all cases. In the 55-64 group, the series are more noisy and the trend breaks less clear. The biggest Covid shifts in the earlier retired share trend appear for men, non-college workers, and unmarried workers. Even for these groups, the apparent increase since the onset of Covid is modest relative to significant declines in retired shares since 2010.

Figure 8: Retired share by age group and demographics, 6-month moving average

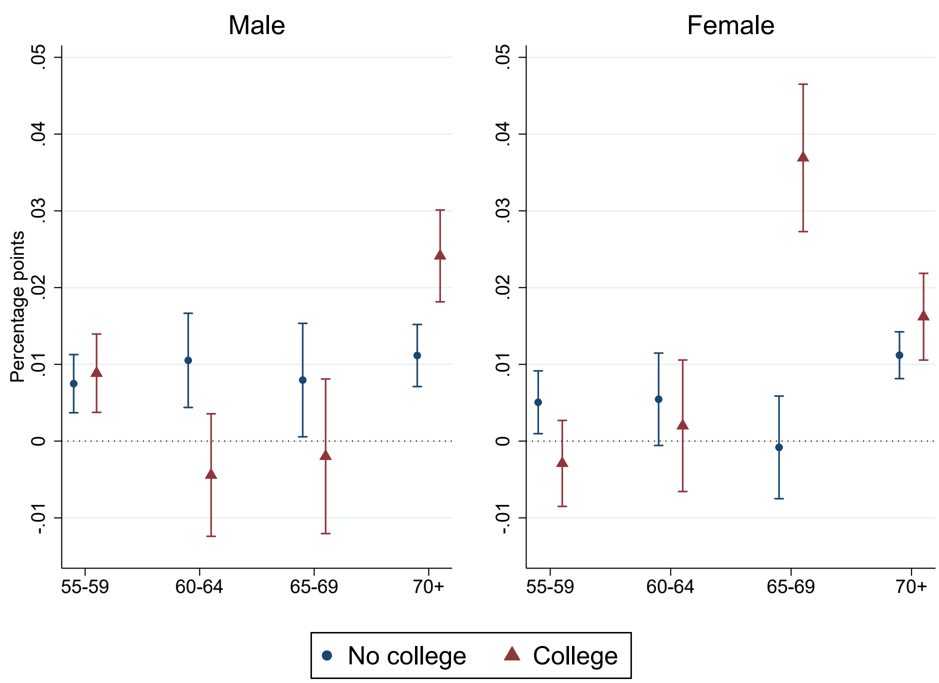


To assess the significance of the apparent trend breaks in the retired share by demographic group, I run a logistic regression of retirement status on demographic covariates and calendar month dummies. I first divide the older population into groups defined by 5-year age groups (with 70+ the oldest group), educational attainment (college vs non-college), and sex. This setup yields 16 different demographic groups. For each group j the regression includes a group-specific intercept term, a group-specific linear trend, and an interaction between group and a Covid dummy that equals 1 beginning April 2020. I also include controls for the month-in-sample or interview wave; see Appendix C for an explanation of CPS month-in-sample bias, which motivates this regressor.

The full form of the model is:

$$Y_{ijt} = \alpha + \beta_j + \gamma_j \text{Date}_t + \delta_j \text{Covid}_t + \theta \text{Month}_t + \phi \text{MIS}_{it} + \pi \text{Covid}_t \times \text{MIS}_{it} + \epsilon_{it} \tag{1}$$

Figure 9: Estimated effect of Covid on probability of being retired



Point estimates and 95% confidence intervals for marginal effect of Covid on retired status by age-sex-education group. Regression includes demographic group-specific intercepts and trends, calendar month dummies, and month-in-sample indicators.

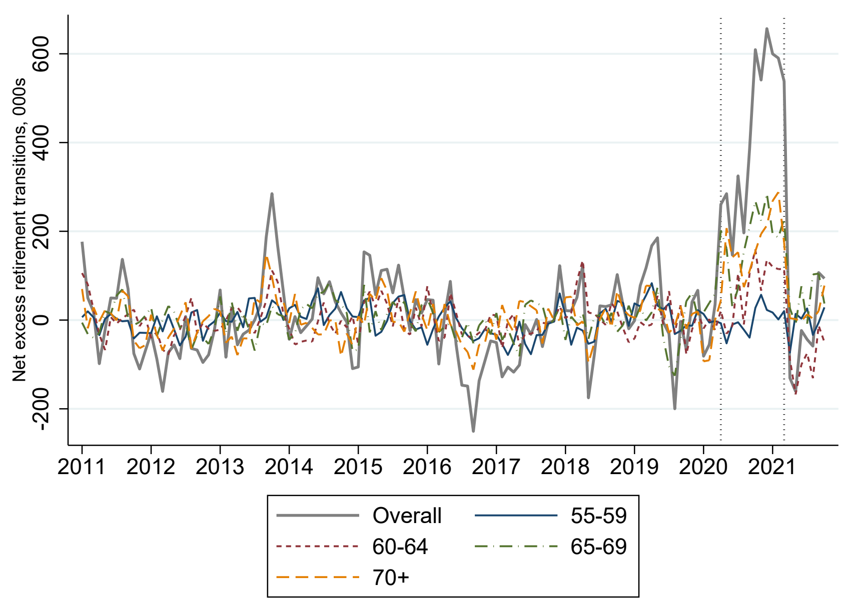
The marginal effects of Covid on group-specific retirement rates, captured by the coefficient δ_j, are presented for each demographic group in Figure 9.[13] The results can be interpreted as estimated percentage-point changes in the probability of being retired for each group. Non-college men face statistically significant increases in retirement probability at all age levels. For college-educated men, estimates point to a (surprising) positive impact of Covid on retirement for the youngest group, 55-59, as well as a large and positive effect for the 70+ group. Non-college women experienced statistically significant increases in the probability of being retired in the late 50s group and the 70+ group. The estimates show little effect for college-educated women younger than 65, a particularly large increase at ages 65-69, and statistically significant increases for 70+. Note that since this regression only captures retirement status cross-sectionally, it does not indicate to what extent the increase in the retired share was due to increased retirement out of employment as opposed to decreased flows from retirement back to employment (see Nie and Yang, 2021).

[13] The analysis is conducted using the `margins` command in Stata, which employs the delta method to estimate changes in the outcome variable in a nonlinear model given marginal changes in a predictor, holding all other variables at their observed values in the sample.

4.2 Longitudinal analysis

The longitudinal aspect of the CPS makes it possible to explore pre- to post-Covid retirement transitions for older workers by demographic group and job characteristics. Before conducting more detailed analysis, however, it is worth exploring to what extent the pandemic retirement surge was spread across age groups or, as the regressions in Quinby et al. (2021) suggest, concentrated among those 70 and older. For a rough answer, I calculate actual and predicted net year-to-year employment-to-retirement transitions for older workers by 5-year age groups (55-59, 60-64, etc) from 2011 to 2021.[14] Differences between the actual net retirement transitions and the predicted series are shown in Figure 10. By this measure, the 70-and-older group made up 39% of the increase in net retirement transitions over the first 12 months of the pandemic. The 65-69 group accounted for 43% of the increase, while the 60-64 share was 17%. Roughly similar patterns hold when considering gross, rather than net, E-R flows. In examining the distribution of pandemic-related retirement, then, workers younger than 70 play an important role.

Figure 10: Net flows from employment to retirement by age group, difference from trend



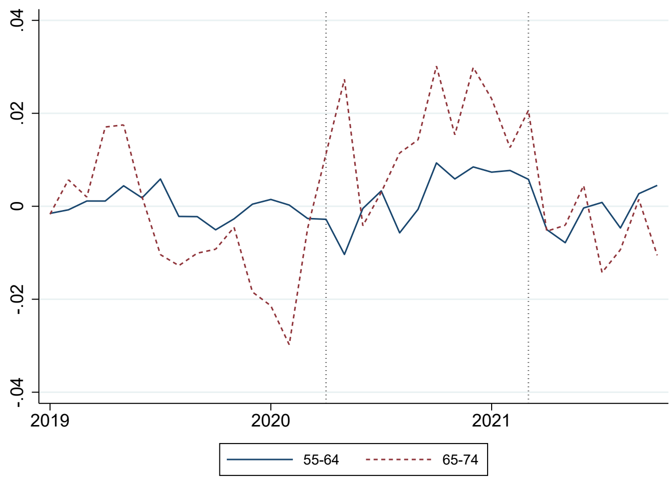
Note: Predicted employment-to-retirement transitions are calculated by regressing each age group's net year-to-year employment-to-retirement transitions on a second-order polynomial time trend, 2011m1–2020m3. The predicted series is then subtracted from actual net E-R series.

In the more detailed analysis that follows, I calculate normalized employment-to-retirement transition rates using the same procedure as for calculating longitudinal employment declines in

[14]To construct each group-specific predicted net retirement series, I regress net E-R transitions on a second-order polynomial time trend with calendar month controls from Jan 2011 to March 2020. These estimates are used to generate predicted net E-R transition series, which are subtracted from the observed series in order to generate a measure of difference from trend in net retirement transitions.

Section 3.3. First I normalize E-R transition rates by subtracting the 5-year average (2015-2019) by month from each group's monthly retirement transition rate from 2020 onward and call the resulting measure *excess retirement*. Note that this gross measure disregards transitions from retired to employed. Figure 11 compares excess retirement for the two older age groups, 55-64 and 65-74. In percentage point terms, the increase in retirement during the pandemic was greater for the older of the two groups and began immediately. For the 55-64 year-old group, excess retirement began only in the latter half of 2020. Appendix Figure A.9 shows the same series for 5-year age groups.

Figure 11: Share retired among those employed 12 months prior, normalized to pre-pandemic average



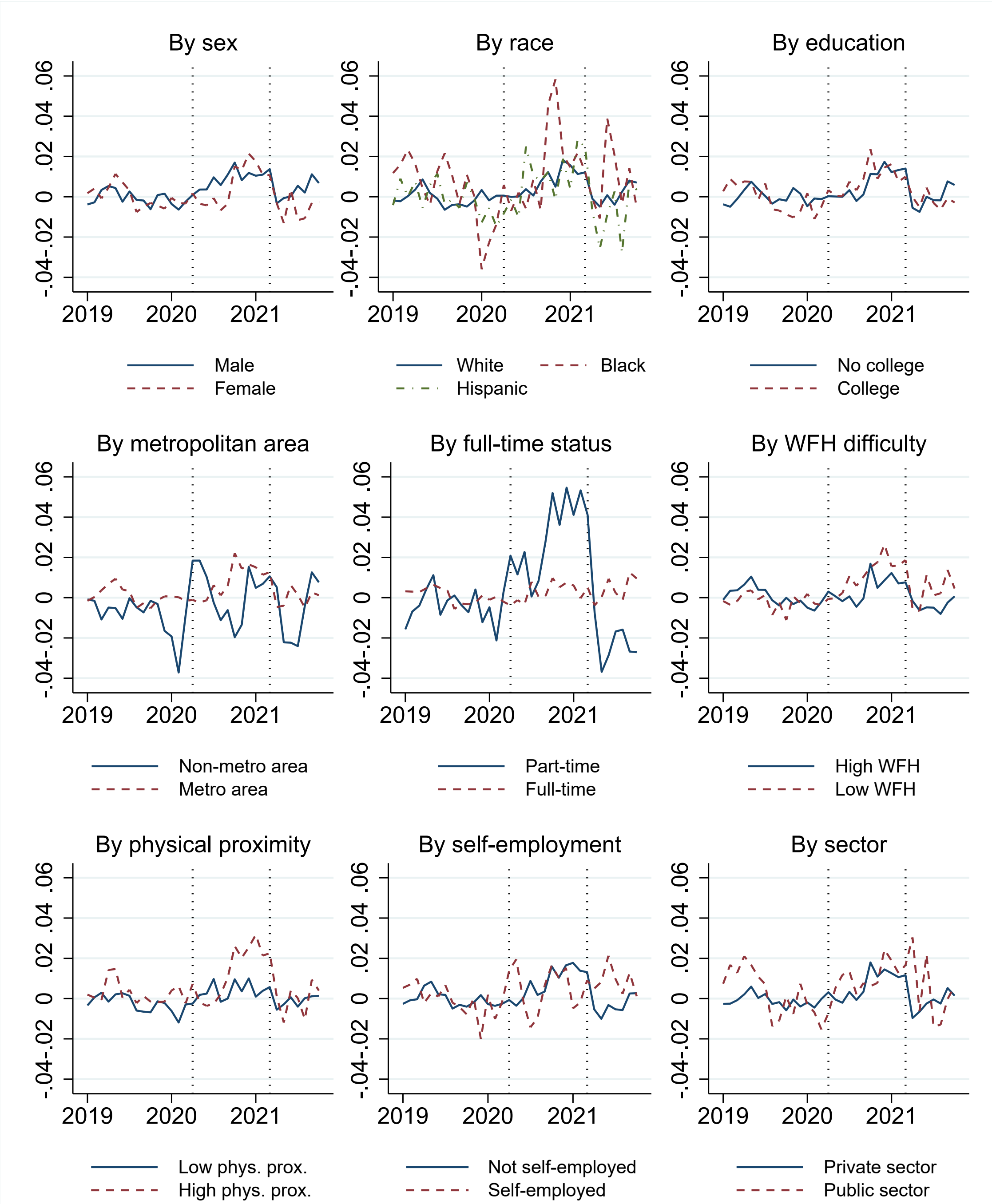
Note: Series show the share of workers who are retired among those employed 12 months prior. Series are normalized by subtracting the 2015-2019 average employed-to-retired transition rate by calendar month for each group.

Figure 12 calculates excess retirement by demographics and prior job characteristics. An increase in the normalized retirement transition rate appears for each demographic group pictured in the top row. There is little difference in retirement transition rates between sexes and between education groups; in both cases, each group experiences comparable excess retirement relative to their pre-pandemic averages, though with possible differences in timing. Trends by race are noisy.

Looking at job characteristics, the largest divergence in excess retirement appears among part-time workers versus full-time workers. This helps confirm that the declines in normalized employment for part-time workers reflected retirement transitions. Once again, however, it is worth considering whether the part-time divergence is driven mostly by age, since part-time work is strongly correlated with age. Workers in low-WFH and HPP occupations also saw disproportionate increases in retirement transitions during the pandemic. In all three cases, the largest increases in retirement transitions occurred in late 2020 and early 2021. The timing is not what would be seen if the sharp initial reductions in employment in April 2020 translated immediately into retirements.

Retirement transition rates disaggregated by earnings quantiles and full-time status underline the importance of work schedules in measuring pandemic retirement trends. Figure 13 presents

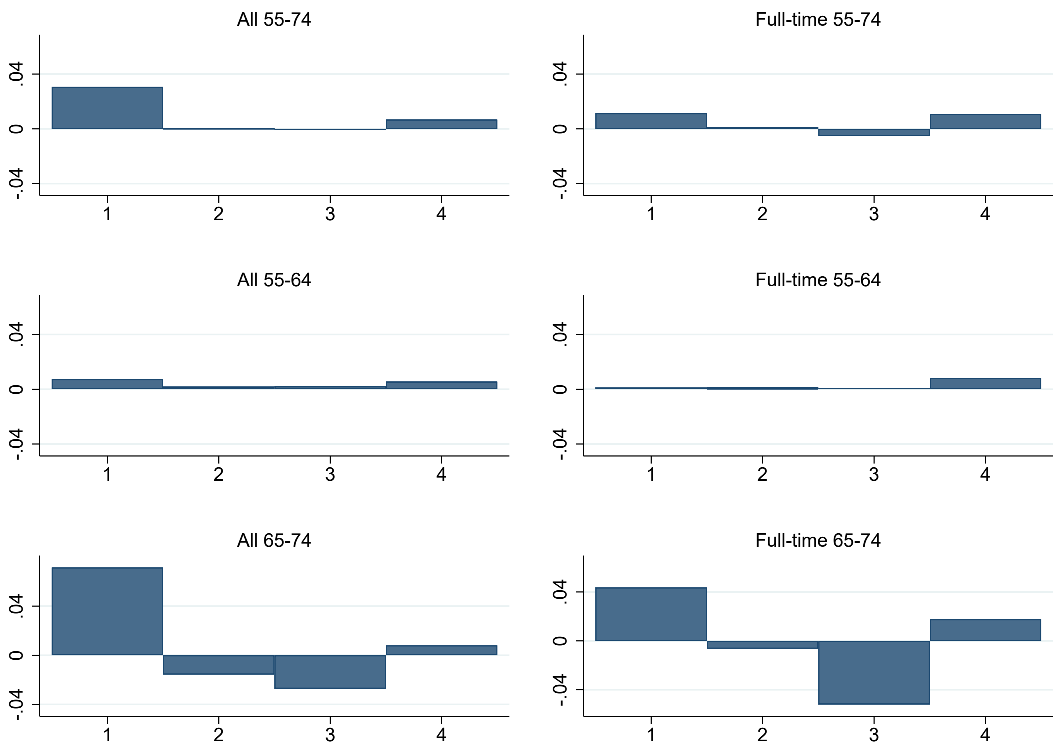
Figure 12: Share retired among those employed 12 months prior, normalized to pre-pandemic average, ages 55-74



Note: Series show the share of workers who are retired among those employed 12 months prior. Series are normalized by subtracting the 2015-2019 average employed-to-retired transition rate by calendar month for each demographic or job characteristic.

the average normalized retirement transition rate for the first year of the pandemic by earnings quartiles; in the left column all workers are included, full- and part-time; in the right column, only full-time workers are included, and quartiles are calculated for full-time workers only.

Figure 13: Normalized employment-to-retirement transition rate by earnings group, 2020m4-2021m3 average



Note: Figures show the average normalized employment-to-retirement transition rate, April 2020 through March 2021, for each earnings/age/hours category. Series are normalized by subtracting the 2015-2019 average transition rate by calendar month for each earnings/age/hours group.

The top-left plot of Figure 13 (which includes all workers 55-74) shows a U-shaped pattern in overall excess retirement by earnings: only the lowest and highest earnings quartiles show appreciable positive changes in retirements. Restricting attention to 10-year age groups in the second and third rows, it is clear that the overall trend is driven by the lowest-paid workers ages 65-74, especially part-time workers. The middle two earnings quartiles saw a decline in retirements for those 65-74. In the 55-64 age group (middle row) the trends are more muted. For those 55-64, including part-timers, excess retirement was limited to the highest- and lowest-paid workers. Among full-time workers 55-64, only the highest quartile saw excess retirement. The large employment declines experienced by the lowest-paid older workers ages 55-64 did not result in a corresponding increase in retirements in the aggregate.

Figures A.10 and A.11 use the normalized retirement transition rates averaged over the first year of the pandemic to estimate excess retirement by major occupation and industry. Major industry groups experiencing the greatest increases in retirement were education and health services, leisure and hospitality, and wholesale trade. While leisure and hospitality was hard hit by the pandemic, health services and wholesale trade experienced lower declines in overall employment at the outset of Covid than the total nonfarm workforce—another indication that retirement patterns in the pandemic were not one-to-one reflections of employment loss.

Among occupations, personal care and service, healthcare support, and protective service occupations saw the largest increases in retirement transitions (Figure A.11). The first two of these are characterized by a high share of part-time employment among older workers and all three are HPP occupations. The sharply increased retirement in protective service, which includes police officers, is consistent with news media reporting connecting police retirements to the increased scrutiny of police forces in 2020 (MacFarquhar, 2021).

4.3 Pandemic retirement transitions: regression evidence

Table 2, column 1, reports results of heteroskedastic probit regression of retirement in the reference month on selected covariates among workers 55 and older who were employed 12 months prior and in the CPS Outgoing Rotation Group. The sample extends from January 2018 (workers employed in January 2017) through March 2021. The covariates are the same as those used in the employment regression described in Section 3.5.[15] Appendix Table A.5 presents the same set of models estimated as linear probability models. As in the case of the employment regressions, the linear models yield the same qualitative conclusions as the results discussed below.

The regression results show that once other covariates are taken into account, increases in retirement transitions from employment were not concentrated along lines of race, gender, or education, coefficient estimates of which are all imprecisely estimated. The Covid indicator, which is negative and imprecisely estimated, is not very informative, since it reflects the combined effects of the baseline groups for all the categorical variables. State-level death rates fail to predict retirement transitions. In all models, the age 70+ coefficient is large and positive; in model 3, with both industry and occupation controls, this coefficient significant at the 10% level.

In Model 1, which controls for state and month fixed effects but not industry or occupation, the only coefficient estimates that achieve conventional statistical significance are HPP and part-time status, both of which predict higher rates of retirement. Introducing industry (model 2) and industry and occupation (model 3) moves the HPP coefficient toward zero—unsurprisingly, given strong correlation between HPP and industry/occupation. At the same time, the introduction of industry and occupation covariates increases the coefficient estimates for part-time work. Restricting the sample to workers younger than 70 (model 4) yields qualitatively similar results; the part-time

[15]These are: five-year age groups, education, sex, race, marital status, metro area, self-employment, full-time status, occupational WFH difficulty, HPP status, state, major industry group and major occupation group (the latter two are added in models 2 and 3). All of the preceding variables are interacted with a Covid dummy. Regressions also control for state-level Covid death rates, month and state fixed effects.

Table 2: Regression results for the effect of the pandemic on retired status among those employed 1 year earlier, 2018-2021

	1	2	3	4
Covid	-0.918	-2.260	-1.153	-3.282
	(1.185)	(1.554)	(1.547)	(7.981)
ages 60-64	-0.175	-0.234	-0.124	-0.466
	(0.330)	(0.344)	(0.337)	(1.540)
ages 65-69	-0.00107	-0.000771	0.0657	0.687
	(0.386)	(0.401)	(0.400)	(2.020)
ages 70+	0.830	0.916	0.993*	
	(0.560)	(0.594)	(0.603)	
Black	0.181	0.238	0.205	1.066
	(0.501)	(0.525)	(0.523)	(2.574)
Hispanic	-0.167	-0.218	-0.436	-2.473
	(0.561)	(0.582)	(0.589)	(2.968)
other race	0.298	0.295	0.306	1.678
	(0.639)	(0.662)	(0.654)	(3.207)
female	-0.0930	-0.154	-0.0328	0.151
	(0.289)	(0.319)	(0.329)	(1.668)
college	-0.166	-0.188	-0.240	-1.157
	(0.303)	(0.325)	(0.343)	(1.729)
married	0.0386	0.0164	-0.0337	-0.791
	(0.309)	(0.320)	(0.318)	(1.625)
metro area	0.133	0.0729	0.0823	-0.310
	(0.383)	(0.399)	(0.396)	(2.008)
part-time	0.680*	0.720*	0.759*	4.314**
	(0.364)	(0.387)	(0.396)	(2.189)
self-employed	-0.134	-0.0632	-0.232	-1.804
	(0.367)	(0.407)	(0.424)	(2.292)
low WFH	0.0420	0.0371	-0.273	-1.077
	(0.315)	(0.347)	(0.511)	(2.614)
high phys. prox.	0.666**	0.590	0.574	1.338
	(0.334)	(0.369)	(0.436)	(2.122)
state death rate	-0.199	-0.174	-0.159	-0.180
	(0.346)	(0.358)	(0.354)	(1.759)
Month FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Industry controls	No	Yes	Yes	Yes
Occupation controls	No	No	Yes	Yes
70+ included	Yes	Yes	Yes	No
N	56240	56240	55794	48889

Standard errors in parentheses
* p<0.1, ** p<0.05, *** p<0.01

Note: Results of heteroskedastic probit regressions of retired status among workers who were employed 12 months prior to the reference month. Sample restricted to CPS ORG respondents ages 55 and older except where indicated. To reduce clutter, coefficient estimates for regressors not interacted with Covid dummy are left out of the table above. All listed coefficients are interacted with the pandemic dummy aside from the state Covid death rate variable (which equals zero pre-pandemic).

coefficient is positive and statistically significant even for those younger than 70.

These regression results largely confirm the trends in descriptive data presented in previous sections. Aside from the age gradient in excess retirement, demographics appear to be less important in understanding excess retirement transitions during the pandemic than job characteristics, the most important of which were employment in high-contact occupations and working part-time.

4.4 Recovering from the pandemic

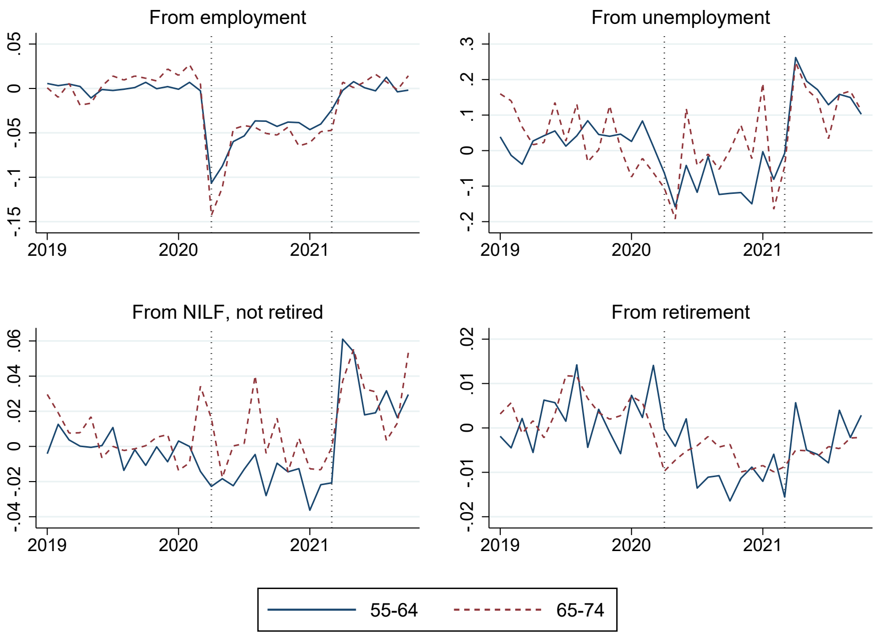
One final area of interest is how those who lost jobs or left work amid Covid have recovered. Some of the tools used in the preceding analysis are less useful here. Normalizing labor market transitions to their 2015-2019 averages makes less sense once the initial period of the transition falls during the pandemic. Still it is worthwhile examine tends in normalized 12-month employment transitions more than one year after the initial Covid shock, .

Figures 5 and 12 presented earlier extend to October 2021, providing some insight into this question. The still-employed shares of those who remained employed in the first 6 months of the pandemic roughly match pre-Covid trends. Retirement transitions show some evidence of divergence, however. While employment-to-retirement transitions appear to be down slightly for women and Hispanic workers in the second half of 2021, the retirement rate has risen above prior trends for full-time workers, Black workers, men and the self-employed. Appendix Figure A.9, which breaks down excess retirement by 5-year age group, also suggests that gross retirement transitions remain elevated for the 55-59 group in the months after April 2021. Whether these are meaningful patterns is highly uncertain.

Given the high rate of labor force exit and unemployment in the pandemic, it is also important to look at transitions from unemployment and NILF/not-retired to employment and retirement since the start of the pandemic. Figures 14 and 15 present normalized transition rates to employment and retirement, respectively, by initial labor force status and older age group. The unusually high share of workers transitioning back to employment a year after unemployment (Figure 14, top right) reflects the fact that an unusually large share of early pandemic job losses (more than 80%) were temporary layoffs. The temporary nature of much of the pandemic job loss also explains the high share of employment post-March 2021 for those who were NILF/not-retired in the early months of the pandemic (Figure 14, bottom left). The year-to-year transition rate from retirement to employment appears to be returning to its pre-pandemic average for both older age groups.

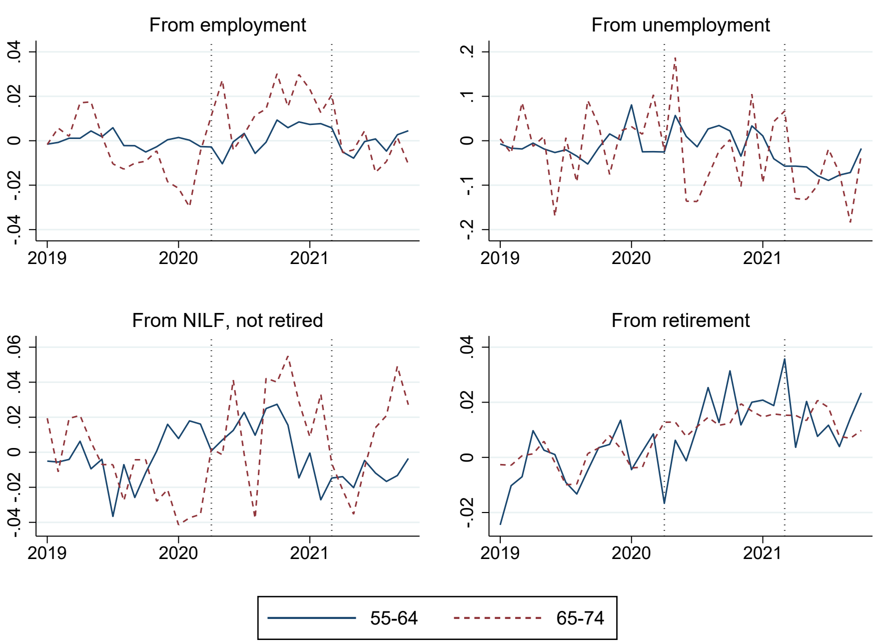
The plots in Figure 15 tell a similar story. The year-to-year retirement transition rate among those who remained employed during the pandemic differs little from pre-pandemic. Transitions to retirement from unemployment are below the pre-pandemic average, again due to the temporary nature of a large share of pandemic unemployment. The NILF-to-retired data are noisier, but show diverging trends for 55-64 and 65-74 year-olds. Finally, the one-year persistence of retirement for those who were retired between March 2020 and September 2020 remains above average.

Figure 14: Normalized share employed 12 months after listed labor force status



Note: Figures show the share of those who are employed among those who were in the listed labor force category 12 months prior. Series are normalized by subtracting the 2015-2019 average transition rate by calendar month for each age group.

Figure 15: Normalized share retired 12 months after listed labor force status



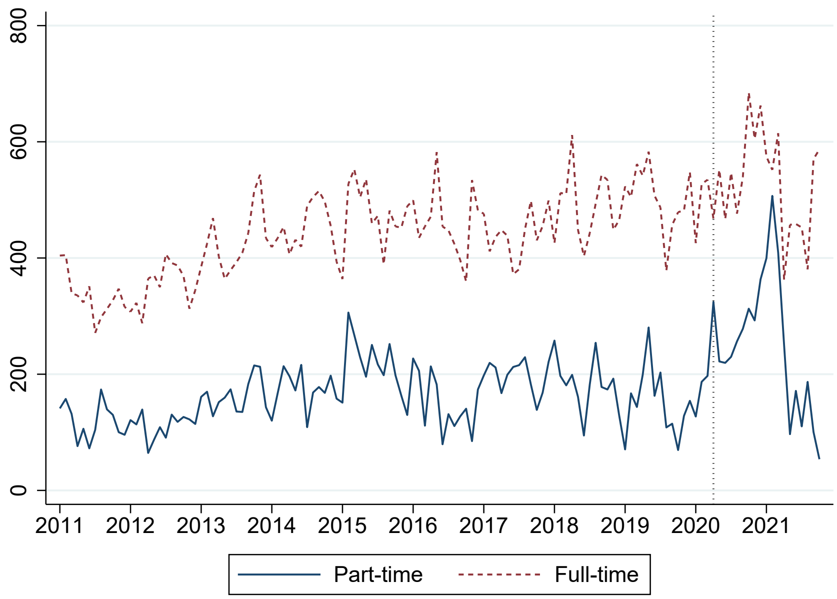
Note: Figures show the share of those who are retired among those who were in the listed labor force category 12 months prior. Series are normalized by subtracting the 2015-2019 average transition rate by calendar month for each age group.

5 Discussion

5.1 Part-time work and retirement in the pandemic

A chief contribution of this study is to highlight the role of part-time work the post-Covid retirement surge. How much of the overall retirement surge was driven by part-time workers? A rough answer comes from decomposing net year-to-year flows from employment to retirement among workers 55-74, Figure 16. Overall, the net flow of older workers into retirement increased 32% in the first 12 months following the Covid shock relative to the 12 months prior. The increase was significantly larger for part-time workers (78%) than for full-time workers (14%). Part-time workers made up 69% of the total increase in net flows from employment to retirement during the first 12 months of the pandemic, relative to the year prior.[16]

Figure 16: Net flows from employment to retirement by full-time status, workers ages 55-74



The importance of part-time work for Covid retirements may also help explain an apparent puzzle: while the retired share rose in the pandemic—including for those younger than 70—Social Security retirement applications have not (Goda et al., 2021; Van Dam, 2021). Excess retirement of part-time workers who already claimed Social Security retirement benefits may help resolve the paradox. Even in ordinary times, a large share of older workers collect Social Security benefits even while working. Using Health and Retirement Study data linked to Social Security Administration records for respondents born 1942-1947, Ghilarducci et al. (2020) found that by age 62, 35% of

[16] The same patterns hold when the sample is restricted to adults 55-69. For this group, the increase in the net flow to retirement is 27%, 68% of which is made up of part-time workers. Note that because these figures do not incorporate flows to and from unemployment and NILF/not-retired, they do not reflect the full increase in the retired share during the pandemic.

part-time and 9% of full-time workers claimed Social Security benefits. By age 65, 73% of part-time and 23% of full-time workers claimed. After full retirement age (66), the vast majority of both groups claimed even while working.[17]

The existence of working-while-claiming among older workers, particularly those in part-time jobs, helps account for how the retired share could rise even as the rate of new Social Security applications fell. These trends could coexist if excess retirement came disproportionately from those already claiming while other older adults delayed claiming—an option that was made more attractive by federal stimulus payments and, for some, enhanced unemployment benefits.

The importance of part-time workers to pandemic retirement trends also brings attention to the role of bridge jobs for older workers. Between one-half and two-thirds of workers who retire from full-time jobs take some kind of bridge job at another employer before full retirement, a majority of which are part-time (Cahill and Quinn, 2020; Bennett et al., 2016). A significant share of CPS respondents report working part-time because they are (partly)[18] retired or because they need to stay below the Social Security earnings test threshold. In 2019, the share of employed workers who reported working part-time for these reasons was 4% at age 62, 10% at age 65, 23% at age 70, and 29% age age 75.[19] While it is not yet clear whether the excess retirements of the pandemic were driven by (part-time) bridge jobs, the possibility of a bridge-job collapse merits further investigation.

The role of part-time jobs in the retirement surge may also have ramifications for how long the increase in the retired share will last, though it is not easy to say in which direction. On one hand, if these part-time jobs were predominantly bridge jobs intended to be held just before retiring, many workers may not come back, given how close to retirement they already were. On the other hand, we might expect retirement from full-time jobs to be stickier than from part-time work; thus a greater share of part-timers entering retirement might suggest easier returns to employment among Covid retirees. The effectiveness of vaccines and strength of the labor market are factors pushing towards a return to work among recent retirees, though increased pandemic-related job stress and workplace turnover might push older workers away.

5.2 Demographic patterns in Covid employment and retirement

The findings presented here also highlight the uneven nature of the pandemic retirement surge. The pandemic's disparate employment impacts by race, gender, education, and earnings, which have been well-documented elsewhere (Dalton et al., 2021; Cortes and Forsythe, 2021), are confirmed and extended here. Yet the distribution of Covid employment impacts does not map perfectly onto the

[17] These figures reflect actuarial adjustments accounting for the presence of the Social Security earnings test, which withholds benefits from workers who have not yet reached full retirement age and who earn more than a set amount. Workers who have technically claimed but have benefits withheld due to the earnings limits are not counted as claiming in the figures listed above.

[18] This raises definitional questions about retirement. For the purposes of this paper, retirement means a respondent is not working and tells survey-takers that retirement is the reason for not working. Partly retired workers who take on bridge jobs do not meet this definition.

[19] Pooled 2019 CPS-IPUMS data.

distribution of excess retirement. The remainder of this section summarizes and compares Covid employment and retirement patterns by gender, race, education, and earnings groups.

Gender. Older women experienced larger employment declines early in the pandemic than older men, but these differences mostly faded by early 2021. In regression results controlling for industry and occupation, gender was not a significant predictor of employment loss during the first 12 months of the pandemic among those employed a year earlier. Comparable regression results of retirement on industry, occupation and other covariates show no significant role for gender in retirement transitions during the pandemic, though as the results reported in Figure 9 suggest, the age profiles of trend breaks in the retired share may differ by gender. Overall, there is no clear evidence that the greater employment declines experienced by women early in the pandemic led to disproportionate excess retirement for women.

Race. Employment declines early in the pandemic were larger for Black and Hispanic older workers and the decomposition results presented in Figure A.6 show that for the first 12 months of the pandemic, these declines could not be explained by industry and occupation alone. Yet regression results do not suggest a significant role for race for employment outcomes for Black and Hispanic older workers, at least after controlling for industry, occupation, education, part-time status and other covariates. These same results do suggest a significant and negative role for "other" race, which largely represents Asians. In retirement outcomes, race appears to have little effect either in descriptive evidence or regression results.

Education. Employment losses for non-college older workers were greater than for those with a college degree, a pattern that holds up in regressions controlling for industry, occupation, and a range of other covariates. Comparable evidence for the role of education in retirement outcomes is less clear. In regression results for retirement transitions controlling for the same covariates, the coefficient on college degree was not statistically significant.

Earnings. The disconnect between employment declines and excess retirement is clearest when comparing the earnings gradients of employment declines to the earnings gradients of excess retirement. Across age groups, and whether restricting to full-time or not, employment losses were generally greater the lower were workers' initial earnings. By contrast, excess retirement followed an inverted U-shape, in which only the lowest- and highest-earning quartiles saw excess retirements. Excess retirements were thus not limited to the hardest-hit sections of the labor market.

The lack of clear differences in Covid retirement trends between demographic groups, particularly in the regression results, reflects the complexity of retirement decisions and outcomes. As noted in the introduction, push factors like Covid risk and age discrimination occurred alongside the pull of higher asset prices. Meanwhile, the same populations exposed to higher job loss were also overrepresented in frontline occupations protected from job loss (Farmand et al., 2020). Uncertainty likely led some to delay retirement plans. Each of the above factors has heterogeneous impacts across and within demographic groups. High-income professionals with substantial savings may have retired at higher rates due to asset price gains while low-income workers in HPP occupations retired due to job loss, Covid risk, or discouragement in finding a new job. For these reasons, it is difficult to make broad judgments about the welfare consequences of heightened retirement during the pandemic.

6 Conclusion

This study explored employment and retirement outcomes for older workers in the pandemic. I documented the uneven declines in employment that faced older workers at the start of the pandemic and confirmed that the fall in the employed share of this group relative to mid-career workers could not be explained by industry and occupation alone.

Turning to retirement, I demonstrated that the increase in the retired share of the older population occurred across demographics groups and was not limited to those 70 and older. A major contributor to the increased retired share, as yet unexplored in the literature, is part-time employment pre-pandemic. Older workers with part- time schedules in the year before the pandemic saw greater declines in employment after the pandemic hit and retired at higher rates than full-time workers. Among all demographic and job-related characteristics—and after controlling for age, industry and occupation—part-time status and occupation in high-contact jobs were the clearest predictors of retirement transitions among those employed in the 12 months preceding April 2020.

The unprecedented nature of the labor market impacts stemming from Covid-19 mean that the full ramifications of the pandemic for older workers' employment and retirement patterns may not be fully known for years. More immediately, however, additional research is needed drawing from a wider array of data sources to corroborate and clarify trends in retirement during the pandemic. More work is needed as well to explore potential biases arising from pandemic impacts on survey response, a topic briefly outlined in Appendices C and D.

References

Bauer, Peter, Jonas Brugger, Franz König, and Martin Posch (2021) "An international comparison of age and sex dependency of COVID-19 deaths in 2020: a descriptive analysis," *Scientific Reports*, 11 (1), 19143.

Bennett, Misty M, Terry A Beehr, and Lawrence R Lepisto (2016) "A Longitudinal Study of Work After Retirement: Examining Predictors of Bridge Employment, Continued Career Employment, and Retirement," *The International Journal of Aging and Human Development*, 83 (3), 228–255, `https://doi.org/10.1177/0091415016652403`.

Brynjolfsson, Erik, John J Horton, Adam Ozimek, Daniel Rock, Garima Sharma, and Hong-Yi TuYe (2020) "COVID-19 and Remote Work: An Early Look at U.S. Data," Working Paper 27344, National Bureau of Economic Research.

Bui, Truc Thi Mai, Patrick Button, and Elyce G Picciotti (2020) "Early Evidence on the Impact of Coronavirus Disease 2019 (COVID-19) and the Recession on Older Workers," *Public Policy & Aging Report*, 30 (4), 154–159.

Cahill, Kevin E and Joseph F Quinn (2020) "The Importance of Gradual Retirement in America Today," *Public Policy & Aging Report*, 30 (3), 107–112.

Chen, Anqi and Alicia H. Munnell (2020) "Can Older Workers Work from Home?" Working Paper 2020-9, Center for Retirement Research, Boston.

Coibion, Olivier, Yuriy Gorodnichenko, and Michael Weber (2020) "Labor Markets During the COVID-19 Crisis: A Preliminary View," Working Paper 27017, National Bureau of Economic Research.

Cortes, Guido and Eliza Forsythe (2021) "The Heterogeneous Labor Market Impacts of the Covid-19 Pandemic," working paper, `http://publish.illinois.edu/elizaforsythe/files/2021/08/Cortes_Forsythe_Covid-demo_revision_8_1_2021.pdf`.

Dahl, Gordon B and Matthew M Knepper (2020) "Age Discrimination across the Business Cycle," Working Paper 27581, National Bureau of Economic Research.

Dalton, Michael, Jeffrey A Groen, Mark A Loewenstein, David S Piccone, and Anne E Polivka (2021) "Correction to: The K-Shaped Recovery: Examining the Diverging Fortunes of Workers in the Recovery from the COVID-19 Pandemic Using Business and Household Survey Microdata," *The Journal of Economic Inequality*, 19 (4), 895–896.

Davis, Owen, Bridget Fisher, Teresa Ghilarducci, and Siavash Radpour (2020) "A First in Nearly 50 Years, Older Workers Face Higher Unemployment than Mid-Career Workers," Working Paper 2020-10, Schwartz Center for Economic Policy Analysis at The New School for Social Research.

Dingel, Jonathan I and Brent Neiman (2020) "How many jobs can be done at home?," *Journal of Public Economics*, 189, 104235, https://doi.org/10.1016/j.jpubeco.2020.104235.

Farmand, Aida, Teresa Ghilarducci, Siavash Radpour, and Bridget Fisher (2020) "Older Women and Older Black Workers Are Overrepresented in High-Risk Jobs," policy note, Schwartz Center for Economic Policy Analysis at The New School for Social Research.

Flood, Sarah, Miriam King, Renae Rodgers, Steven Ruggles, J. Robert Warren, and Michael Westberry (2021) "Integrated Public Use Microdata Series, Current Population Survey: Version 9.0 [dataset]."

Frazis, Harley J., Edwin L. Robison, Thomas D. Evans, and Martha A. Duff (2005) "Estimating gross flows consistent with stocks in the CPS," *Monthly Labor Review*, 128 (9).

Ghilarducci, Teresa, Michael Papadopoulos, and Anthony Webb (2020) "The Illusory Benefits of Working Longer on Financial Preparedness for Retirement," Working paper 2020-2, Schwartz Center for Economic Policy Analysis at The New School for Social Research.

Gittleman, Maury (2019) "Declining labor turnover in the United States: evidence and implications from the Panel Study of Income Dynamics," *Monthly Labor Review*.

Goda, Gopi Shah, Emilie Jackson, Lauren Hersch Nicholas, and Sarah See Stith (2021) "The Impact of Covid-19 on Older Workers' Employment and Social Security Spillovers," Working Paper 29083, National Bureau of Economic Research.

Horowitz, Juliana Menasce, Anna Brown, and Rachel Minkin (2021) "A Year Into the Pandemic, Long-Term Financial Impact Weighs Heavily on Many Americans," report, Pew Research Center, `https://www.pewresearch.org/social-trends/2021/03/05/a-year-into-the-pandemic-long-term-financial-impact-weighs-heavily-on-many-americans`.

Johnson, Richard W. and Corina Mommaerts (2021) "A Year Into the Pandemic, Long-Term Financial Impact Weighs Heavily on Many Americans," Working paper 2011-3, Boston College Center for Retirement Research, `https://www.pewresearch.org/social-trends/2021/03/05/a-year-into-the-pandemic-long-term-financial-impact-weighs-heavily-on-many-americans`.

Levine, Phillip B. L and Olivia S. Mitchell (1988) "The Baby Boom's Legacy: Relative Wages in the Twenty-First Century," *The American Economic Review*, 78 (2), 66–69.

MacFarquhar, Neil (2021) "Departures of Police Officers Accelerated During a Year of Protests," *New York Times*.

Marmora, Paul and Moritz Ritter (2015) "Unemployment and the Retirement Decisions of Older Workers," *Journal of Labor Research*, 36 (3), 274–290.

Mongey, Simon, Laura Pilossoph, and Alexander Weinberg (2021) "Which workers bear the burden of social distancing?," *The Journal of Economic Inequality*, 19 (3), 509–526.

Nie, Jun and Shu-Kuei X. Yang (2021) "What Has Driven the Recent Increase in Retirements?"Technical report, Federal Reserve Bank of Kansas City.

Quinby, Laura, Matthew S. Rutledge, and Gal Wettstein (2021) "How Has COVID-19 Affected the Labor Force Participation of Older Workers?" Working paper CRR WP 2011-13, Boston College Center for Retirement Research.

Rothbaum, Jonathan and Adam Bee (2021) "Coronavirus Infects Surveys, Too: Nonresponse Bias During the Pandemic in the CPS ASEC," Working paper SEHSD WP2020-10, United States Census Bureau.

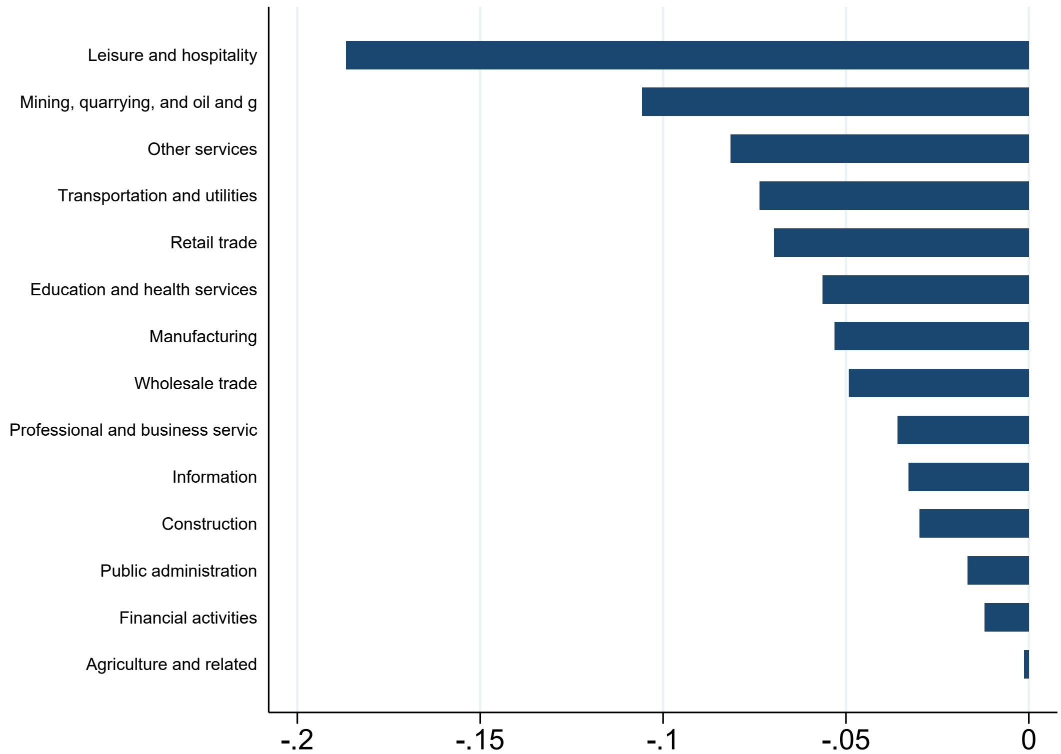
U.S. Bureau of Labor Statistics (2020) "Employee Tenure Summary,"Technical report, `https://www.bls.gov/news.release/tenure.nr0.htm`.

Van Dam, Andrew (2021) "The latest twist in the 'Great Resignation': Retiring but delaying Social Security," *Washington Post*.

Yatchew, Adonis and Zvi Griliches (1985) "Specification Error in Probit Models," *The Review of Economics and Statistics*, 67 (1), 134–139.

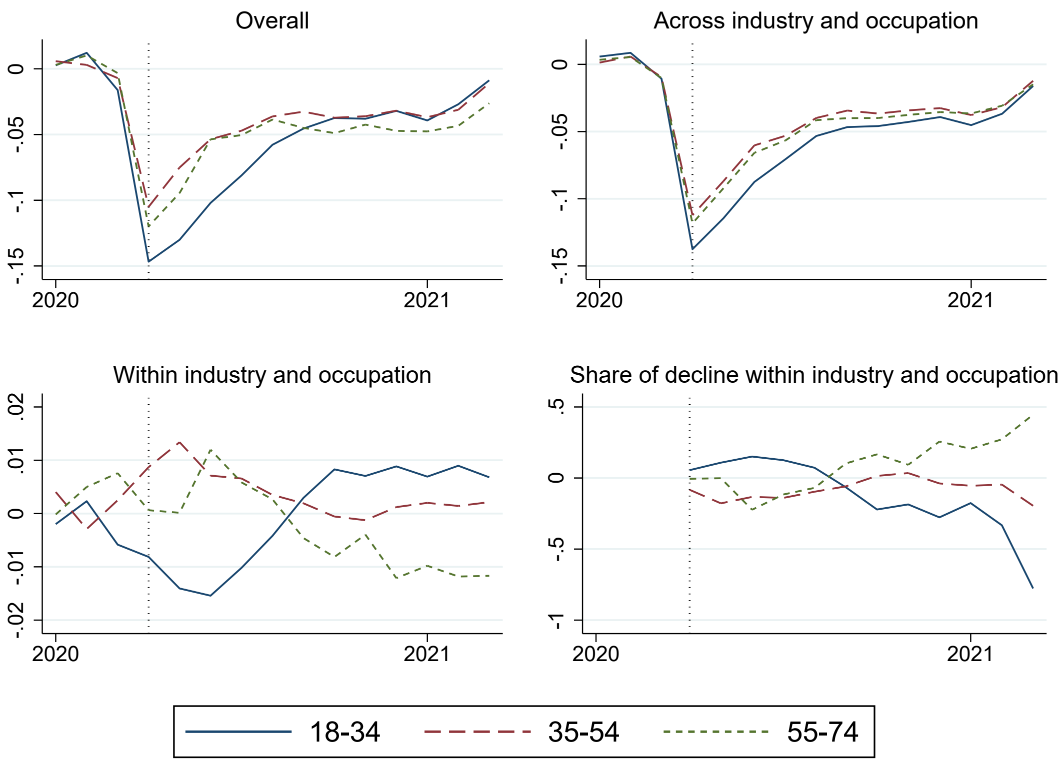
A Additional Tables and Figures

Figure A.3: Normalized still-employed share by industry



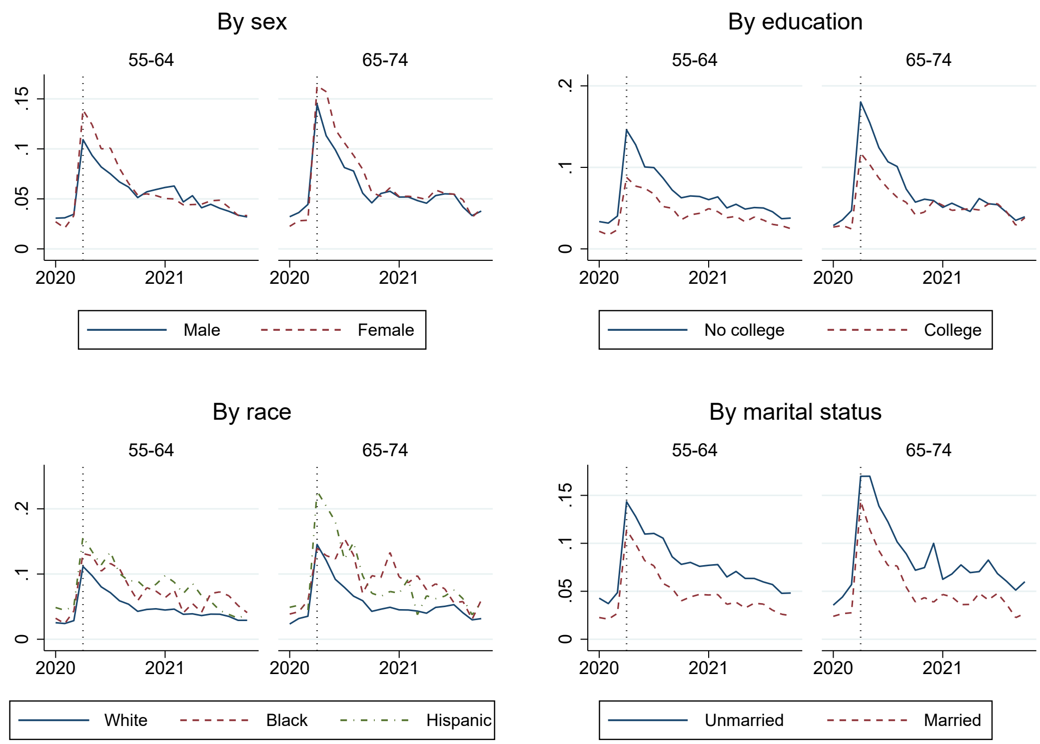
Note: Bars show the normalized still-employed share, averaged over April 2020 through March 2021, for each major industry group. The normalized still-employed share is computed by first calculating the share of workers who are still employed among those who were employed in each industry a year prior. The 2015-2019 average for each calendar month is then subtracted from each series to normalize it.

Figure A.1: Normalized change in employment by age group, decomposition results with respect to industry-occupation combination



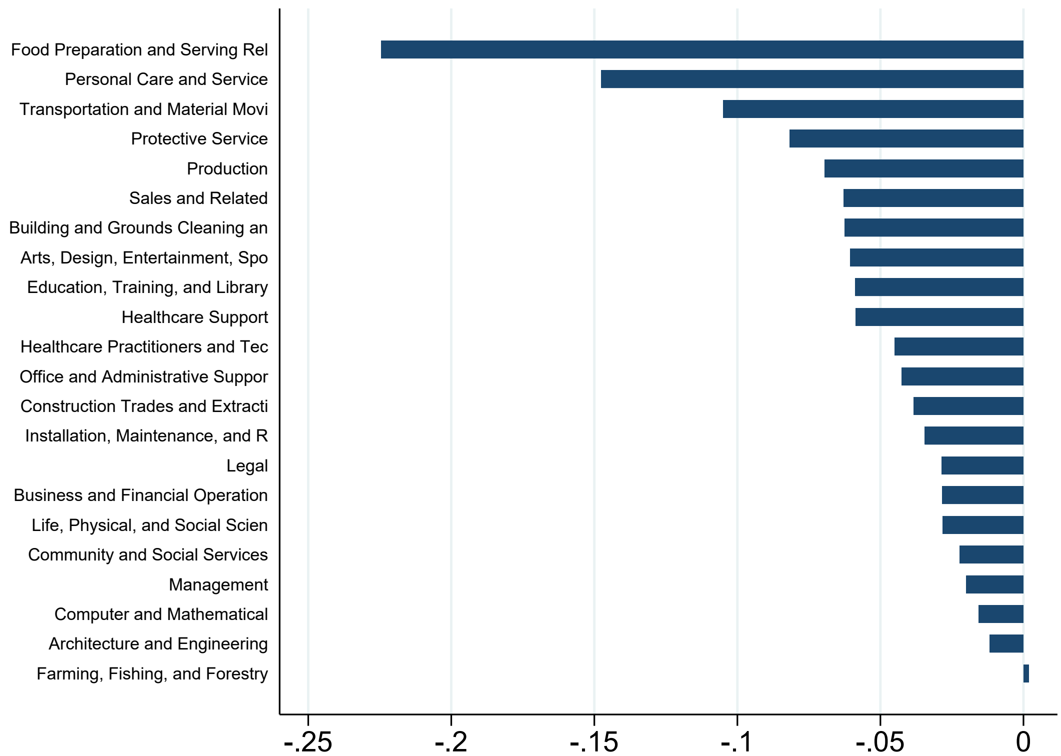
Note: Plots reflect results of decomposition methodology described in Appendix B. The *overall* plot displays the share of those who were employed 12 months prior who are still employed in the reference month, normalized to shares still employed over 2015-2019. The *across* plot displays the change in employment for each group that is due to the distribution of that group's employment across industries/occupations. The *within* plot shows the change in employment specific to each age group within industries/occupations. The bottom-right plot shows the share of overall employment change due to within-industry/occupation changes.

Figure A.2: Unemployment rates by age group and demographics, ages 55-75



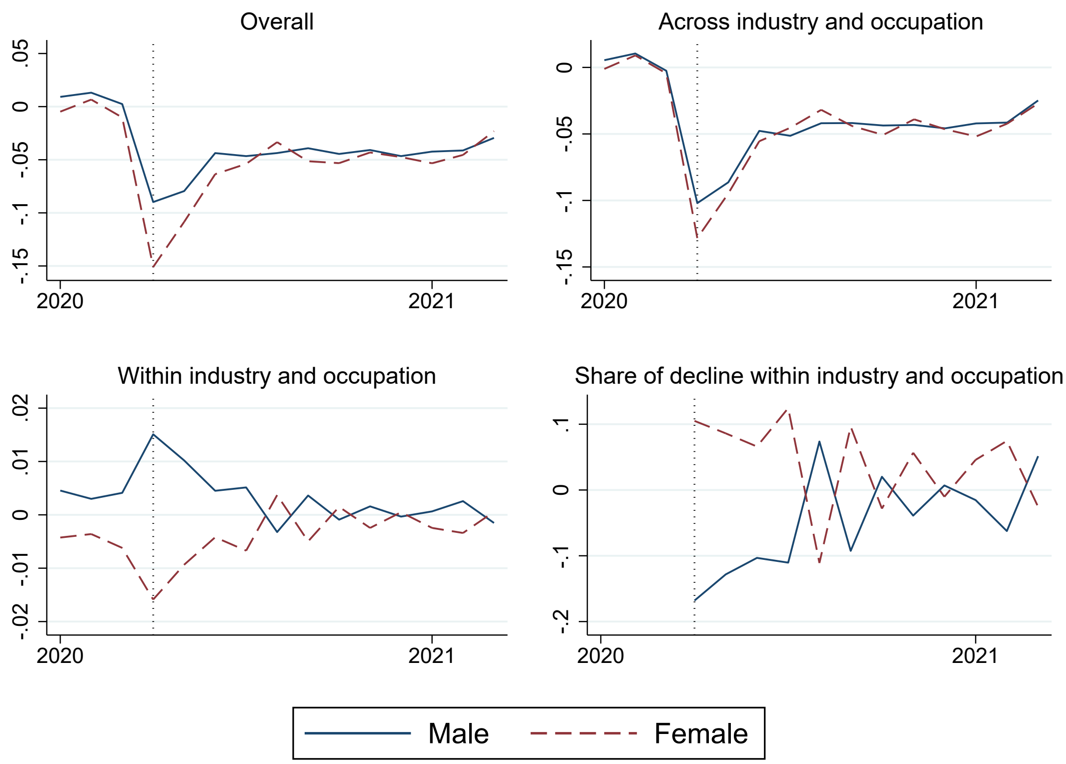
Note: Employment rates indexed to full-year 2019 averages. Not seasonally adjusted.

Figure A.4: Normalized still-employed share by occupation



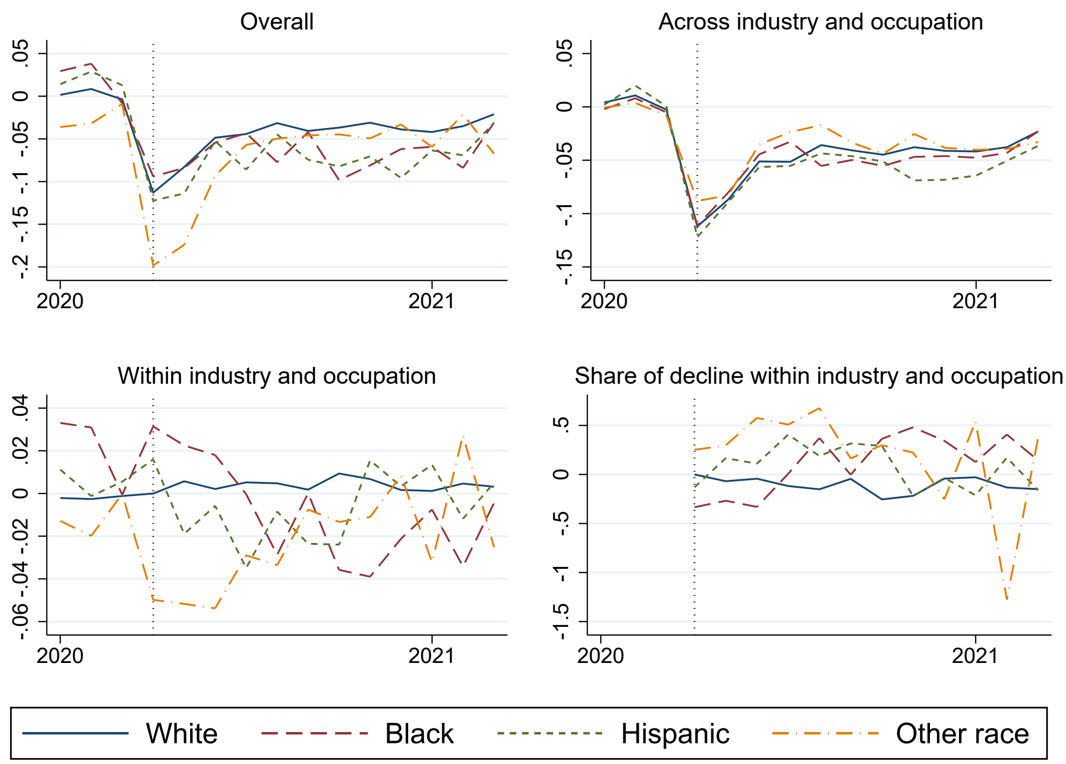
Note: Bars show the normalized still-employed share, averaged over April 2020 through March 2021, for each major occupation group. The normalized still-employed share is computed by first calculating the share of workers who are still employed among those who were employed in each occupation a year prior. The 2015-2019 average for each calendar month is then subtracted from each series to normalize it.

Figure A.5: Normalized change in employment by sex, decomposition results with respect to industry and occupation, ages 55-74



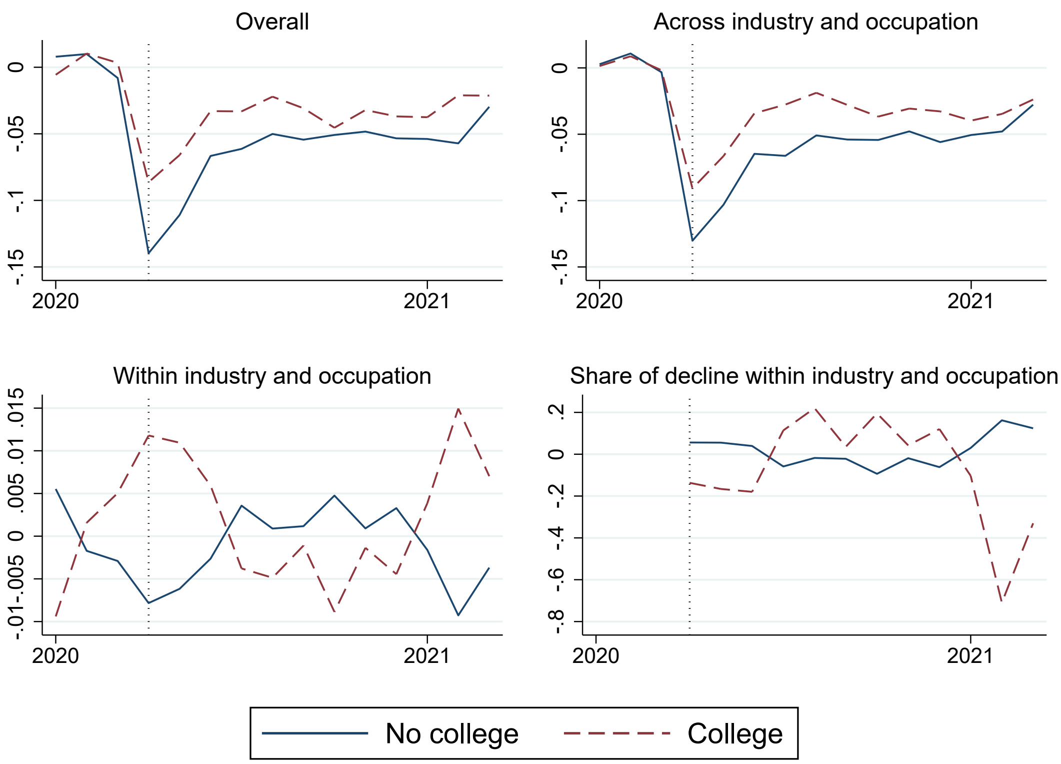
Note: Plots reflect results of decomposition methodology described in Appendix B. The *overall* plot displays the share of those who were employed 12 months prior who are still employed in the reference month, normalized to shares still employed over 2015-2019. The *across* plot displays the change in employment for each group that is due to the distribution of that group's employment across industries. The *within* plot shows the change in employment specific to each group within industries. The bottom-right plot shows the share of overall employment change due to within-industry changes.

Figure A.6: Normalized change in employment by race, decomposition results with respect to industry and occupation, ages 55-74



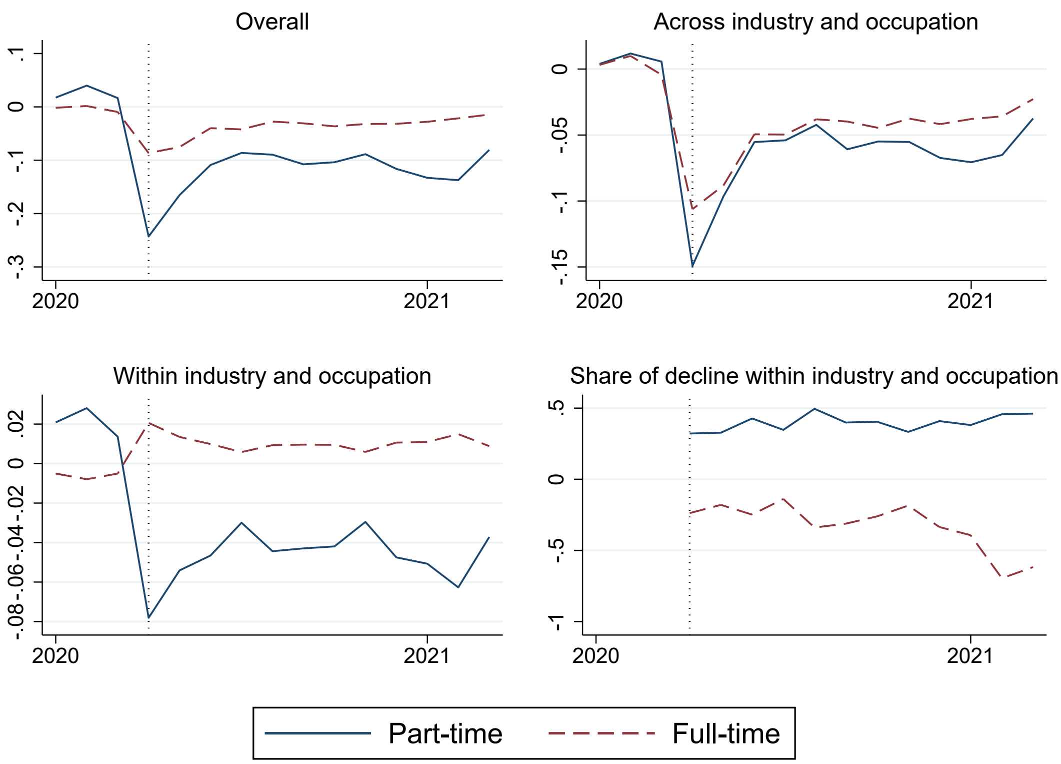
Note: Plots reflect results of decomposition methodology described in Appendix B. The *overall* plot displays the share of those who were employed 12 months prior who are still employed in the reference month, normalized to shares still employed over 2015-2019. The *across* plot displays the change in employment for each group that is due to the distribution of that group's employment across industries. The *within* plot shows the change in employment specific to each group within industries. The bottom-right plot shows the share of overall employment change due to within-industry changes.

Figure A.7: Normalized change in employment by education, decomposition results with respect to industry and occupation, ages 55-74



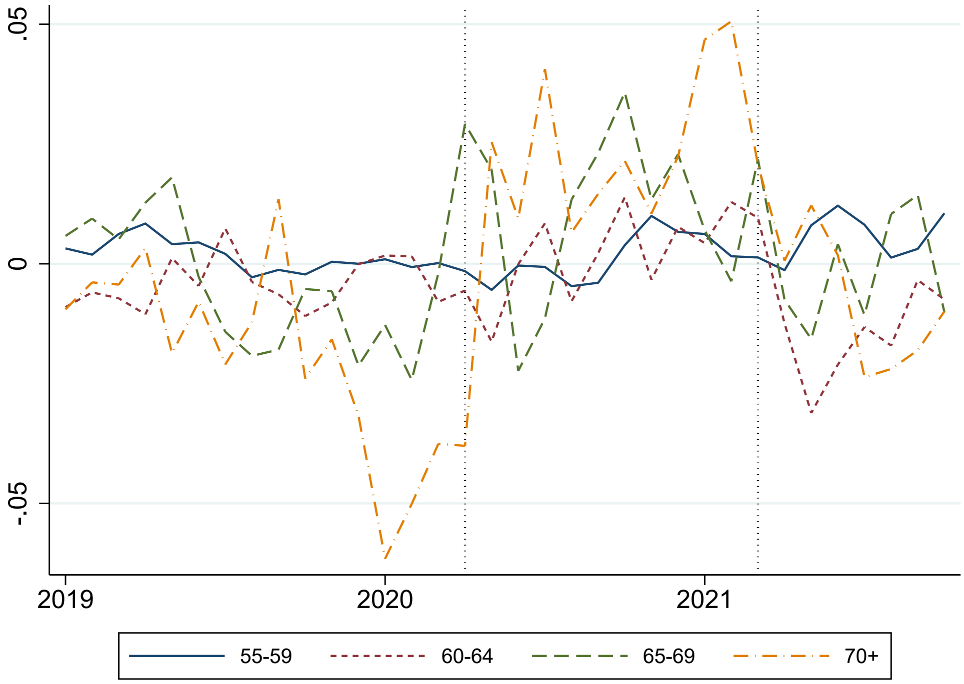
Note: Plots reflect results of decomposition methodology described in Appendix B. The *overall* plot displays the share of those who were employed 12 months prior who are still employed in the reference month, normalized to shares still employed over 2015-2019. The *across* plot displays the change in employment for each group that is due to the distribution of that group's employment across industries. The *within* plot shows the change in employment specific to each group within industries. The bottom-right plot shows the share of overall employment change due to within-industry changes.

Figure A.8: Normalized change in employment by full-time status, decomposition results with respect to industry and occupation, ages 55-74



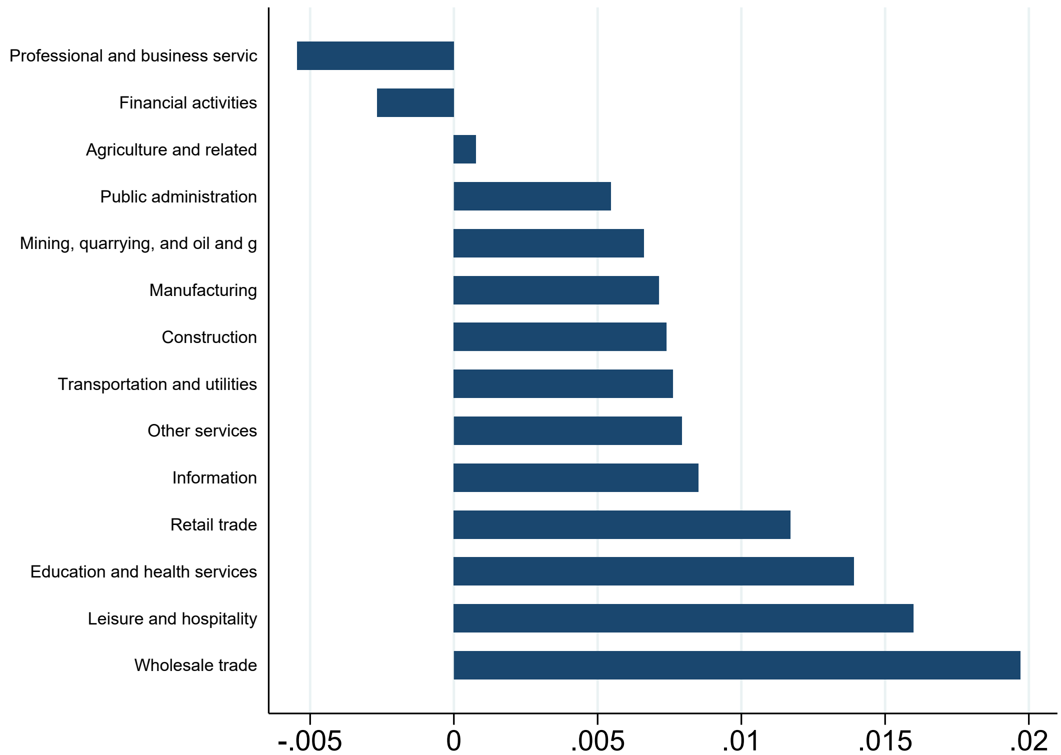
Note: Plots reflect results of decomposition methodology described in Appendix B. The *overall* plot displays the share of those who were employed 12 months prior who are still employed in the reference month, normalized to shares still employed over 2015-2019. The *across* plot displays the change in employment for each group that is due to the distribution of that group's employment across industries. The *within* plot shows the change in employment specific to each group within industries. The bottom-right plot shows the share of overall employment change due to within-industry changes.

Figure A.9: Share retired among those employed 12 months prior, normalized to pre-pandemic average



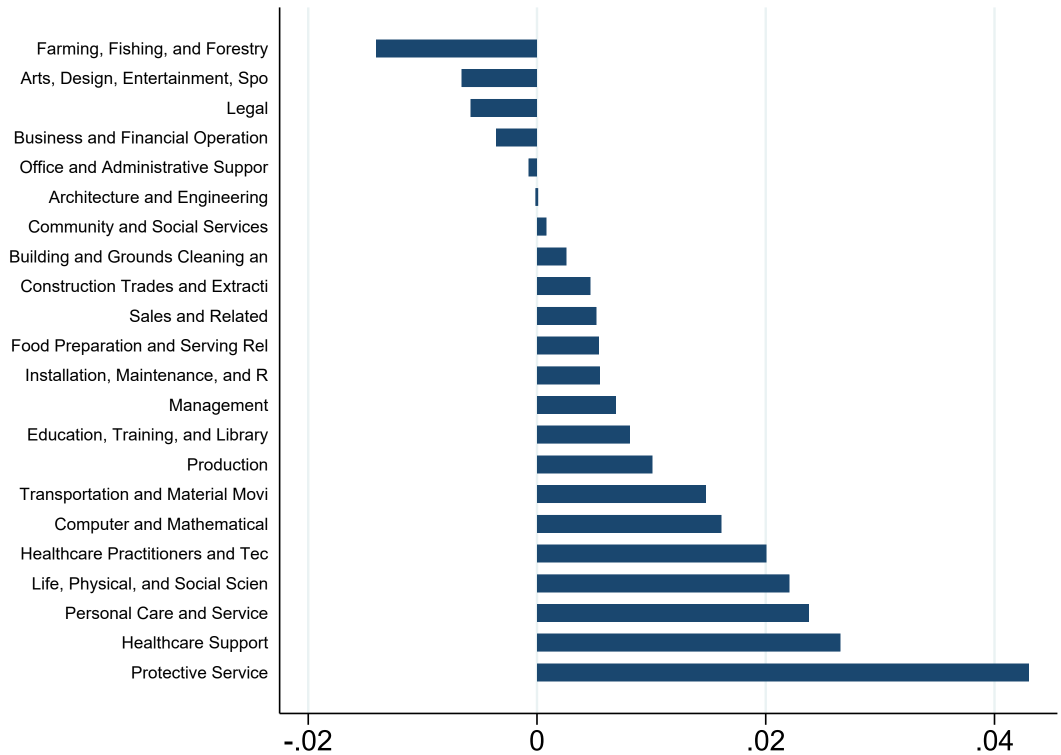
Note: Series show the share of workers who are retired among those employed 12 months prior. Series are normalized by subtracting the 2015-2019 average employed-to-retired transition rate by calendar month for each age group.

Figure A.10: Normalized employment-to-retirement transition rate by industry



Note: Bars show the normalized employment-to-retirement transition rate, averaged over April 2020 through March 2021, for each major industry group. The normalized employment-to-retirement transition rate is computed by first calculating the share of workers who are retired among those who were employed in each industry a year prior. The 2015-2019 average for each calendar month is then subtracted from each series to normalize it.

Figure A.11: Normalized employment-to-retirement transition rate by occupation



Note: Bars show the normalized employment-to-retirement transition rate, averaged over April 2020 through March 2021, for each major occupation group. The normalized employment-to-retirement transition rate is computed by first calculating the share of workers who are retired among those who were employed in each industry a year prior. The 2015-2019 average for each calendar month is then subtracted from each series to normalize it.

Table A.1: Summary statistics

	55-59	60-64	65-69	70+
Female	0.474	0.473	0.461	0.436
White	0.698	0.724	0.757	0.781
Black	0.106	0.101	0.089	0.081
Hispanic	0.128	0.109	0.090	0.077
Other race	0.067	0.065	0.065	0.060
College	0.372	0.372	0.428	0.432
Married	0.677	0.680	0.666	0.616
Metro area	0.861	0.859	0.855	0.843
Full-time	0.875	0.824	0.682	0.544
High phys. prox.	0.412	0.409	0.424	0.422
Low WFH	0.446	0.449	0.412	0.420
Self-employed	0.127	0.146	0.202	0.277
Public sector	0.160	0.158	0.136	0.121

Note: Pooled sample of adults surveyed in 2019 who were in the labor force.

Table A.2: Selected employment rates by age group and demographics

	2019 average	Apr 2020	Oct 2021
Male			
55-64	0.700	0.629	0.681
65-74	0.324	0.271	0.304
Female			
55-64	0.584	0.508	0.580
65-74	0.235	0.191	0.220
No college			
55-64	0.594	0.507	0.573
65-74	0.237	0.191	0.226
College			
55-64	0.736	0.683	0.734
65-74	0.352	0.297	0.321
White			
55-64	0.655	0.585	0.640
65-74	0.285	0.236	0.261
Black			
55-64	0.556	0.508	0.528
65-74	0.237	0.199	0.247
Hispanic			
55-64	0.636	0.554	0.648
65-74	0.249	0.205	0.238
Unmarried			
55-64	0.575	0.506	0.570
65-74	0.254	0.217	0.244
Married			
55-64	0.675	0.598	0.663
65-74	0.290	0.234	0.269

Note: Not seasonally adjusted.

Table A.3: Linear probability model regression results for the effect of the pandemic on employment among those employed 1 year earlier, 2018-2021

	1	2	3	4
Covid	0.00871	0.0882**	0.0678	0.0381
	(0.0269)	(0.0389)	(0.0416)	(0.0449)
ages 60-64	0.0127	0.0120	0.0102	0.0104
	(0.00836)	(0.00834)	(0.00836)	(0.00836)
ages 65-69	0.00596	0.00479	0.00475	0.00568
	(0.0120)	(0.0120)	(0.0120)	(0.0121)
ages 70+	-0.0120	-0.0139	-0.0147	
	(0.0143)	(0.0143)	(0.0144)	
Black	-0.0199	-0.0223	-0.0159	-0.0137
	(0.0153)	(0.0154)	(0.0155)	(0.0160)
Hispanic	-0.0181	-0.0139	-0.00315	0.000451
	(0.0147)	(0.0147)	(0.0147)	(0.0151)
other race	-0.0427**	-0.0373**	-0.0320*	-0.0288
	(0.0181)	(0.0181)	(0.0182)	(0.0188)
female	0.00290	-0.00132	-0.00583	-0.00810
	(0.00790)	(0.00833)	(0.00877)	(0.00911)
college	0.0247***	0.0197**	0.0171*	0.0206**
	(0.00808)	(0.00836)	(0.00889)	(0.00924)
married	-0.00119	-0.00118	-0.00197	0.00150
	(0.00847)	(0.00846)	(0.00846)	(0.00882)
metro area	-0.0185*	-0.0138	-0.0148	-0.00676
	(0.0105)	(0.0106)	(0.0106)	(0.0111)
part-time	-0.0752***	-0.0712***	-0.0675***	-0.0712***
	(0.0114)	(0.0114)	(0.0115)	(0.0127)
self-employed	0.0269***	0.0253**	0.0275**	0.0319***
	(0.00998)	(0.0106)	(0.0109)	(0.0115)
low WFH	-0.00492	0.00220	0.0233*	0.0222
	(0.00876)	(0.00934)	(0.0139)	(0.0146)
high phys. prox.	-0.0603***	-0.0562***	-0.0519***	-0.0435***
	(0.00827)	(0.00914)	(0.0117)	(0.0121)
state death rate	0.000223	0.00151	0.000999	-0.00183
	(0.00817)	(0.00955)	(0.00945)	(0.0101)
Month FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Industry controls	No	Yes	Yes	Yes
Occupation controls	No	No	Yes	Yes
70+ included	Yes	Yes	Yes	No
N	56240	56240	55794	48889

Standard errors in parentheses
* p<0.1, ** p<0.05, *** p<0.01

Note: Results of linear regressions of employment status among workers who were employed 12 months prior to the reference month. Sample restricted to CPS ORG respondents ages 55 and older except where indicated. To reduce clutter, coefficient estimates for regressors not interacted with Covid dummy are left out of the table above. All listed coefficients are interacted with the pandemic dummy aside from the state Covid death rate variable (which equals zero pre-pandemic). Robust standard errors.

Table A.4: Regression results for the effect of listed regressors on the probability of working from home, employed workers May 2020-October 2021

	1	2	3
female	0.192***	0.216***	0.150***
	(27.52)	(28.12)	(17.95)
college	1.683***	1.497***	0.956***
	(223.91)	(188.92)	(107.91)
Black	-0.196***	-0.195***	-0.0692***
	(-15.51)	(-15.09)	(-4.98)
Hispanic	-0.372***	-0.323***	-0.123***
	(-32.53)	(-27.43)	(-9.75)
other race	0.306***	0.294***	0.309***
	(26.90)	(25.03)	(24.02)
metro area	1.053***	0.977***	0.919***
	(82.59)	(74.82)	(67.35)
self-employed	-0.475***	-0.502***	-0.459***
	(-37.20)	(-36.20)	(-31.26)
18-34	-0.147***	-0.0945***	-0.0634***
	(-17.90)	(-11.14)	(-7.00)
55-74	-0.124***	-0.121***	-0.135***
	(-14.16)	(-13.57)	(-14.34)
Month FE	Yes	Yes	Yes
Industry controls	No	Yes	Yes
Occupation controls	No	No	Yes
Observations	795387	795387	786213

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Results of logistic regressions on whether working remotely among workers who were employed in the reference month. Robust standard errors.

Table A.5: Linear probability model regression results for the effect of the pandemic on retirement among those employed 1 year earlier, 2018-2021

	1	2	3	4
Covid	-0.0321	-0.0628**	-0.0419	-0.0148
	(0.0207)	(0.0311)	(0.0344)	(0.0356)
ages 60-64	-0.000643	-0.00128	0.000319	0.000451
	(0.00602)	(0.00602)	(0.00603)	(0.00602)
ages 65-69	0.00574	0.00594	0.00676	0.00657
	(0.0102)	(0.0102)	(0.0102)	(0.0102)
ages 70+	0.0296**	0.0303**	0.0317**	
	(0.0125)	(0.0125)	(0.0126)	
Black	0.00713	0.00778	0.00647	0.00786
	(0.0118)	(0.0119)	(0.0120)	(0.0121)
Hispanic	-0.00296	-0.00490	-0.00848	-0.0130
	(0.0102)	(0.0103)	(0.0103)	(0.0100)
other race	0.00505	0.00396	0.00432	0.00504
	(0.0139)	(0.0139)	(0.0141)	(0.0141)
female	-0.00158	-0.00295	-0.0000553	0.00111
	(0.00613)	(0.00653)	(0.00691)	(0.00688)
college	-0.00371	-0.00391	-0.00576	-0.00726
	(0.00647)	(0.00669)	(0.00708)	(0.00704)
married	0.00334	0.00317	0.00259	0.0000832
	(0.00637)	(0.00638)	(0.00640)	(0.00634)
metro area	0.00783	0.00631	0.00644	0.00525
	(0.00859)	(0.00862)	(0.00865)	(0.00863)
part-time	0.0246***	0.0245***	0.0247***	0.0258***
	(0.00922)	(0.00928)	(0.00934)	(0.00996)
self-employed	-0.00152	0.000137	-0.00362	-0.00861
	(0.00808)	(0.00849)	(0.00876)	(0.00868)
low WFH	0.000353	0.000500	-0.00676	-0.00418
	(0.00681)	(0.00724)	(0.0110)	(0.0110)
high phys. prox.	0.0172***	0.0152**	0.0154*	0.00507
	(0.00640)	(0.00707)	(0.00887)	(0.00884)
state death rate	0.00145	-0.00303	-0.00279	0.00150
	(0.00632)	(0.00729)	(0.00732)	(0.00764)
Month FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Industry controls	No	Yes	Yes	Yes
Occupation controls	No	No	Yes	Yes
70+ included	Yes	Yes	Yes	No
N	56240	56240	55794	48889

Standard errors in parentheses
* p<0.1, ** p<0.05, *** p<0.01

Note: Results of linear regressions of retired status among workers who were employed 12 months prior to the reference month. Sample restricted to CPS ORG respondents ages 55 and older except where indicated. To reduce clutter, coefficient estimates for regressors not interacted with Covid dummy are left out of the table above. All listed coefficients are interacted with the pandemic dummy aside from the state Covid death rate variable (which equals zero pre-pandemic). Robust standard errors.

B Employment Decomposition

To better understand the determinants of employment change in the first year of the pandemic, it is possible to decompose employment declines into within-sector and between-sector components. For instance, when comparing employment declines between different broader age groups (young, mid-career, and older), it is useful to know to what extent the larger declines for the youngest group are driven by the distribution of younger workers across high-risk industries as opposed to greater employment losses within industries.

The decomposition methodology used here follows that of Dalton et al. (2021). We observe workers who are employed in some base year and then calculate the share of this group that is still employed when observed 12 months later. To determine the share of workers still employed within some group j in month t, I use

$$\%\Delta W_{jt} = \frac{W_{jt}^S - W_{jt}^B}{W_{jt}^B} \tag{2}$$

where the superscript B refers to base (or initial) year employment, and S denotes still employed in the subsequent year. For t =April 2020, then, W_{jt}^B refers to the number of workers in group j who were employed that month in the base year, April 2019, while W_{jt}^S refers to the number of workers from this group who were still employed in April 2020.

To decompose changes in employment into between-sector and within-sector changes, I define employment in group j and sector k as E_{jkt}; as before, E_{jkt}^B reflects baseline employment in this group and E_{jkt}^S reflects the sum of those in this baseline group who are still working a year later. The variables N_{kt}^B and N_{kt}^S are analogously defined, reflecting total sector-k employment across all j groups of workers, where j can stand for demographic categories, types of workers (full- or part-time), etc. Finally, the share of sector k's employment in either period that is made up of type-j workers is $s_{jkt} = \frac{E_{jkt}}{N_{kt}}$, with s_{jkt}^B and s_{jkt}^S defined in the same way as the other variables.

The change in employment for group j workers can then be decomposed as follows:

$$\begin{aligned}
\Delta W_{jt} &= W_{jt}^S - W_{jt}^B \\
&= \sum_k E_{jkt}^S - \sum_k E_{jkt}^B \\
&= \sum_k [(\frac{E_{jkt}^S}{N_{kt}^S} - \frac{E_{jkt}^B}{N_{kt}^B})N_{kt}^S] + \sum_k [\frac{E_{jkt}^B}{N_{kt}^B}(N_{kt}^S - N_{kt}^B)] \\
&= \sum_k [(s_{jkt}^S - s_{jkt}^B)N_{kt}^S] + \sum_k [s_{jkt}^B(N_{kt}^S - N_{kt}^B)]
\end{aligned} \tag{3}$$

Dividing through by prior year employment for group j in month t (which I estimate using the 12-month average ending in the month one year prior), the first term in the final equation of Eq. 3 gives the within-sector change in employment for group j and the second term gives the across-sector change in employment for group j.

C Reconciling year-to-year flows, monthly flows data, and the retirement surge

A puzzle emerges when one examines monthly labor force flows into and out of retirement in light of the increased retired share (this is in contrast to the year-to-year flows examined above). As Nie and Yang (2021) document, the monthly rate of transition from employment to retirement fell at the start of the pandemic, a counterintuitive result given the rise in the retired share. At the same time, the transition rate from retirement to employment also fell. They conclude that the pandemic-era rise in the retired share was "driven by a decline in the number of people transitioning from retirement back to employment, rather than an increase in the number of people transitioning from employment to retirement." Nie and Yang argue that, given the relatively small size of the unemployed population even amid unemployment, transitions from unemployment to employment are relatively unimportant.

Analysis of monthly rates of transition also addresses a different question than the one posed here, i.e, that of the pandemic's affects on the employment and retirement transitions of workers previously employed in relatively normal labor market conditions. Monthly transition rates are conditional on employment status in the prior month, and by April 2020, the employed population differed greatly in composition from that of the month or year prior.[20] The monthly transition rate in May 2020 (the share retired in May who were working in April) means something very different than the transition rate in April 2020. By contrast, using year-to-year transition rates conditions transitions on labor market status in a healthy labor market. The time series of year-to-year transitions is thus comparable over time until April 2021.

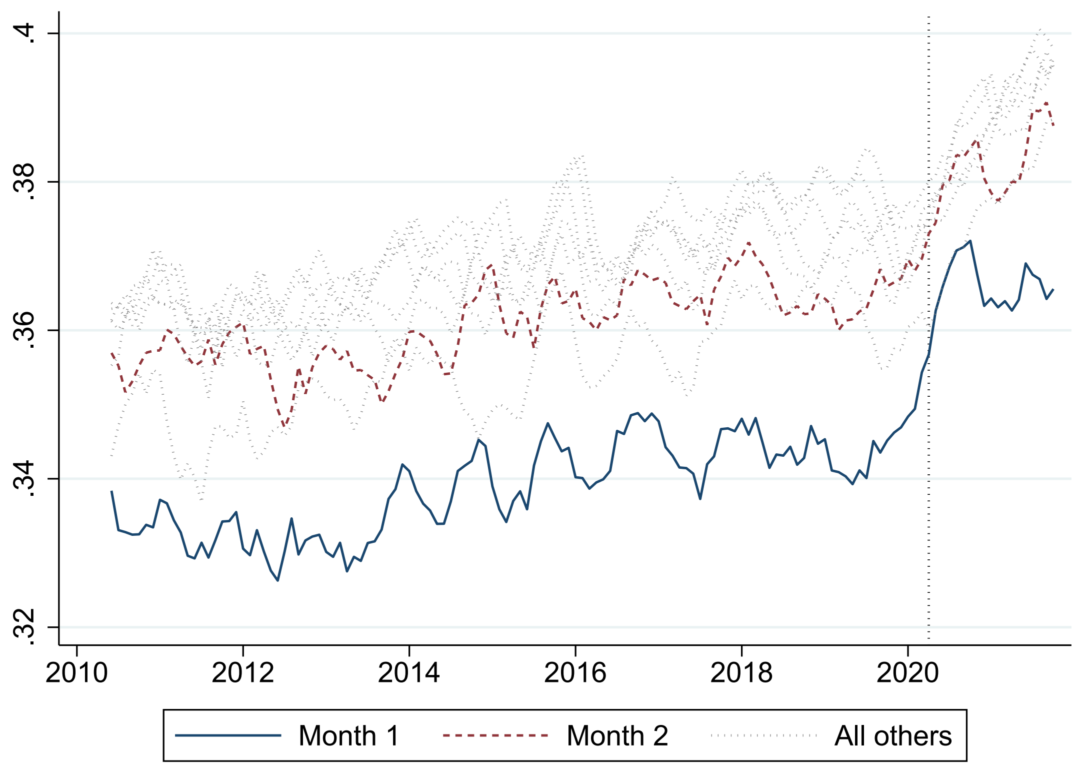
A second benefit of using year-to-year flows is to mitigate biases arising from sampling methodology and respondent error. A well-established phenomenon in the CPS sample is month-in-sample bias: respondents are significantly more likely to report labor force participation in the first and fifth months-in-sample (MIS) than in each subsequent month of the two rotations (Frazis et al., 2005). MIS bias has a sizable impact on estimates of retirement transitions. A significant share of apparent retirement transitions in the CPS data arise from respondents misreporting their first MIS as employed or NILF/not-retired and then revising it to retired in later months in the rotation, perhaps as they get better at answering the survey. The bias for transitions involving the fifth MIS, the first month respondents are back in the CPS after the 8-month break, is not as severe as for the first MIS.

To illustrate the bias, Figure C.1 shows the retired share for respondents in each MIS. Between 2010 and 2019, the average difference in the retired share between months 2 and 1 in sample was 2.2 percentage points. This spurious discrepancy is greater than the entire estimated increase in the

[20] In fact, it is possible for the probability of retiring to increase for all workers and yet the overall employed-to-retired transition rate to fall, as long as the composition of workers shifts sufficiently towards those with a lower initial probability of retiring.

retired share over trend due to the pandemic. (It is interesting to note that the pandemic-era rise in the retired share of the first MIS seemed to precede that of other MIS groups, then flattened.)

Figure C.1: Retired share by month-in-sample, 6-month moving average



Note: Retired shares calculated separately by CPS respondents' month-in-sample.

MIS bias affects both the monthly transition rate from employed to retired (E-R) and the transition rate from NILF/not-retired to retired (N-R). Between 2015 and 2019, the average E-R transition rate between the first and second months was 3.3%, versus 2.3% for all other monthly transitions. The comparable 2015-2019 averages rates for N-R transitions are 15.2% for months 1-to-2 versus 7.7% for all other months, averaged—a more severe bias than for E-R transitions. These biases persisted during the pandemic.

MIS bias in retirement transitions is mitigated by using year-to-year transitions rather than monthly transitions. The retirement transition rate for longitudinal observations involving a respondent's first MIS is still higher than for subsequent months, but to a lesser degree. Between 2015 and 2019, the average E-R transition between months 1 and 5 was 9.0%, compared to 8.4% for all subsequent transitions. For the N-R transition rate, the pre-pandemic five-year average was 29.0% for the months 1-to-5 transition, versus 24.0% for all subsequent MIS. For monthly transitions, the E-R transition rate involving the first MIS is 1.5 times that of other months; by comparison, the year-to-year transition rate involving the first MIS is just 1.1 times that of subsequent months. The comparable bias in the monthly N-R transition rate is a 2.0 times greater transition rate for transitions involving the first MIS, versus 1.2 times for year-to-year transitions.

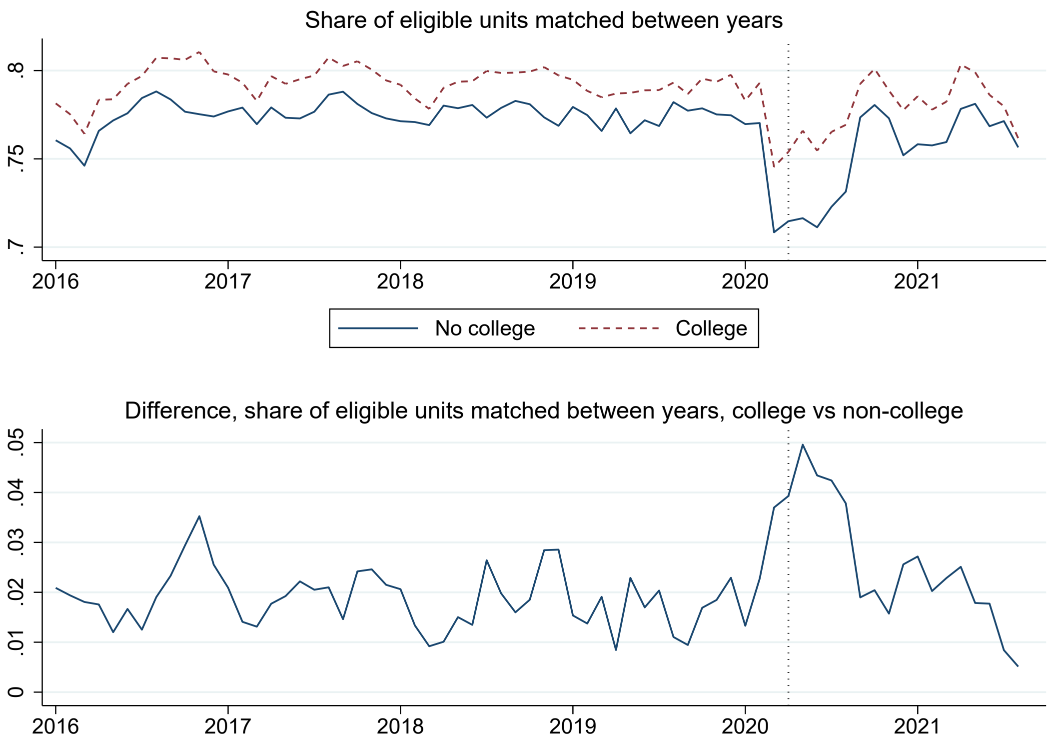
D Non-response bias and the pandemic

A final concern about the data has to do with differential changes in respondent non-response brought about by the pandemic. Rothbaum and Bee (2021) document differential increases in non-response by age, education, Hispanic origin, citizenship, and nativity. Second-year sample non-response increased dramatically early in the pandemic, starting in March 2020, and recovered roughly to pre-pandemic levels by the third quarter of 2020. The longitudinal weights provided by IPUMS-CPS reweight matching observations to the race, sex, age, and geographic distribution of the entire eligible-to-match CPS population. Yet if rates of non-response changed during the pandemic along demographics not covered by this weighting procedure, the results presented here may be biased.

Education provides one such demographic. Between 2016 and 2019, an average 79.4% of eligible-to-match college-educated respondents 25 and older were observed 12 months later. For non-college respondents over this period, an average 77.5% matched, a 1.9 percentage point difference in non-response. During the first 6 months of the pandemic, that gap more than doubled to an average of 4.2 percentage points as non-response rates increased more for non-college workers than college-educated ones, as Figure D.1 illustrates. The education non-response gap returned to its pre-pandemic level in late 2020 and thereafter.

If retirement and non-response were correlated over this period, the result may be a downward bias in estimates of retirement transitions for all workers, a bias that is greater for non-college workers. Future work is needed to examine all aspects of potential non-response bias that arose during the pandemic.

Figure D.1: CPS non-response bias by education



Note: Sample is adults 25 and older. Outcome is the share of prior-year respondents eligible to match in the reference month who are actually observed in the reference month. Observations are weighted using the prior-year population weights (CPS-IPUMS *wtfinl*). Vertical dotted line is April 2020.