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

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The Covid-19 pandemic upended labor markets and prompted a sharp and sustained increase in the share of U.S. adults who are retired. This paper uses the longitudinal structure of the Current Population Survey to explore patterns in employment and retirement transitions among older workers during the pandemic. Employment declines among older workers were greatest for low-earning, non-white, and non-college-educated workers. By contrast, increased transitions to retirement occurred more evenly 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 persistence of the pandemic retirement boom.

1 Introduction

The Covid-19 pandemic dealt an unprecedented 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, 37% of the older unemployed (4.6 million workers) were permanent job losers in the fourth quarter of 2020. As of August 2023, the seasonally adjusted employment-population ratio of workers 55 and older remained 1.5 percentage points below its February 2020 level. The decline in older workers' employment rate can be largely explained by a nearly equivalent increase in the retired share of the older population. As Figure 1 shows, the retired share of the U.S. population has diverged significantly from the predicted pre-pandemic trend,

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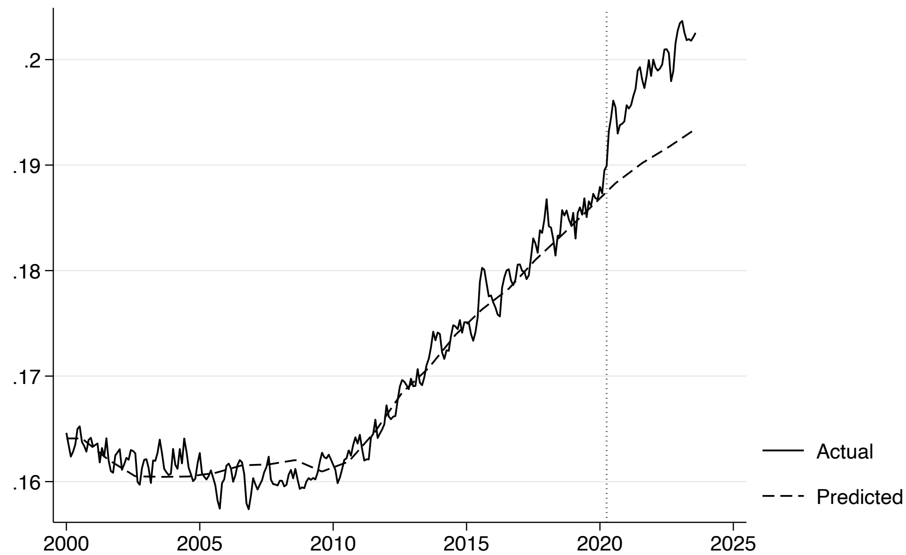
with an estimated 2.2 million more adults in retirement than would have been expected; as of late 2023, the retired share shows no sign of normalizing.[1]

Figure 1: Retired share of U.S. civilian noninstitutional population, 2000-2023



Note: Monthly CPS and author's calculations. Predicted series is constructed following methodology of Montes, Smith and Dajon (2022), described in Section 4.1. Final observation is August 2023.

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 relationship of demographic factors (age, sex, race, and education) as well as job characteristics (occupation, industry, and other measures) on employment and retirement outcomes. Although it is impossible to tease out causality among the many overlapping drivers of labor market outcomes during the first year of the pandemic, careful analysis of employment and retirement transitions can bring to light factors most strongly associated with certain outcomes after taking other worker characteristics into account.

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. 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

[1]Section 4.1 describes the model used to predict retirement shares, which follows the methods introduced in Montes, Smith and Dajon (2022).

the pandemic. Potential push factors into retirement included job loss and concomitant loss of job-specific human capital, health risks, and heightened occupational stress and overwork. 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 market recovery following the Great Recession. Care responsibilities in the household, whether for spouses affected by Covid or grandchildren home from school, may have also pulled older adults into retirement. 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, Brown and Minkin, 2021). Generous unemployment insurance may also have influenced the labor force decisions of older workers who faced job loss (Coile and Levine, 2007; Marmora and Ritter, 2015).

Using the year-to-year longitudinal structure of the CPS, I find 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 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 50-64 year-old range, especially non-college men. Examining year-to-year retirement transitions out of employment, I find that pandemic retirement transitions did not follow the same earnings gradient as employment loss, but instead a 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, Button and Picciotti (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, Gorodnichenko and

Weber (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. Coile and Zhang (2022) found no relationship between local labor market conditions or Covid outbreak intensity on retirement decisions, findings that are consistent with those reported here. Analyzing survey evidence from the 2021 Survey for Income and Program Participation, Thomspon (2022) found that 2.9% of those ages 55–70 reported that Covid led them to shift their planned retirement earlier, compared to 2.3% who shifted later. Less healthy older adults and the lowest-earning older workers reported the largest net shifts toward earlier retirement. Although the present study does not examine the effects of actual or suspected Covid cases on labor force outcomes, its findings are consistent with Goda and Soltas (2022), who used an event-study design to show that work absences likely caused by Covid illness predict a dramatically higher probability of being retired a year later among those 55 and older. Goda et al. (2023) reported 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.

Section 2 describes the data used in this paper and regression models. 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 and Methodology

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. I use a wide range of demographic and work-related variables captured by the survey, including age, race, ethnicity, education, sex, marital status, work hours (full or part time), occupation and industry, and geographic characteristics (state and residence in metropolitan area). A worker is retired if they are out of the labor force and report their reason for not working as retirement. Being retired is one of the three broader categories of not-in-the-labor force delineated in CPS data, the other two being disabled/unable to work and "other."

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 July–October 2019 and July–October 2020). The 4-8-4 structure allows researchers to link households from month to month or year to year (Madrian and Lefgren, 1999). In longitudinal regression analyses I restrict the sample to individuals in their fourth and eighth months-in-sample, otherwise known as Outgoing Rotation Groups (ORG), which are conducted exactly one year apart. I exclude from the sample individuals with inconsistencies in sex, race, and age between linked observations (sex and race should stay constant between observations, while age is allowed to change by as many as two years between observations). Section B in the Appendix further motivates the use of year-to-year transition rates, particularly in light of evident biases in responses to CPS questions on labor force participation.

Although BLS provides population weights for cross sectional analysis, longitudinal analysis using the panel structure of the CPS requires the use of weighting variables that account for attrition and other changes to sample composition that occur over the course of a year. For descriptive analyses of year-to-year transitions I use observations of households in all months-in-sample of their CPS rotation; in this case the IPUMS weighting variable `lnkfw1ywt` is appropriate. In regressions in which the sample is limited to the ORG, I construct a weight following BLS weighting procedures that matches the linked ORG sample to the race, sex, age and geographic composition of the initial month sample.

A separate weighting issue arises from the Census population weight adjustments that came into effect in 2022 following the decennial Census. As described in Montes, Smith and Dajon (2022), these population weights served to make the population appear younger on average, leading to sharp shifts in outcomes such as the retired share or employment-population ratio. To mitigate the effect of this purely mechanical change in sample composition, I follow Montes, Smith and Dajon's strategy of smoothing population weights from 2012-2021, multiplying the underlying weights by adjustment factors that spread the 2021–2022 population weight changes linearly over the prior 10-year period. To implement this "backcasting" procedure, I use the adjustment weights provided by Bauer et al. (2023).

To supplement the CPS data, I adopt measures of job-related work-from-home (WFH) difficulty and high physical proximity (HPP) from Mongey, Pilossoph and Weinberg (2021). Building on Dingel and Neiman (2020), these measures use O*NET job characteristics data to generate binary indicators reflecting WFH difficulty and physical proximity at the detailed occupation level. The analysis uses these variables to help test the degree to which Covid-induced changes to work characteristics affected the labor supply of older workers. I also use state-level Covid death rates from Chetty et al. (2020), calculated as the maximum monthly Covid death rate experienced in a state up to that point.

Since labor market outcomes and labor force composition vary significantly by age for older workers, this paper breaks older workers into different age groups for both descriptive analysis and regressions. In much of the descriptive analysis, I separate older workers into two groups: 50–64 years old and 65 and older. In regressions, I use more fine-grained groups: 50–61, 62–64, 65–69, and 70+. The three cutoff ages of 62, 65, and 70 reflect highly salient policy thresholds: 62

and 70 for Social Security initial eligibility and latest claim year, and 65 for Medicare eligibility. Table 1 displays summary statistics for variables of interest by these more fine-grained groups.

For the main regression analyses—reported separately for employment and retirement in sections 3.3 and 4.3, respectively—I use a linear probability model that leverages the panel nature of the CPS to explore potential drivers behind pandemic-driven changes in employment and retirement transitions. The sample is restricted to CPS ORG respondents who report wage or salary employment in their fourth month-in-sample and who are also observed in their eighth month-in-sample one year later. The outcomes of interest are employment or retirement status in the second observation. The sample is limited to those whose first observation occurred prior to the pandemic, April 2018–March 2020. This includes two years or pre-pandemic employment transitions and one year of transitions in which the second observation occurred during the pandemic.

The regression model is:

$$Y_{ist} = \alpha + \beta X_{i,t-12} + \gamma(X_{i,t-12} \cdot Covid_t) + \tau_t + \tau_s \cdot Covid_t + \epsilon_{i,t} \tag{1}$$

where Y_{ist} is the outcome (employed or retired) for a worker i in state s and time t. The vector $X_{i,t-12}$ records job- and worker-related characteristics captured a year earlier (pre-pandemic for those observed after March 2020). The vector of coefficients β captures how transition probabilities were associated with characteristics before the pandemic while γ reflects to what *additional* degree those characteristics were associated with transitions during the pandemic, relative to the change from pre- to post-pandemic experienced by the omitted group. Fixed effects τ_t capture how national economic conditions varied month to month. State and state-by-Covid fixed effects are picked up in the fixed effects $\tau_s \cdot Covid_t$, capturing underlying state-level differences in employment and retirement transition probabilities as well as the broad effects of state-wide policy responses to the pandemic.

This empirical strategy assumes that the sample of older workers observed pre-pandemic provides a plausible counterfactual for those whose second observation fell during the pandemic. This assumption requires both that the composition of workers remained stable between periods and that no major unobserved confounders coincided with the pandemic, changing the relative transition rates between different types of workers. Although there is some indication that pandemic disruptions affected the composition of CPS respondents (Rothbaum and Bee, 2021), this issue is mitigated by the weighting adjustments described above. While it is impossible to rule out unobserved confounders, it is difficult to conceive of any other factors that would have affected *relative* changes in employment and retirement outcomes between different groups of workers and types of jobs.

The model includes a wide range of covariates intended to isolate potential drivers of Covid-induced excess retirement. Demographic controls include detailed age groups, education, sex, race, and marital status. Local effects are captured using state indicators as well as an indicator for whether the respondent lives in a metro area, both interacted with the pandemic dummy. I also control for state-level Covid death rates, calculated on the 10th of the month of the CPS survey, to capture the local severity of the pandemic. Job-related controls are part-time status, occupational WFH difficulty, and employment in a HPP job. Some models add controls for major industry group and major occupation group as well as indicators for wage quartiles. With the exception of state Covid death rates, all controls listed above are interacted with a Covid dummy in order to estimate the extent to which the pandemic differentially affected different types of workers.

Table 1: Summary statistics

	All	Ages 50-64	Ages 65 +
	Mean	Mean	Mean
Age	58.50	56.04	68.62
Female	0.49	0.49	0.48
White	0.70	0.69	0.75
Black	0.11	0.11	0.10
Hispanic	0.12	0.13	0.09
Other race	0.07	0.07	0.07
College	0.39	0.39	0.42
Married	0.69	0.70	0.65
Metro area	0.86	0.87	0.85
Full-time	0.84	0.88	0.66
Public sector	0.19	0.19	0.18
High phys. prox.	0.41	0.40	0.43
Low WFH	0.43	0.44	0.42
Observations	65,389	51,226	14,145

Note: CPS-ORG. Sample consists of wage and salary workers who were interviewed between April 2017–March 2020 and who were subsequently interviewed 12 months later. Observations weighted using adjusted matching weights as described in the text.

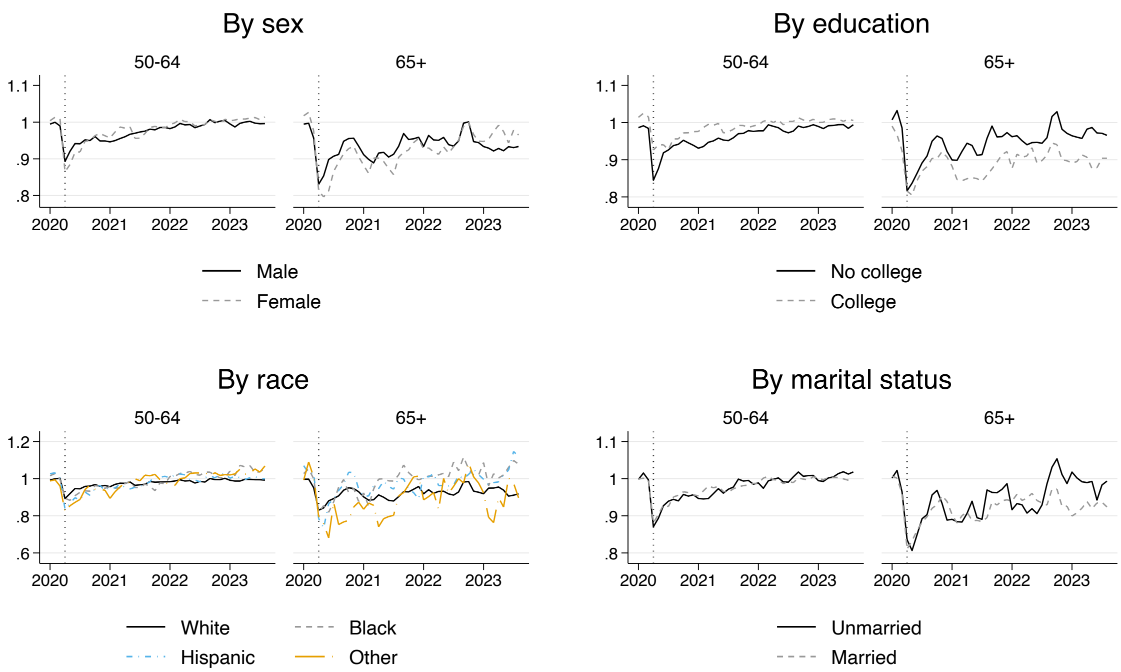
3 Employment

3.1 Employment trends among older workers

Pandemic employment declines varied significantly between different demographic groups of older workers. Figure 2 plots indexed employment-to-population ratios (EPOPs) for two older age groups (50–64 and 65+), disaggregated by sex, education (defined by having a four-year college degree), race (white, Black, Hispanic, or other race), and marital status. EPOPs are indexed to the full-year 2019 average by group. Appendix Table A.1 presents unadjusted EPOPs for these demographic groups at three points in time: the 2019 average, the April 2020 nadir, and November 2021.

The largest and most persistent declines among older workers generally occurred among 65+ age group, most notably for college-educated adults 65 and older. Among those 50–64, em-

Figure 2: Employment rates by age group and demographics



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

ployment rates by mid-2023 had returned to—and in some cases exceeded—their pre-pandemic benchmarks. Women and non-college older workers experienced greater employment declines in the early months of the pandemic. Among women, 50–64 year-olds soon caught up with 50–64 year-old men, yet the older female group remained behind men 65+ until mid-2022. Non-college workers 50–64 have trailed college-educated workers of the same ages.

Surprisingly, at later ages (65+), non-college workers have moved closer to their pre-pandemic EPOP than college-educated workers, a pattern that might reflect increased retirement (see Section 4). Yet it is important to note that there was less "catching up" to do for the non-college population 65+; the baseline 2019 EPOPs for non-college and college workers 65+ were 16.6% and 27.8%, 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, nonwhite workers suffered greater initial declines in employment than white workers, though these patterns shifted over time. At ages 50–64 white workers recovered more quickly than Black or Hispanic workers, though by 2022 Black workers and those of other races had pulled ahead relative to their pre-pandemic employment rates. A similar pattern emerges at ages 65+: by late 2021, Black and Hispanic workers of this age group had essentially regained their pre-pandemic EPOPs. In August 2023, Black and Hispanic workers 65 and older were employed at higher rates than in 2019, while white workers' EPOP was 9% below its pre-pandemic 2019 average, a fall from 20.4% to 18.7%. As in the case of college versus non-college workers, baseline EPOPs among workers 65 and older were lower for Black and Hispanic workers than white workers.[2]

Taken together, the demographic trends in older workers' pandemic-era employment rates reflect some existing patterns of vulnerabilities among demographic groups in the first year of the pandemic. Yet as time wore on and the labor market strengthened in mid-2021 and thereafter, not all employment disparities that emerged in 2020 persisted. 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.

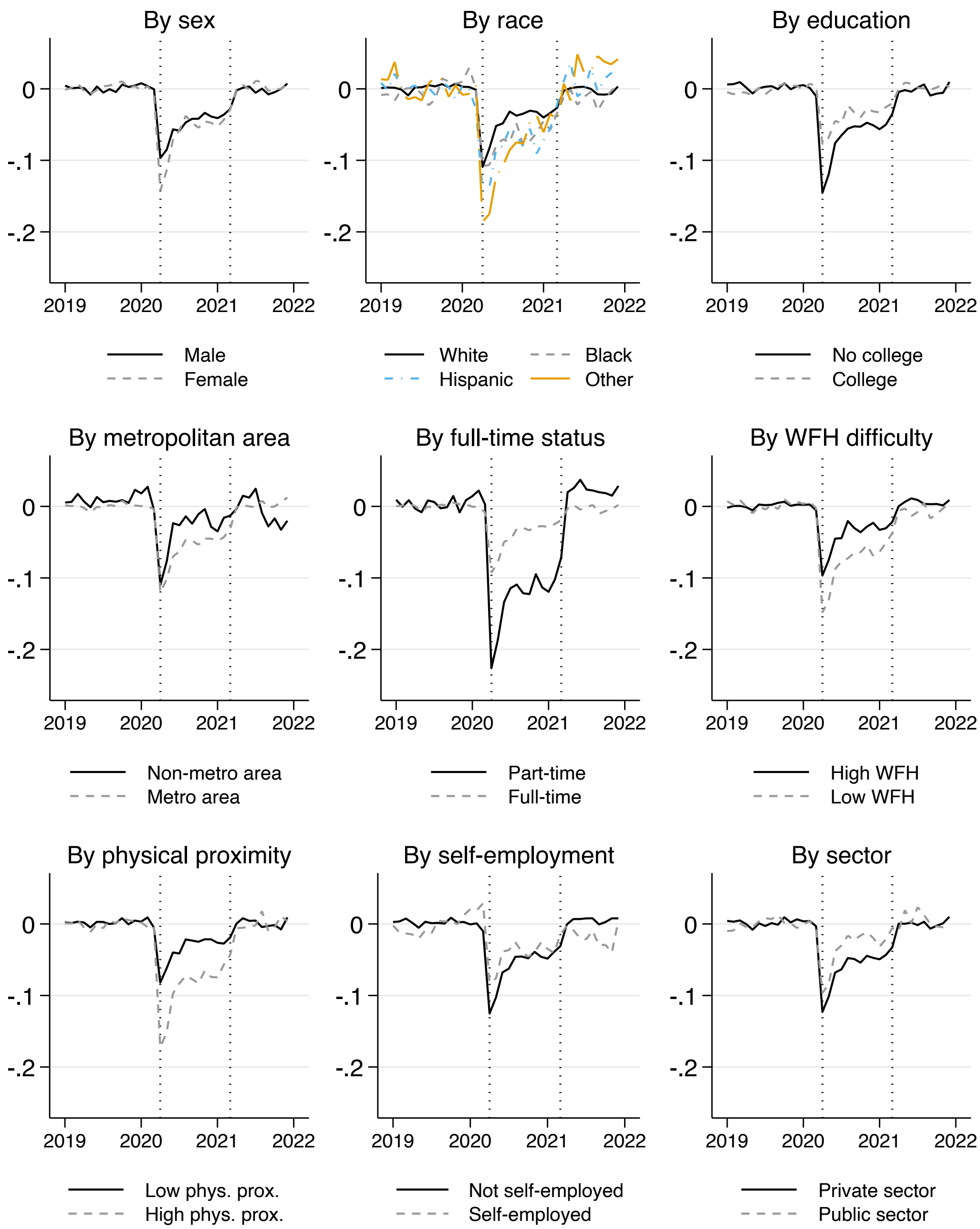
3.2 Employment transitions

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 to produce normalized measures of the employed-to-employed transition rate, i.e., the still-employed share.

Figure 3 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 each plot 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 a poor comparison for the pre-pandemic population. For this reason, caution is warranted in interpreting post-March-2021 trends. Note also that these transition rates may be biased by nonrandom patterns in survey non-response brought about by the pandemic; while CPS response fell across the board, Rothbaum and Bee (2021) document differential increases in

[2]The analysis up to here has focused on EPOP rather than unemployment rates, since labor force dropout can reduce the unemployment rate. Figure A.1 shows unemployment trajectories. As in the case of EPOP, the initial pandemic shock hit women, non-college, and non-white workers hardest.

Figure 3: Share still employed among those employed 12 months prior, normalized to pre-pandemic average, ages 50+



Note: Monthly CPS linked year-to-year. 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.

non-response by age, education, Hispanic origin, citizenship, and nativity. Employment declines will be underestimated when non-response and job loss are correlated.

The demographic patterns in employment transitions 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 of job-specific impacts of the pandemic. Older workers in non-metro areas experienced a more rapid employment return to pre-pandemic patterns in employment transitions. Public sector workers and the self-employed also experienced smaller declines in the still-employed share.

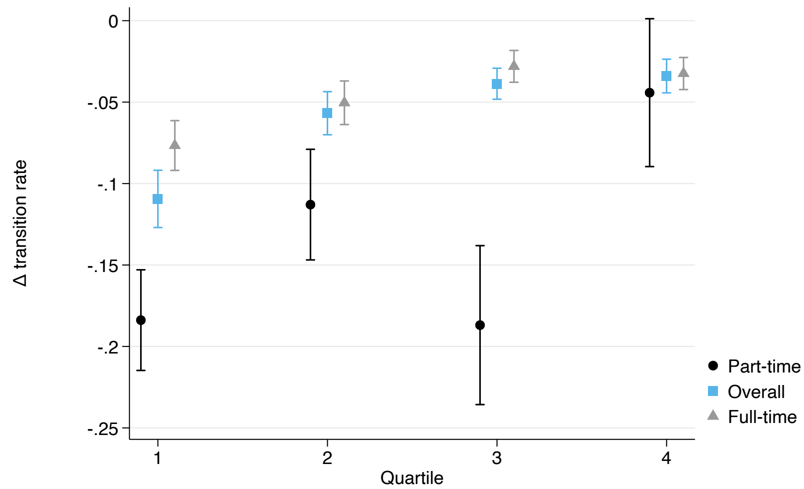
To examine the pandemic's employment effects by wage groups, I compute hourly wage quartiles for workers 50 and older (for those not paid hourly, earnings are calculated by dividing usual weekly earnings on the main job by usual weekly hours on the main job). To condense information, I show the difference in means between the average still-employed share by group pre-pandemic and the corresponding average during the pandemic.[3] In calculating changes in employment transitions by earnings quartile, I split the sample by full- and part-time status as well as calculating results for the entire population. Cutoffs for hourly earnings quartiles are the same regardless of hours. Figure 4 summarizes the results.

In the overall sample as well as for full-time workers, a clear gradient emerges, with the largest employment declines occurring in the lowest weekly earnings quartile and declines shrinking at higher earnings groups. Among the lowest-earning older workers, the average still-employed share during the first year of the pandemic was 11 percentage points lower than the average still-employed share in the five years before the pandemic. Restricting attention to part-time older workers shows a different pattern. The bottom three hourly earnings quartiles of part-time workers all saw large employment declines in the first year of the pandemic—ranging from 12 percentage points for the second quartile to 18 percentage points for the bottom and third quartiles—while employment declines for the top quartile were nearly the same as employment declines for full-time workers in the highest-earning quartile, 4-5 percentage points.

The panel form of CPS also allows examination of employment transitions by industry and occupation. Appendix Figures A.2 and A.3 show the change in average still-employed shares, pre-pandemic to pandemic period, for the 14 industry sectors and 22 major occupation groups, respectively. Declines in employment transitions among industry sectors are led by leisure

[3] 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 transition calculations in Table 3.

Figure 4: Change in still-employed share by hourly earnings quartile, pre-pandemic versus pandemic, workers 50+



Note: Monthly CPS. Plots show the difference in means of the still-employed share by hourly earnings quartile and full-time status, pre-pandemic versus pandemic period, with 95% confidence intervals. Pre-pandemic period is April 2015 through March 2020; pandemic period is April 2020 through March 2021.

and hospitality, mining, transportation and utilities, other services and retail trade. Among occupations, the greatest declines were in food preparation and serving, personal care services, transportation, and building and grounds cleaning and maintenance.

3.3 Employment of older workers in the pandemic: regression evidence

Although the analysis above provides suggestive evidence about the correlates of employment declines during the first year of the pandemic, it does not allow for direct comparisons between potential drivers. To that end, I estimate the linear probability model outlined in Equation 1 using employment in the reference month as the outcome. Recall that the sample is all respondents in their eighth and final month-in-sample who match to and were employed in their prior-year observation. The results reported in Table 2 show coefficient estimates for interactions between the listed variables and the Covid indicator. These coefficient estimates can be interpreted as indicating the degree to which the characteristic was associated with greater or lesser changes in employment relative to the omitted group during Covid (and conditional on all other characteristics). Since monthly date fixed effects pick up overall employment declines, these interacted coefficient estimates do not account for entirety of the change in employment during Covid relative to the pre-Covid period, but only the differential employment change associated with that characteristic during Covid.

The baseline employment results in column 1 point to differential declines in employment transitions along a number of the dimensions that were also apparent in the descriptive re-

Table 2: Regression results for the effect of the pandemic on employment among those employed one year earlier

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Ages 62-64	0.00861	0.00869	0.00833	0.00921		0.00858	
	(0.0112)	(0.0111)	(0.0111)	(0.0112)		(0.0112)	
Ages 65-69	0.00189	0.00190	0.00195	0.00413		0.00219	
	(0.0130)	(0.0130)	(0.0129)	(0.0130)		(0.0130)	
Ages 70+	-0.0118	-0.0123	-0.0133	-0.00825			
	(0.0166)	(0.0165)	(0.0165)	(0.0166)			
Black	-0.0156	-0.0183	-0.0161	-0.0119	-0.0152	-0.0158	-0.0159
	(0.0126)	(0.0127)	(0.0127)	(0.0127)	(0.0126)	(0.0129)	(0.0128)
Hispanic	-0.0181	-0.0145	-0.00874	-0.0118	-0.0188	-0.0153	-0.0163
	(0.0119)	(0.0118)	(0.0119)	(0.0121)	(0.0120)	(0.0120)	(0.0120)
Other race	-0.0366*	-0.0328*	-0.0270	-0.0331*	-0.0367*	-0.0348*	-0.0358*
	(0.0146)	(0.0145)	(0.0145)	(0.0146)	(0.0146)	(0.0148)	(0.0147)
Female	0.00403	0.0000158	-0.00394	0.00871	0.00433	0.00219	0.00246
	(0.00676)	(0.00717)	(0.00758)	(0.00691)	(0.00676)	(0.00686)	(0.00685)
College	0.0302***	0.0262***	0.0211**	0.0225**	0.0292***	0.0315***	0.0308***
	(0.00700)	(0.00723)	(0.00770)	(0.00750)	(0.00701)	(0.00708)	(0.00709)
Married	0.00316	0.00236	0.000869	0.00231	0.00391	0.00321	0.00311
	(0.00729)	(0.00728)	(0.00728)	(0.00729)	(0.00729)	(0.00743)	(0.00742)
Metro area	-0.0234*	-0.0219*	-0.0226*	-0.0250**	-0.0231*	-0.0176	-0.0173
	(0.00931)	(0.00935)	(0.00937)	(0.00934)	(0.00930)	(0.00948)	(0.00947)
Part-time	-0.0913***	-0.0833***	-0.0774***	-0.0812***	-0.0918***	-0.0920***	-0.0924***
	(0.0117)	(0.0118)	(0.0119)	(0.0119)	(0.0117)	(0.0126)	(0.0126)
Low WFH	-0.00506	0.00634	0.0318**	0.0000538	-0.00589	-0.00834	-0.00833
	(0.00779)	(0.00814)	(0.0122)	(0.00782)	(0.00778)	(0.00791)	(0.00789)
High phys. prox.	-0.0583***	-0.0532***	-0.0496***	-0.0559***	-0.0580***	-0.0512***	-0.0513***
	(0.00734)	(0.00796)	(0.0101)	(0.00734)	(0.00733)	(0.00746)	(0.00745)
State death rate	-0.00116	-0.00110	-0.00112	-0.00114	-0.00128	-0.00131	-0.00133
	(0.00108)	(0.00108)	(0.00108)	(0.00107)	(0.00108)	(0.00112)	(0.00112)
Bottom wage quartile				-0.0395***			
				(0.00994)			
Second wage quartile				-0.0144			
				(0.00891)			
Top wage quartile				0.000531			
				(0.00863)			
N	65387	65387	65387	65387	65387	60617	60617
Industry x Covid FE		X	X				
Occupation x Covid FE			X				
Wage quartiles				X			
Quadratic age contols					X		X
Age 70+ excluded						X	X

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Monthly CPS April 2018–March 2021. Results of linear probability models of employment status among workers who were employed 12 months prior to the reference month. Sample restricted to CPS ORG respondents ages 50 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. All models include monthly date and state-by-Covid fixed effects. Robust standard errors.

sults: greater employment declines for non-white workers, those without a college degree, those in metropolitan areas, those in part-time jobs pre-pandemic, and those in HPP occupations. Marital status and gender do not predict differential employment loss over the first year of the pandemic after controlling for other characteristics. The only age group with a negative coefficient is ages 70 and up, yet none of the coefficients on age groups (relative to the 50–61 omitted category) is statistically significant. In column 4, adding wage quartile indicators yields a negative and significant coefficient for the bottom wage quartile, in line with other research showing wage gradients in pandemic job loss.

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. The estimated coefficients on these variables remain large and statistically significant even after controlling for major industry and occupation and controlling for wages. To help ensure that these results (and in particular the part-time coefficients) are not confounded by age differences within age groups, columns 5 and 7 use a quadratic in age interacted with the Covid dummy to control for age, while columns 6 and 7 exclude from the samples those ages 70 and older. The part-time coefficients remain statistically significant and in the same range when these changes are made, which provides some assurance that these results are not driven by the correlation between age and working part-time.[4]

The negative and significant sign on work in a high-contact occupation is not surprising. But what explains the importance of part-time work in pandemic employment transitions, even after controlling for industry, occupation, and age? 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 incidence 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.

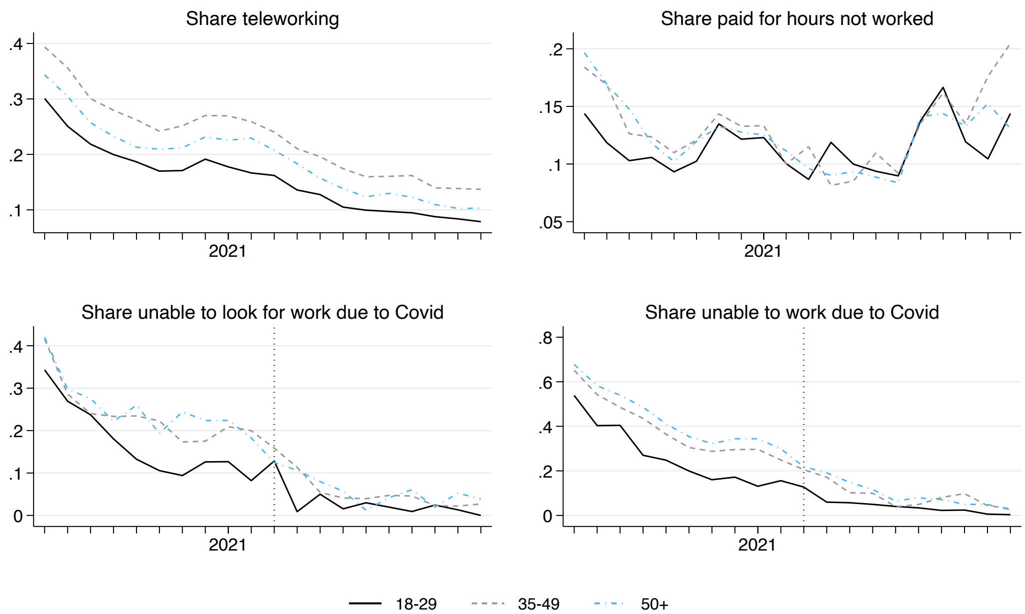
3.4 Covid-specific survey evidence

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 older workers were differentially impacted by the pandemic.

Figure 5 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, the sample is workers who were employed in the

[4]All of the controls suffer some degree of collinearity, which leads to difficult decisions as to which variables to include. Due to this high degree of model uncertainty it is worthwhile to present coefficient estimates across a large range of alternate model specifications. To this end, Appendix Figure A.4 presents specification curves recording coefficient estimates and confidence intervals for four of the variables of interest reported above—metro, HPP, part-time, and bottom wage quartile—across 32 different specifications. The estimates are largely stable and remain significant across virtually all specifications.

Figure 5: Covid-related labor market impacts by age group



Note: Monthly CPS, May 2020–December 2021. 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.

prior year and were neither working nor retired in the reference month. Both groups of samples are affected by sample selection issues which a more detailed analysis would need to address.

The Covid-specific labor market measure that exhibits the largest and most consistent differential between older and mid-career workers is the share teleworking. Throughout the first year of the pandemic (starting in May 2020), the share of employed mid-career workers teleworking was on average 4.1 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. Older workers also exhibited a slightly higher propensity to report being unable to work due to the pandemic relative to mid-career workers.

One possible driver of the descriptive patterns in the share teleworking is that older workers were more likely to work in jobs that are difficult to perform remotely before the pandemic. Although the share of older workers in low-WFH occupations in 2019 was virtually identical to the share of mid-career workers in such occupations (44.0% versus 44.7%), variation among workers within those detailed occupations may still have driven the results. To test for this possibility, I run several linear probability model regressions of telework on age group, controlling for sex, education, race, metro area, self-employment, major industry and occupation groups, and month fixed effects. With the full set of controls, the results show that older workers were less likely to work from home during the pandemic than mid-career workers by statistically significant 2.3 percentage points (see Appendix Table A.2 for full results). These results hold when the sample is limited to only high-WFH occupations as well as when continuous WFH and HPP scores are added as covariates (columns 4 and 5 in Appendix Table A.2).

The results for telework outcomes are 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 telework options or relevant training. Brynjolfsson et al. (2020) come to similar conclusions regarding older workers. 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. Yet caution is warranted interpreting the results, as they may be affected by selection effects: the sample is limited to those who were working in the first year of the pandemic.

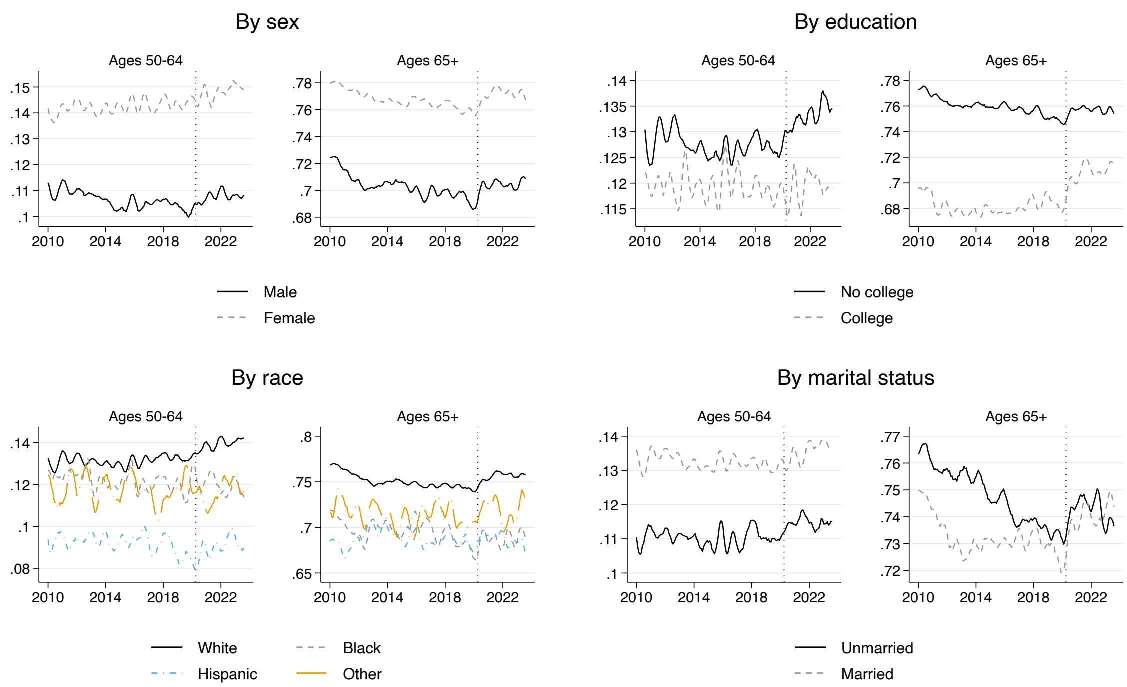
4 Retirement

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 older workers frequently transition into and out of retirement or between different categories of not-in-labor force (NILF).

4.1 Retirement: Time series cross-sectional analysis

As evident in Figure 1 above, the retired share of the older population grew significantly from the start of the pandemic. Yet the rise in the retired share did not occur evenly across demographic groups. Figure 6 displays the retired share by sex, education, race, and marital status for both older age groups, with series plotted in 6-month moving averages. Trend breaks around Covid are more apparent for the 65+ group in nearly all cases. In the 50-64 group, however, the series are noisier and the trend breaks less clear. The largest Covid shifts in the pre-65 retired share trend appear for men and non-college adults. Yet these patterns remain somewhat unclear due to both noisiness in the data and underlying demographic shifts predating Covid that make it somewhat unclear what the counterfactual trend in each demographic group's retired share would be absent Covid.

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



Note: Monthly CPS.

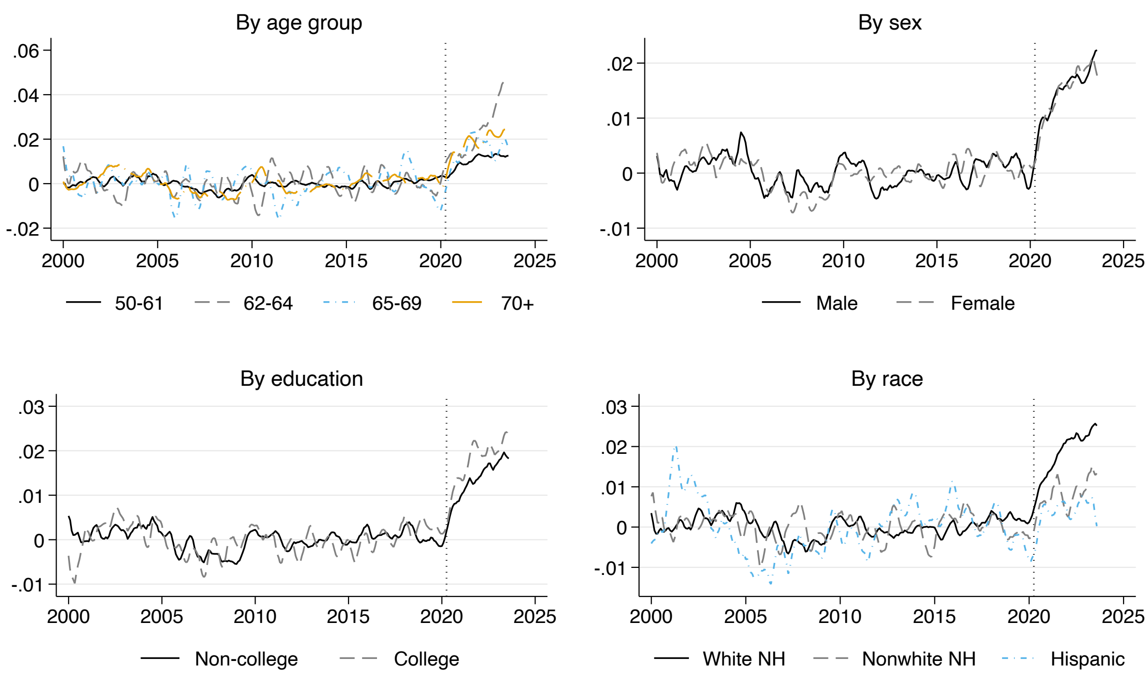
To get a better sense of how Covid retirement trends broke from their pre-Covid trend, I replicate the analysis of Montes, Smith and Dajon (2022), who construct a model of the aggregate retired share that is a function of demographics, macroeconomic performance, and policy-driven retirement incentives. To construct retirement counterfactuals, I break the 18-and-older population into 756 demographic categories defined by the combination of age (each age from 18 to 79 and 80+), race (white, nonwhite non-Hispanic, and Hispanic), and education (non-college and Bachelor's attainment or higher). I then compute retired shares for each group over the period 2000–2019 and regress these retired shares independently for each demographic group on three covariates: a linear time trend; the deviation of the unemployment rate from the natural rate of unemployment estimated by the Congressional Budget Office; and the average Social Security primary insurance amount (PIA) for someone of each age in a given month. This latter variables is a measure of the generosity of Social Security benefits for potential retirees; as a result of past Social Security reforms, the full retirement age has increased steadily since 2000, shifting the incentives associated with retirement and claiming of Social Security benefits.[5] The

[5]The PIA is determined based on the age in months at the time of Social Security claiming. It is a function of both full retirement age (FRA) in months for someone of a given birth year (a threshold that has increased in two-month increments since 2000) as well as the number of months away from FRA that person is. Since birth month is not recorded in the CPS, a person of a given age in a given year may occupy one of 12 different possible

results of these regressions are used to predict demographic group–specific retired shares, which are then aggregated to produce the counterfactual pictured in Figure 1.

To explore demographic variation in deviation from trend in the retired share, I aggregate the actual and predicted retired shares by age groups, sex, race and education, for ages 50 and older. For ease of analysis, Figure 7 plots the deviation from trend by aggregated demographic group in six-month moving averages. The results show increases in the retired share above the predicted trend across demographic groups. Every age group in the 50-and-older range exhibited higher-than-expected retired shares after the pandemic, with the largest changes from trend in the 62–64 year-old group and those 70 and older.[6] Men and women experienced roughly equal deviations from the retirement trend. The increase was slightly larger for those with a college education and substantially larger for white adults relative to nonwhite.

Figure 7: Deviation from counterfactual retired share by demographic group



Note: CPS and author's calculations. Figures show the six-month moving average of the difference between the observed retired share by group and the predicted retired share, as described in text. NH stands for non-Hispanic.

As the cross-sectional data show, Covid led to a sharp and sustained increase in the retired share of the U.S. population, a boom that cut across age and demographic groups. These

birth months and thus face as many as 12 separate possible PIAs. To deal with this complication I calculate each possible PIA given the month of observation and possible birth year for each respondent and then average these 12 values for each individual. These average PIAs are then collapsed by demographic group to form effective PIAs used in the regressions.

[6]These trends hold broadly when different age group cutoffs are used or when a quadratic time trend is substituted for the linear in the predicted retired share model.

increases in retirement were larger for college-educated adults and white adults, groups that are on average better-off than non-college-educated or nonwhite adults. This indicates that the drivers of excess retirement during the pandemic may not have been limited to the factors associated with pandemic-related job loss, since white and especially college-educated workers experienced lower rates of employment loss at the onset of Covid.

4.2 Retirement transitions

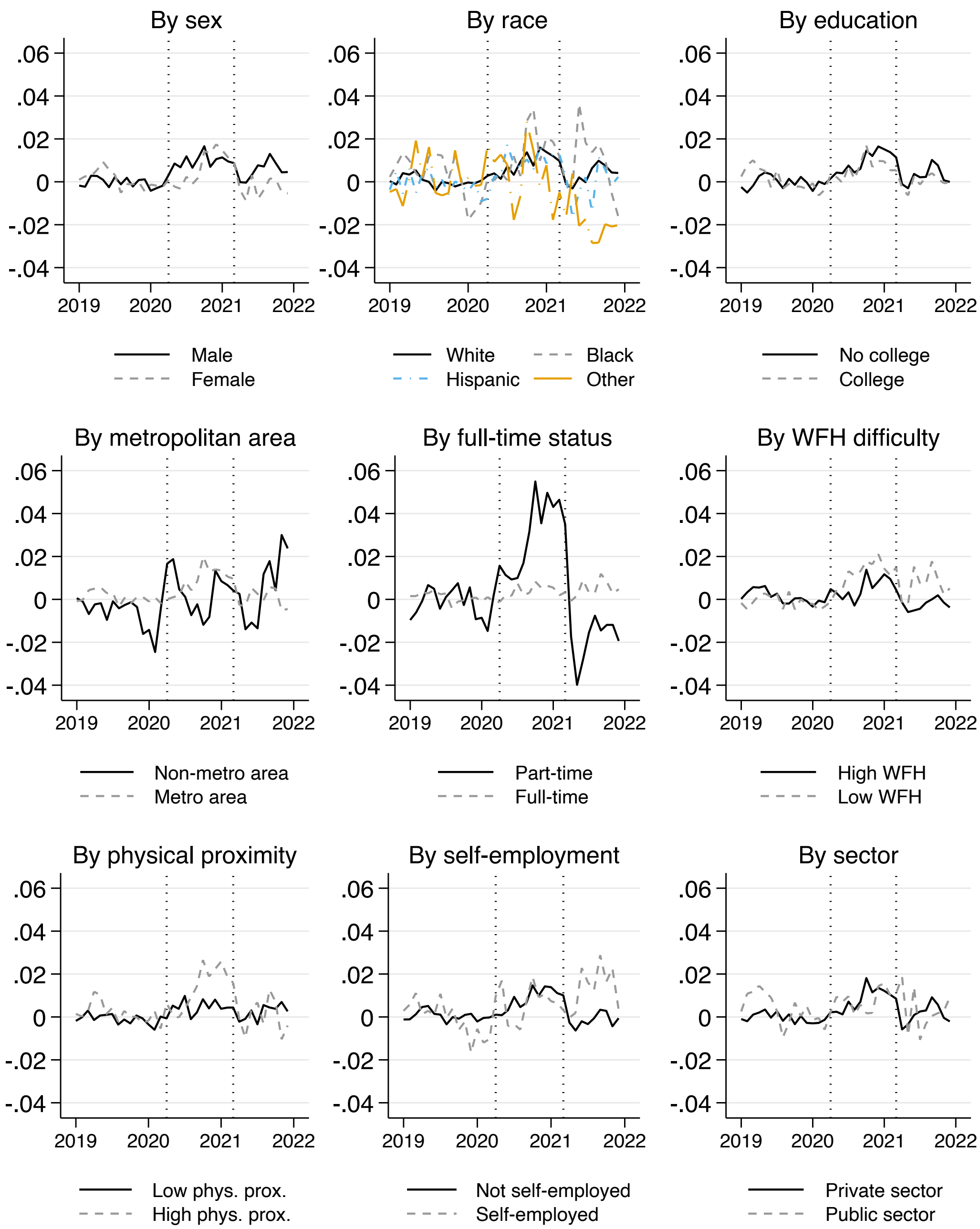
The longitudinal aspect of the CPS makes it possible to explore pre- to post-Covid retirement transitions for older workers by demographic group and job characteristics. In what follows, I calculate normalized employment-to-retirement transition rates using the same procedure as for calculating longitudinal employment declines in Section 3.2. 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. I call the resulting measure *excess retirement*. Note that this gross measure disregards transitions from retired to employed. Appendix Figure A.5 compares excess retirement for the two older age groups, 50-64 and 65+. In percentage point terms, the increase in retirement during the pandemic was greater for the older of the two groups and began immediately (after an unusually low rate of retirement in the six months preceding April 2020). For the 50-64 year-old group, excess retirement began only in the latter half of 2020. Appendix Figure A.6 shows the same series for more detailed age groups.

Figure 8 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 too noisy to draw firm conclusions.

Looking at job characteristics, the largest divergence in excess retirement appears among part-time workers versus full-time workers (though, interestingly, retirement transitions remained elevated through 2021 for full-time workers despite the shift in prior-year group composition). The part-time pattern helps confirm that the declines in normalized employment documented in Section 3.2 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.

Changes from pre-pandemic to the pandemic period in retirement transition rates by hourly earnings quartiles underline the importance of both earnings and work schedules in measuring

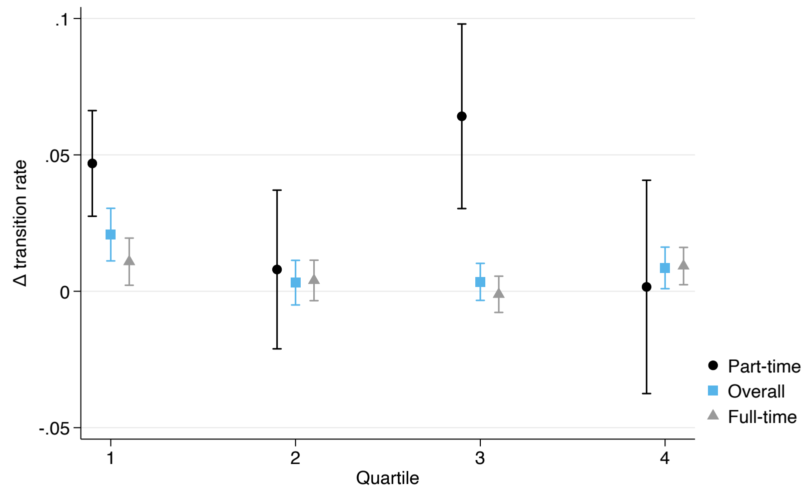
Figure 8: Share retired among those employed 12 months prior, normalized to pre-pandemic average, ages 50+



Note: Monthly CPS linked year-to-year. 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.

pandemic retirement trends. Figure 9 presents the change in the average retirement transition rate from the five years pre-pandemic to the first year of the pandemic, by hourly earnings quartiles.

Figure 9: Difference in means of employed-to-retired transition rate by hourly earnings quartile, pre-pandemic versus pandemic, workers 50+



Note: CPS-ORG linked year-to-year. Plots show the difference in means of the employed-to-retired transition rate by hourly earnings quartile and full-time status, pre-pandemic versus pandemic period, with 95% confidence intervals. Pre-pandemic period is April 2015 through March 2020; pandemic period is April 2020 through March 2021.

For workers overall, Figure 9 shows a roughly U-shaped pattern in increased retirement transitions by earnings: only the lowest and highest earnings quartiles show appreciable positive changes in the retirement transition rate. This pattern is similar when looking only at full-time older workers, though the increase in the retirement transition rate for the lowest quartile is not as great. Restricting the sample to part-time workers reveals a different pattern: the lowest-earning and third quartiles experienced greater retirement transition rates on average in the first year of the pandemic relative to pre-pandemic, while the highest-earning part-timers did not. This result underscores important heterogeneities within the older part-time population. Compared to all other part-time workers, the highest-earning quartile of part-time workers is more educated (70% college-educated versus 25%), more white (84% versus 65%) and significantly less likely to work in low-WFH and HPP occupations (these figures calculated for workers 50+, pooled 2019 monthly CPS).

Appendix Figures A.7 and A.8 use the normalized retirement transition rates averaged over the first year of the pandemic to estimate excess retirement by major industry and occupation groups. Industry groups experiencing the greatest increases in transitions to retirement were leisure and hospitality, transportation and utilities, and other services. While leisure and hospitality was hard hit by the pandemic, transportation and utilities 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 major occupation groups, healthcare support, protective service, and personal care and service occupations saw the largest increases in retirement transitions (Figure A.8). The health and personal care occupation groups 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

In Table 3 I repeat the regression model outlined in 1 and produced for employment transitions in Table 2. The outcome is retirement in the reference month and the sample is those 50 and older who were employed as wage and salary workers 12 months prior and in the CPS ORG in both observations. 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 regressions described in Section 3.3.[7]

The results indicate that once other covariates are taken into account, Covid-related changes in retirement transitions from employment did not differ meaningfully along lines of race, gender, or education, coefficient estimates of which are all imprecisely estimated. State-level death rates also fail to predict retirement transitions. In all models, the age 70+ coefficient is positive and statistically significant, confirming that excess retirement was greatest among the oldest workers even after other factors are taken into account.

In the baseline model in column 1, 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 slightly toward zero—unsurprisingly, given strong correlation between HPP and industry and occupation. Introducing these fixed effects does not affect the coefficient estimates for part-time work. Introducing controls for wage quartiles reduces in column 4 reduces the estimate associated with part-time work and leaves HPP basically unchanged. Using quadratic age controls in place of the categorical age variable (model 5) again leaves these estimates essentially unaffected, suggesting that the covariance of age and part-time status within age bins does not drive the part-time results. Restricting the sample to workers younger than 70 (models 6-7) leads to an estimate on part-time that is reduced and no longer statistically significant; the coefficient on HPP is also smaller in these models. This is consistent with Covid-induced changes in retirement transitions having their strongest effects among the oldest workers. While significant at only the 10% level, metropolitan residence also predicts additional

[7]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 the preceding variables are interacted with a Covid dummy. Regressions also control for state-level Covid death rates and month fixed effects.

Table 3: Regression results for the effect of the pandemic on retired status among those employed one year earlier

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Ages 62-64	-0.00246	-0.00285	-0.00238	-0.00252		-0.00224	
	(0.00894)	(0.00893)	(0.00894)	(0.00894)		(0.00893)	
Ages 65-69	0.0109	0.0115	0.0122	0.0104		0.0113	
	(0.0114)	(0.0114)	(0.0114)	(0.0114)		(0.0114)	
Ages 70+	0.0305*	0.0315*	0.0323*	0.0297*			
	(0.0146)	(0.0146)	(0.0146)	(0.0146)			
Black	0.0000537	0.000383	0.0000301	-0.000832	-0.000179	0.00235	0.00277
	(0.00849)	(0.00851)	(0.00858)	(0.00853)	(0.00850)	(0.00834)	(0.00829)
Hispanic	-0.00356	-0.00367	-0.00420	-0.00474	-0.00229	-0.00688	-0.00526
	(0.00721)	(0.00726)	(0.00737)	(0.00738)	(0.00724)	(0.00688)	(0.00689)
Other race	0.00696	0.00606	0.00592	0.00608	0.00741	0.00682	0.00843
	(0.00999)	(0.00998)	(0.00995)	(0.0100)	(0.00996)	(0.00969)	(0.00959)
Female	-0.00229	-0.00378	-0.00158	-0.00286	-0.00254	-0.00168	-0.00196
	(0.00466)	(0.00499)	(0.00530)	(0.00483)	(0.00466)	(0.00454)	(0.00451)
College	-0.00272	-0.00343	-0.00380	-0.00198	-0.00146	-0.00260	-0.00184
	(0.00503)	(0.00518)	(0.00551)	(0.00536)	(0.00504)	(0.00488)	(0.00488)
Married	-0.00160	-0.00197	-0.00181	-0.00142	-0.00229	-0.000564	-0.000251
	(0.00492)	(0.00492)	(0.00493)	(0.00492)	(0.00491)	(0.00475)	(0.00473)
Metro area	0.0125	0.0121	0.0123	0.0126	0.0122	0.00919	0.00878
	(0.00680)	(0.00682)	(0.00682)	(0.00682)	(0.00680)	(0.00663)	(0.00661)
Part-time	0.0170*	0.0170*	0.0170*	0.0142	0.0169*	0.0148	0.0145
	(0.00853)	(0.00860)	(0.00866)	(0.00870)	(0.00851)	(0.00871)	(0.00861)
Low WFH	0.00000222	-0.00101	-0.00660	-0.000770	0.00113	0.00347	0.00344
	(0.00536)	(0.00565)	(0.00869)	(0.00542)	(0.00536)	(0.00522)	(0.00519)
High phys. prox.	0.0205***	0.0186***	0.0177**	0.0199***	0.0202***	0.0140**	0.0141**
	(0.00499)	(0.00541)	(0.00671)	(0.00499)	(0.00499)	(0.00483)	(0.00481)
State death rate	0.00000721	0.0000164	-0.0000201	0.000000375	0.000158	0.0000322	0.0000456
	(0.000639)	(0.000634)	(0.000633)	(0.000639)	(0.000644)	(0.000630)	(0.000629)
Bottom wage quartile				0.0101			
				(0.00685)			
Second wage quartile				-0.000669			
				(0.00603)			
Top wage quartile				0.00237			
				(0.00629)			
N	65387	65387	65387	65387	65387	60617	60617
Industry x Covid FE		X	X				
Occupation x Covid FE			X				
Wage quartiles				X			
Quadratic age contols					X		X
Age 70+ excluded						X	X

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Monthly CPS April 2018–March 2021. Results of linear probability models of retirement status among workers who were employed 12 months prior to the reference month. Sample restricted to CPS ORG respondents ages 50 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. All models include monthly date and state-by-Covid fixed effects. Robust standard errors.

Covid-era retirement transitions in the baseline model. This coefficient becomes substantially smaller and less precisely estimated in models 6-7, excluding workers 70 and older.

Due to the presence of considerable model uncertainty in these results, Appendix Figure A.9 presents specification curves for four coefficients of interest: part-time status, HPP, metro area, and bottom wage quartile. The plots record coefficient estimates and confidence intervals across

32 separate models which vary by whether they control for industry and/or occupation; whether wage quartiles are included as controls; whether age enters quadratically or categorically; and whether those ages 70 and older are excluded. Each of the variables of interest has positive coefficient estimates across models with some variation in precision. In most cases, restricting the sample to the under-70 population produces coefficient estimates that are not statistically significant at the 90% level. Though this may reflect a simple loss of precision due to smaller sample size, it is also consistent with the possibility that these drivers of excess Covid retirements grew more salient as workers' age increased.

Taken together, 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, conditional on other observables. The most important of these job characteristics were employment in high-contact occupations and working part-time before the pandemic.

5 Further analysis

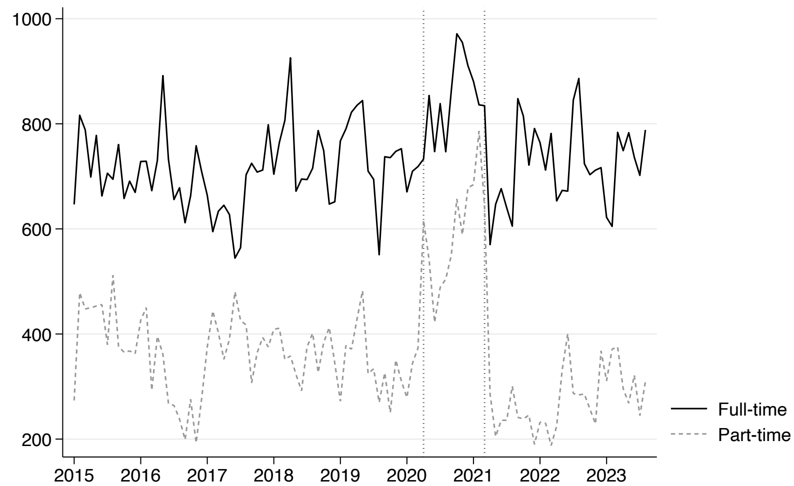
5.1 Part-time work and retirement in the pandemic

A chief contribution of this study is to highlight the role of part-time work for post-Covid retirement trends. 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 50+, Figure 10. Overall, the net flow of older workers into retirement increased 36% in the first 12 months following the Covid shock relative to the 12 months prior. The increase was significantly larger for part-time workers (a 76% increase) than for full-time workers (17%). Part-time workers made up 68% of the total increase in net flows from employment to retirement during the first 12 months of the pandemic relative to the year prior.[8]

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., 2023; Van Dam, 2021). Excess retirement of part-time workers who already claimed Social Security retirement benefits may help resolve the paradox. A large share of older workers typically 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, Papadopoulos and Webb (2020) found that by age 62, 35% of 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

[8]The same patterns hold when the sample is restricted to adults 50-69. 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 these figures do not incorporate flows to and from unemployment and NILF–not retired.

Figure 10: Annual net flows from employment to retirement by full-time status (thousands), workers ages 50+



Note: Monthly CPS linked year-to-year.

(66), the vast majority of both groups claimed even while working.[9]

The existence of working-while-claiming among older workers, particularly those in part-time jobs, helps account for how the retired share could rise for workers younger than 70 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 workers 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, Beehr and Lepisto, 2016). A significant share of CPS respondents report working part-time because they are (partly) retired or because they need to stay below the Social Security earnings test threshold. In 2019, the share of employed workers in CPS who reported working part-time for these reasons was 4% at age 62, 10% at age 65, 23% at age 70, and 29% at age 75 (pooled 2019 monthly CPS). An example of a part-time bridge job affected by the pandemic was school bus drivers, many of whom are older workers retired from their main careers. The combination of layoffs during Covid lockdowns and pandemic health risks drove many of these partly retired workers into full retirement (Alloway and Weisenthal, 2021). While it is not yet clear whether the excess retirements of the pandemic

[9] 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.

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.

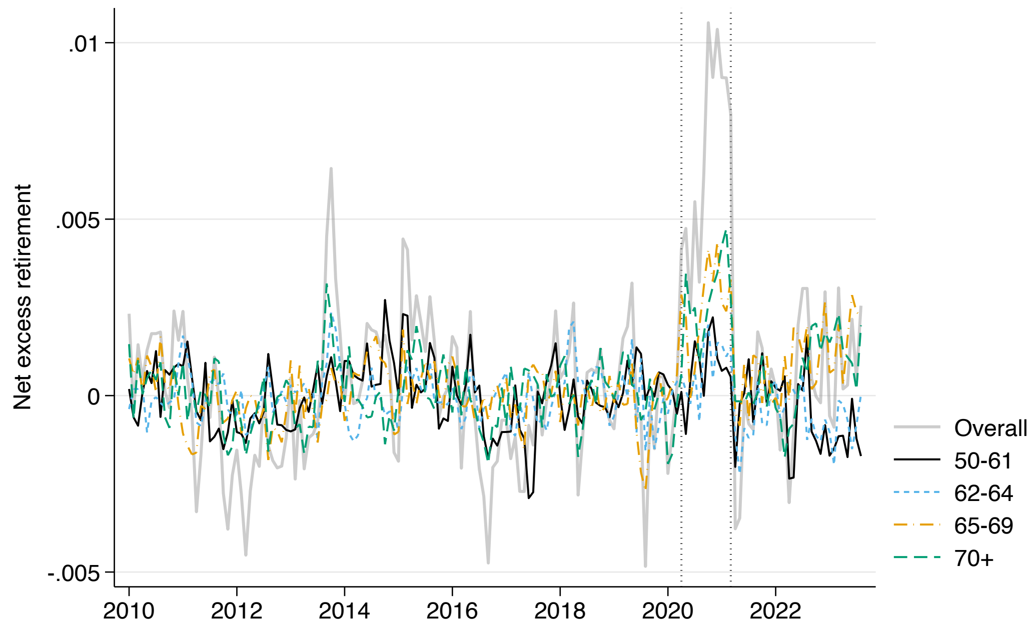
5.2 Demographic patterns in Covid employment and retirement

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 distribution of excess retirement. The remainder of this section summarizes and compares Covid employment and retirement patterns by demographic and earnings categories.

Age. In the regression results reported above, I find that pandemic-driven increases in retirement transition rates increased with age conditional on a wide range of covariates. Yet as Figure 7 indicates, the retired share has diverged from a predicted trend for all age groups. Thus it is worth exploring to what extent the overall surge in pandemic retirement transitions was spread across age groups or 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 detailed age groups from 2010 through 2023m8.[10] Differences between the actual net retirement transitions and the predicted series are shown in Figure 11. 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 (for reference, this group made up 13% of pre-pandemic older worker employment). 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 sum, while those 70 and older made up a disproportionate share of the increase in retirement transitions, workers younger than 70 still made up the majority of excess pandemic retirement transitions.

[10]To construct each group-specific predicted net retirement series, I regress net E-R transitions (as a share of the 55-and-older population) 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 to generate a measure of difference from trend in net retirement transitions.

Figure 11: Net flows from employment to retirement by age group as share of 50+ population, difference from trend



Note: Linked monthly CPS and author's calculations. 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 and divided by the total population 50 and older.

Sex. While older women experienced larger employment declines early in the pandemic, the divergence was temporary. In regression results controlling for industry and occupation, sex was not a significant predictor of non-employment during the first 12 months of the pandemic among those employed a year earlier. I also find no evidence that the greater employment declines experienced by women early in the pandemic led to disproportionate excess retirement. As the plots in Figure 7 indicate, the divergence from trend in the retired share has been greatest among white workers, though this could reflect age differences between racial designations to some degree.

Race. Employment declines early in the pandemic were larger for non-white older workers. Yet regression results do not suggest a significant role for race in employment outcomes for Black and Hispanic older workers after controlling for other demographic and job-related characteristics. 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 in either descriptive evidence or regression results.

Education. Employment loss for non-college older workers was 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, with regression results for pandemic retirement transitions on a range of covariates yielding a negative but insignificant coefficient estimate on having a college degree. As the model in Figure 7 indicates, the percentage-point rise in the retired share has been greater for college-educated workers than for those without a college degree, relative to the counterfactual trend.

Earnings. Across age groups and work schedules, employment losses were generally greater the lower were workers' initial earnings. By contrast, excess retirement followed a U-shape, in which only the lowest- and highest-earning quartiles saw excess retirements. In regressions of retirement on wage quartiles and other covariates, the coefficient on the lowest quartile of hourly wages is positive but not significant. Excess retirements were 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 above, 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. Some 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.

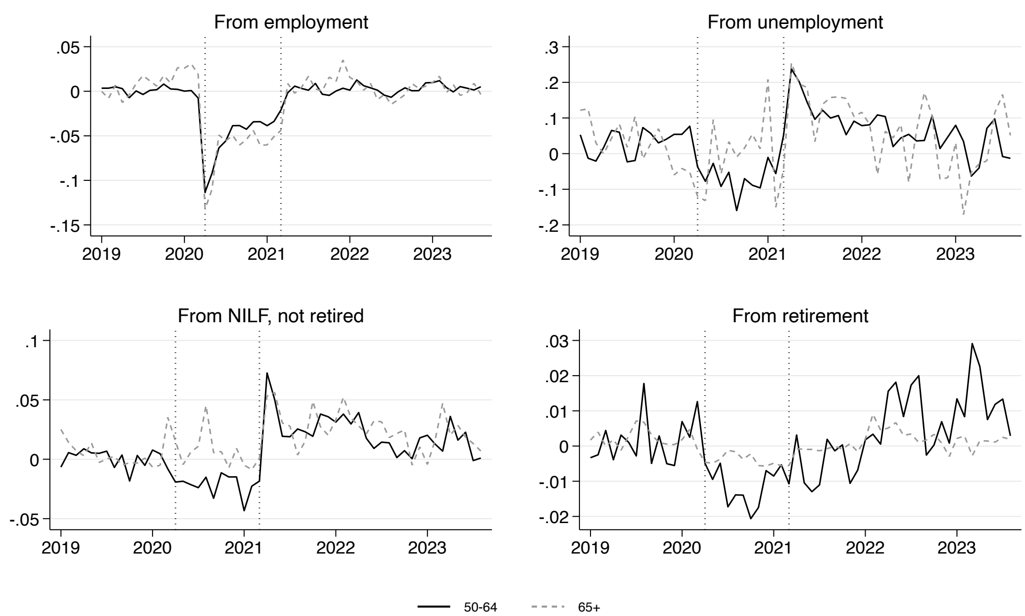
5.3 Recovering from the pandemic

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 provides less information once the initial period of the transition falls during the pandemic, due to large pandemic-driven changes in the composition of the initial-period group. Given the high rate of labor force exit and unemployment in the pandemic, however, it is important to look at transitions from unemployment and NILF/not-retired to employment and retirement since the start of the pandemic.

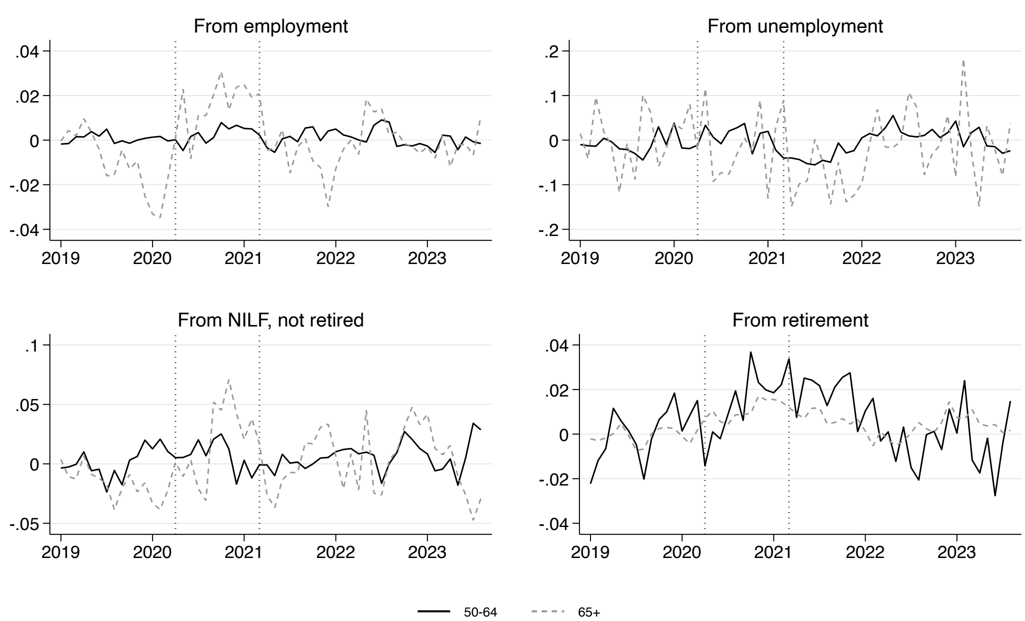
Figure 12 presents normalized transition rates to employment and retirement by initial labor force status and older age group—with the caveat that shifts in the series after April 2021 must be interpreted with caution. The unusually high share of workers transitioning back to employment a year after unemployment (Panel A, top right) reflects the fact that an unusually large share of early pandemic job losses (79%) were temporary layoffs. The temporary nature of much of the pandemic job loss also explains the high rate of employment transitions post-March 2021 for those who were NILF–not retired in the early months of the pandemic (Panel A, bottom left).

Figure 12: Normalized employment and retirement transition rates from listed labor force status

Panel A: Transitions to employment



Panel B: Transitions to retirement



Note: CPS. Figures show the share of those who are employed or 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.

The year-to-year transition rate from retirement to employment rose well above pre-pandemic levels in 2022 and 2023 for the 50-64 group, likely undoing some of the excess retirement that occurred during the first year of the pandemic.

The plots in Panel B of Figure 12 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 fell below the pre-pandemic average in 2021, again due to the temporary nature of a large share of pandemic unemployment, but rose back to trend in 2022. Although te NILF-to-retired data are noisier, they seem to indicate elevated transition rates to retirement from this labor force status in 2022–2023. Finally, the one-year persistence of retirement for those who were retired amid the pandemic remained high throughout 2021 but has drifted back towards pre-pandemic rates.

Taken together, the post-pandemic trends in retirement and employment transitions show a general return to the types of flows that might have been expected from pre-pandemic patterns. While there is some evidence of unretirement from the excess retirements that characterized the early pandemic period, the scale of unretirement has been insufficient to undo the pandemic retirement surge.

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, particularly for non-white workers, those without college degrees, and lower earners. Covid's employment impacts were borne disproportionately by segments of the older workforce already vulnerable to adverse shocks. Yet after the first year of the pandemic, a hot labor market smoothed over the aggregate disparities in employment rates.

Turning to retirement, I demonstrated that the increase in the retired share of the older population occurred across demographics groups and was most significantly associated with high physical proximity on the job, part-time work pre-pandemic, and advanced age (though overall excess retirements were not limited to those 70 and older). A notable contributor to the increased retired share was 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. These findings help clarify patterns in Social Security claiming and suggest that the future of older workers' labor force participation will depend in part on the willingness of those previously in part-time or bridge work to seek employment again.

The results presented here have some potential limitations. First, data from the CPS have important shortcomings. While the CPS provides an unparalleled level of insight into the U.S. labor market at a broad level, other data sources (especially administrative data) will allow for a more granular analysis of employment and retirement flows during the pandemic. One especially significant element missing from the current study is household net worth and retirement wealth measures, which factor heavily into retirement decisions and may have driven a substantial share of Covid-era retirements (Faria e Castro and Jordan-Wood, 2023). A particularly problematic issue in the CPS during the pandemic is nonrandom non-response, as noted in Section 3.2. Rothbaum and Bee (2021) find that lower levels of education were associated with larger increases in non-response at the outset of Covid-19. Given the larger increases in the retired share for non-college workers in 2020 and thereafter, the result is a likely underestimate of total year-to-year employed-to-retired flows in the first year of the pandemic.

This study is also unable to disentangle older workers' reasons for entering retirement, given the relative scarcity of such information in the CPS. Other surveys, such as the Health and Retirement Study, provide more detail into older workers' decision-making around labor force participation. New questions added to the Survey of Income and Program Participation in 2021 asked respondents how the pandemic affected retirement plans (Thomspon, 2022). Research utilizing these surveys will provide valuable context for the findings offered here.

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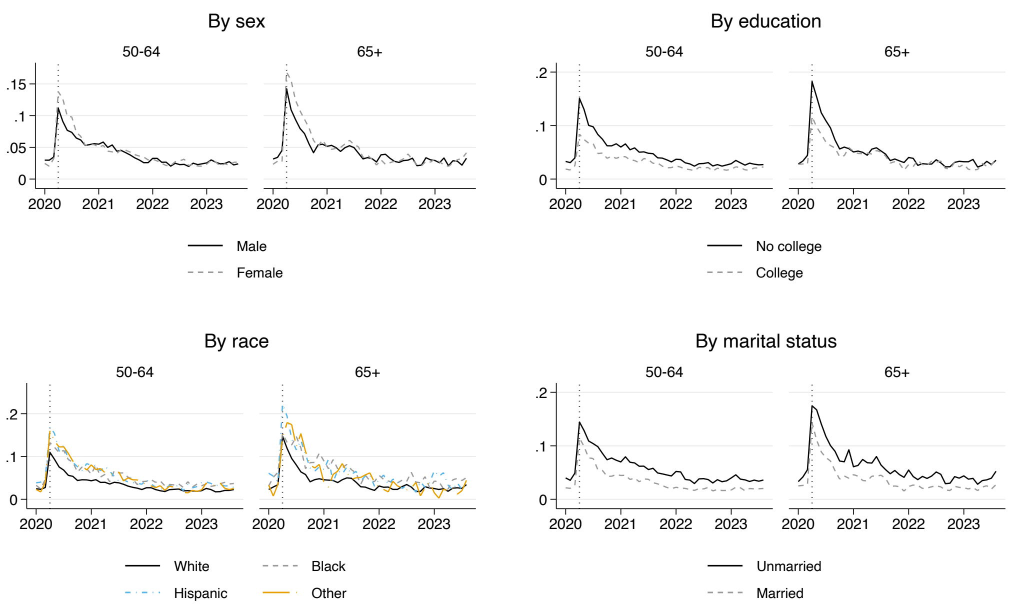
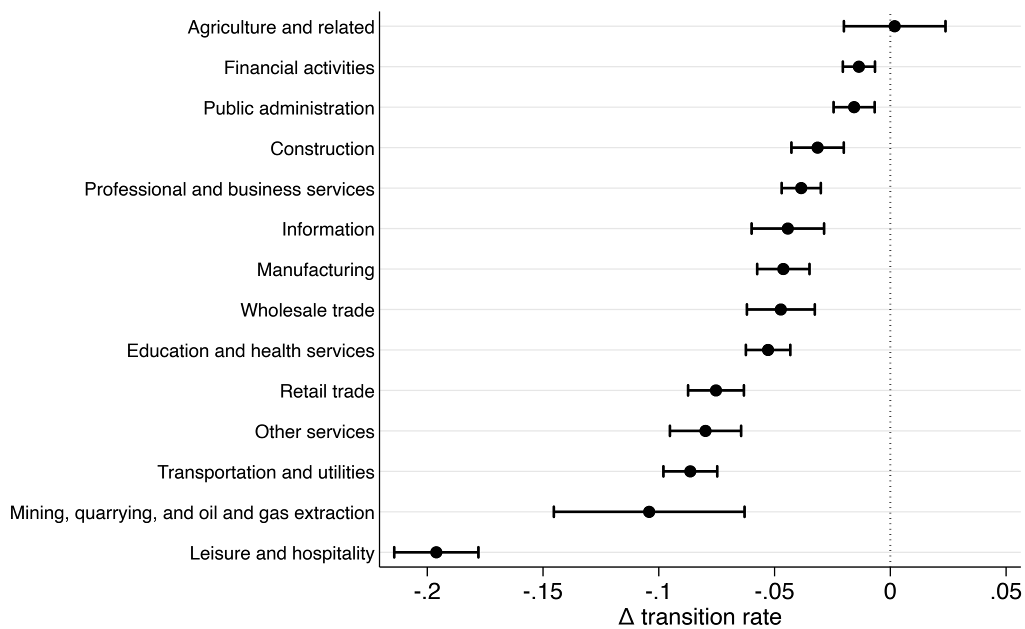
A Additional Tables and Figures

Figure A.1: Unemployment rates by age group and demographics, ages 50+



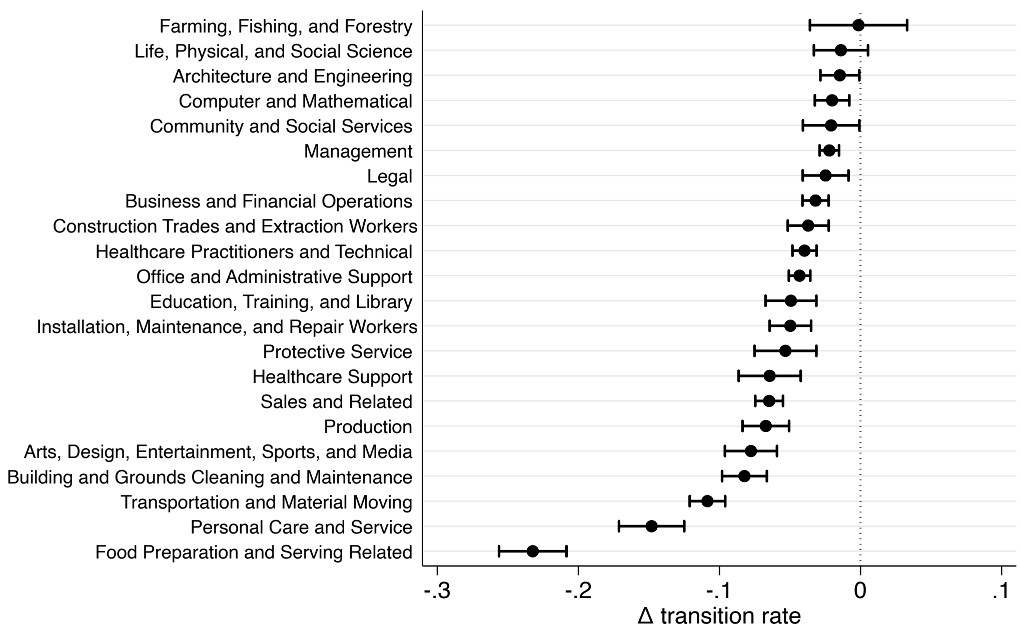
Note: Monthly CPS. Employment rates indexed to full-year 2019 averages. Not seasonally adjusted.

Figure A.2: Change in still-employed share by industry, pandemic versus pre-pandemic, workers 50+



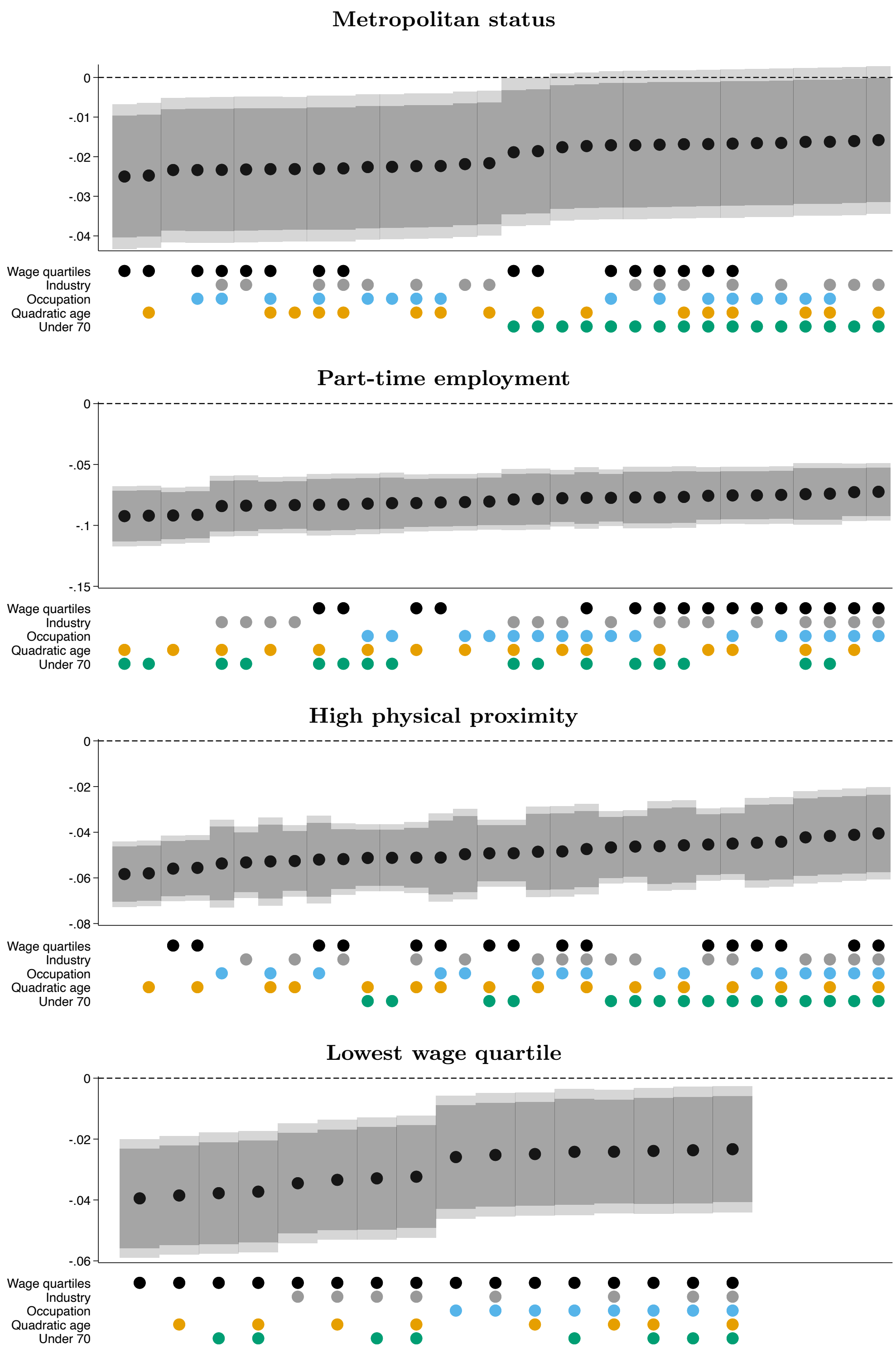
Note: Monthly CPS linked year-to-year. Plot shows differences in means of the still-employed share, pre-pandemic versus first year of the pandemic, for each major industry group. Pre-pandemic period is April 2015 through March 2020; pandemic period is April 2020 through March 2021. 95% confidence intervals included.

Figure A.3: Change in still-employed share by occupation, pandemic versus pre-pandemic, workers 50+



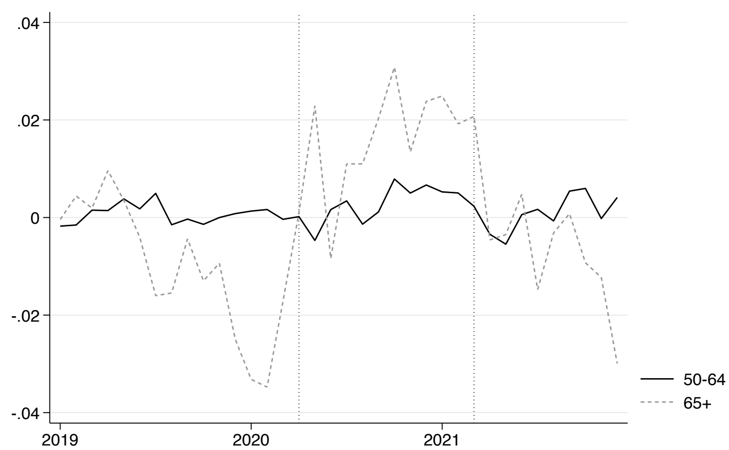
Note: Monthly CPS linked year-to-year. Plot shows differences in means of the still-employed share, pre-pandemic versus first year of the pandemic, for each major occupation group. Pre-pandemic period is April 2015 through March 2020; pandemic period is April 2020 through March 2021. 95% confidence intervals included.

Figure A.4: Specification curves for select coefficients, effect of Covid on employment



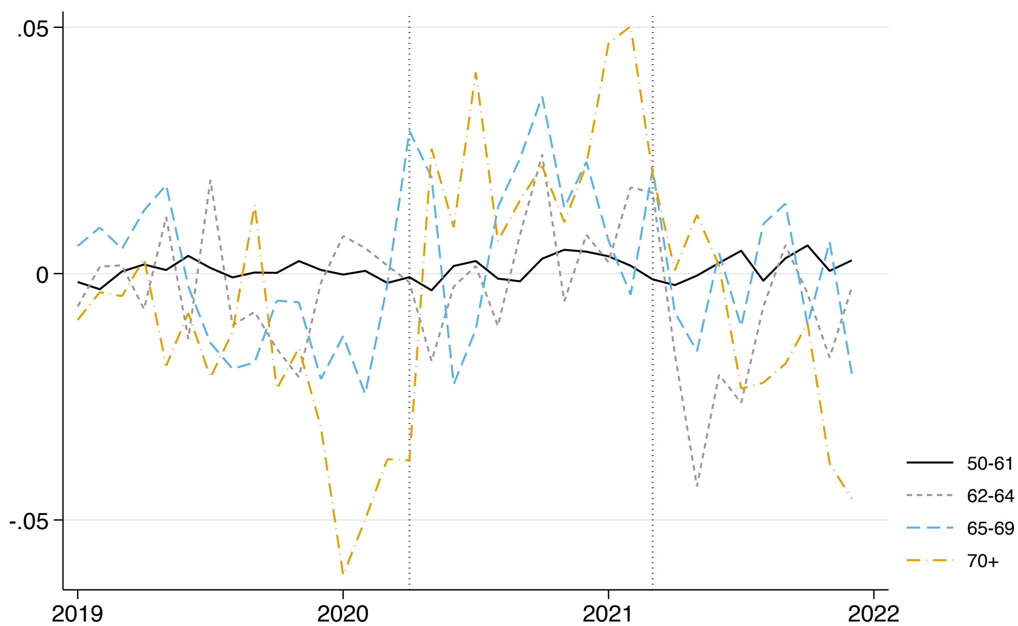
Plots show coefficient estimates and 90% and 95% confidence intervals for specifications listed. Models are described in Section 2. All coefficient estimates reflect interaction of Covid dummy with listed coefficient. Specification "wage quartiles" includes hourly wage indicators; "industry" and "occupation" include major industry and occupation group indicators; "quadratic age" replace age group dummies with a quadratic in age; "under 70" restricts the sample to ages 50–69.

Figure A.5: Share retired among those employed 12 months prior, normalized to pre-pandemic average



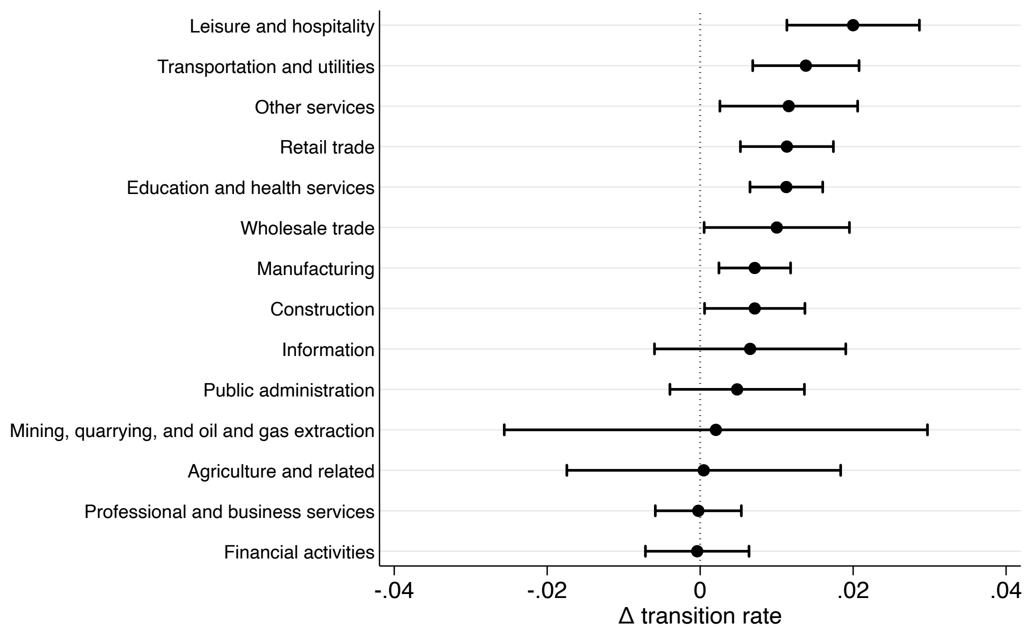
Note: Monthly CPS linked year-to-year. Series show the share of workers who are retired among those employed 12 months prior. Series are normalized by subtracting the 2015-2019 average employed-to-retired transition rate by calendar month for each group.

Figure A.6: Share retired among those employed 12 months prior, normalized to pre-pandemic average



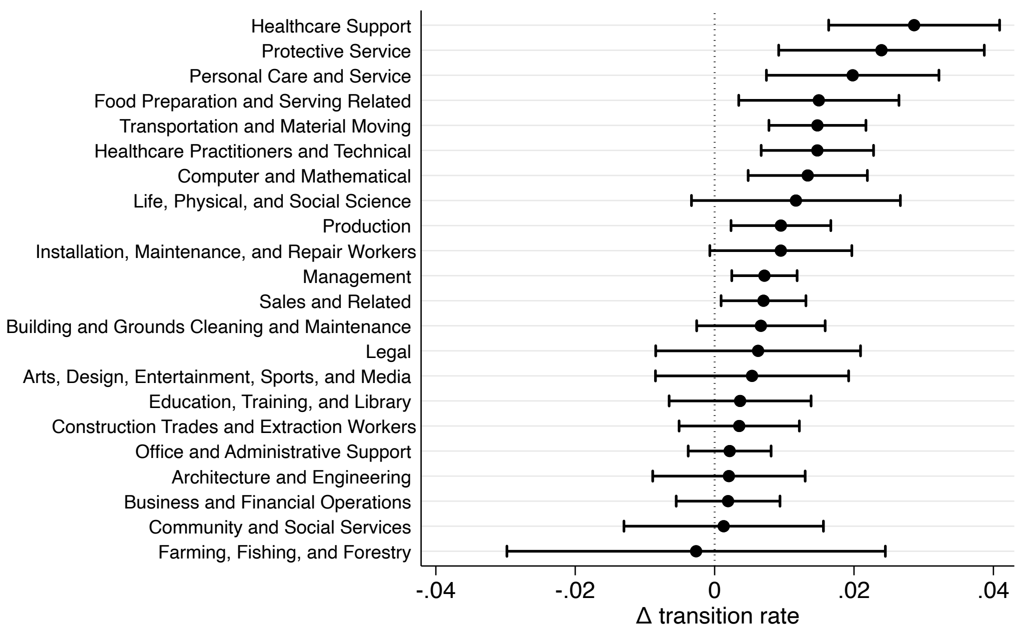
Note: Monthly CPS linked year-to-year. Series show the share of workers who are retired among those employed 12 months prior. Series are normalized by subtracting the 2015-2019 average employed-to-retired transition rate by calendar month for each age group.

Figure A.7: Change in retirement transition rate by industry, pandemic versus pre-pandemic, workers 50+



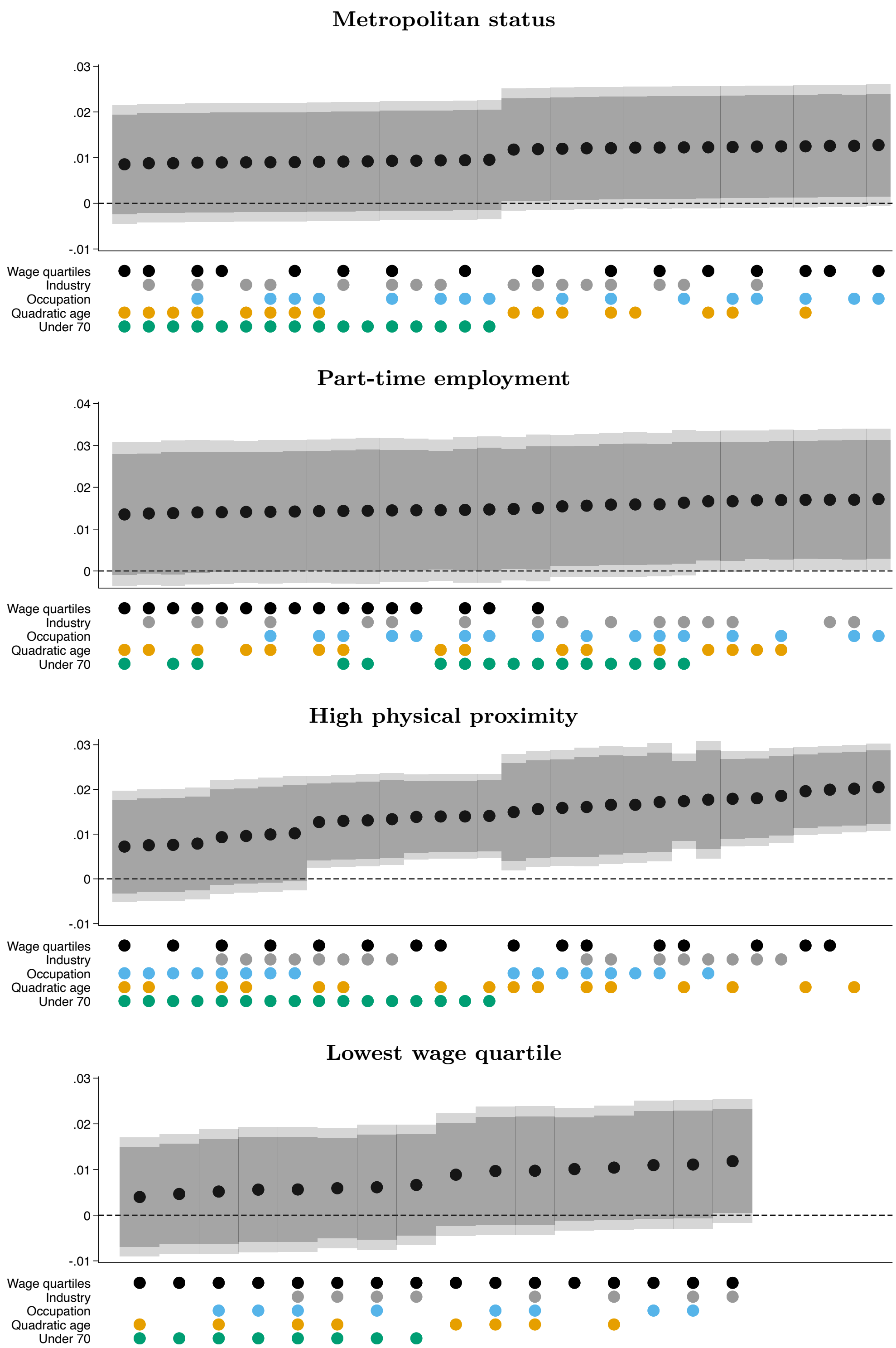
Note: Monthly CPS linked year-to-year. Plot shows differences in means of the employed-to-retired transition rate, pre-pandemic versus first year of the pandemic, for each major industry group. Pre-pandemic period is April 2015 through March 2020; pandemic period is April 2020 through March 2021. 95% confidence intervals included.

Figure A.8: Change in retirement transition rate by occupation, pandemic versus pre-pandemic, workers 50+



Note: Monthly CPS linked year-to-year. Plot shows differences in means of the employed-to-retired transition rate, pre-pandemic versus first year of the pandemic, for each major occupation group. Pre-pandemic period is April 2015 through March 2020; pandemic period is April 2020 through March 2021. 95% confidence intervals included.

Figure A.9: Specification curves for select coefficients, effect of Covid on retirement



Plots show coefficient estimates and 90% and 95% confidence intervals for specifications listed. Models are described in Section 2. All coefficient estimates reflect interaction of Covid dummy with listed coefficient. Specification "wage quartiles" includes hourly wage indicators; "industry" and "occupation" include major industry and occupation group indicators; "quadratic age" replace age group dummies with a quadratic in age; "under 70" restricts the sample to ages 50–69.

Table A.1: Selected employment rates by age group and demographics

	2019 average	Apr 2020	Aug 2023
Male			
50-64	0.746	0.666	0.743
65+	0.246	0.204	0.229
Female			
50-64	0.629	0.544	0.638
65+	0.164	0.133	0.158
No college			
50-64	0.638	0.539	0.635
65+	0.166	0.136	0.160
College			
50-64	0.780	0.722	0.784
65+	0.278	0.226	0.251
White			
50-64	0.700	0.625	0.694
65+	0.204	0.169	0.187
Black			
50-64	0.614	0.549	0.649
65+	0.179	0.147	0.193
Hispanic			
50-64	0.682	0.570	0.682
65+	0.192	0.150	0.215
Other race			
50-64	0.683	0.562	0.730
65+	0.211	0.168	0.189
Unmarried			
50-64	0.623	0.543	0.635
65+	0.166	0.139	0.165
Married			
50-64	0.720	0.634	0.719
65+	0.226	0.183	0.209

Note: Monthly CPS. Not seasonally adjusted.

Table A.2: Regression results for the effect of listed regressors on the probability of working from home, employed workers May 2020-October 2021

	(1)	(2)	(3)	(4)	(5)
Ages 18-29	-0.0215***	-0.0127***	-0.00934***	-0.0105***	-0.00734**
	(0.00161)	(0.00158)	(0.00150)	(0.00246)	(0.00246)
Ages 50+	-0.0228***	-0.0224***	-0.0221***	-0.0307***	-0.0320***
	(0.00149)	(0.00146)	(0.00139)	(0.00217)	(0.00217)
Black	-0.0276***	-0.0268***	-0.00758***	-0.00882*	-0.00561
	(0.00218)	(0.00215)	(0.00205)	(0.00364)	(0.00364)
Hispanic	-0.0634***	-0.0540***	-0.0237***	-0.0256***	-0.0233***
	(0.00175)	(0.00173)	(0.00166)	(0.00318)	(0.00317)
Other race	0.0315***	0.0305***	0.0275***	0.0419***	0.0425***
	(0.00258)	(0.00249)	(0.00234)	(0.00339)	(0.00338)
Female	0.0357***	0.0332***	0.0238***	0.0235***	0.0211***
	(0.00123)	(0.00133)	(0.00134)	(0.00202)	(0.00202)
College	0.286***	0.250***	0.153***	0.172***	0.165***
	(0.00140)	(0.00145)	(0.00154)	(0.00213)	(0.00214)
Married	0.0184***	0.0126***	0.00550***	0.00315	0.00144
	(0.00133)	(0.00130)	(0.00124)	(0.00202)	(0.00202)
Metro area	0.0949***	0.0836***	0.0696***	0.131***	0.131***
	(0.00143)	(0.00144)	(0.00140)	(0.00262)	(0.00261)
Self-employed	-0.0682***	-0.0696***	-0.0675***	-0.104***	-0.102***
	(0.00190)	(0.00197)	(0.00198)	(0.00301)	(0.00302)
Low WFH score					-0.375***
					(0.0231)
HPP score					-0.250***
					(0.0118)
Constant	0.0499***	0.0747***	0.127***	0.188***	0.327***
	(0.00196)	(0.00200)	(0.00199)	(0.00357)	(0.00651)
N	565465	565465	565465	313278	313278
Industry FE		X	X	X	X
Occupation FE			X	X	X
Only high-WFH occupations				X	X
Low-WFH and HPP scores					X

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Monthly CPS, May 2020–April 2021. Results of linear probability models regressing whether working remotely on listed covariates among workers who were employed in the reference month. All models include state and monthly date fixed effects. Robust standard errors.

B 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.

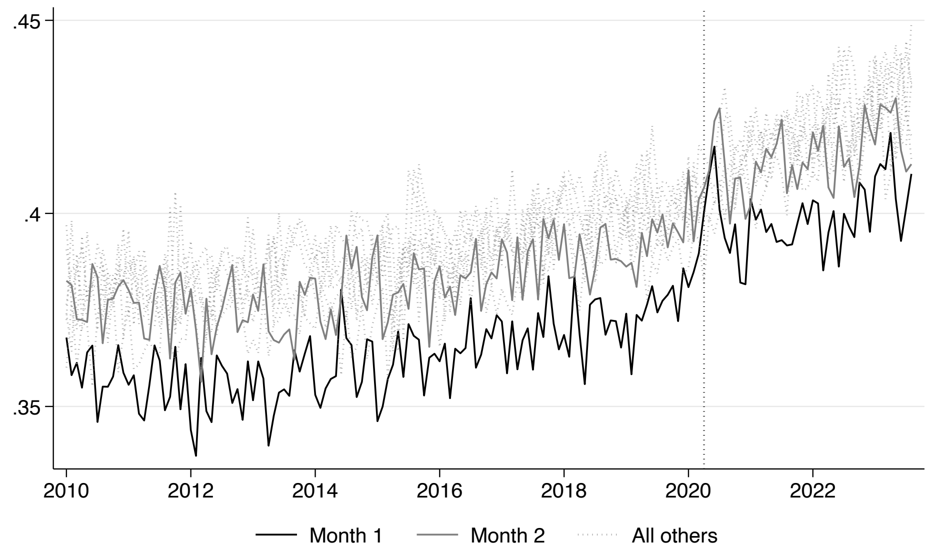
Analysis of monthly rates of transition addresses a different question than the one posed here, i.e, that of the pandemic's effects on the employment and retirement transitions of workers previously employed in relatively normal labor market conditions. Monthly transition rates are conditional on employment status in the prior month, and by April 2020, the employed population differed greatly in composition from that of the month or year prior.[11] 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.

To illustrate the bias, Figure B.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 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.)

[11] 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.

Figure B.1: Retired share by month-in-sample



Note: Monthly CPS. 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.