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SPECIAL ISSUE ARTICLE

Older workers' employment and Social Security spillovers through the second year of the COVID-19 pandemic

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Abstract
The COVID-19 pandemic triggered a large and immediate drop in employment among U.S. workers, along with major expansions of unemployment insurance (UI) and work from home. We use Current Population Survey and Social Security application data to study employment among older adults and their participation in disability and retirement insurance programs through the second year of the pandemic. We find ongoing improvements in employment outcomes among older workers in the labor force, along with sustained higher levels in the share no longer in the labor force during this period. Applications for Social Security disability benefits remain depressed, particularly for Supplemental Security Income. In models accounting for the expiration of expanded UI, we find some evidence that the loss of these additional financial supports resulted in an increase in disability claiming. Social Security retirement benefit claiming is approximately 3% higher during the second year of the pandemic.

Key words: Disability; labor supply; retirement; Social Security programs

JEL codes: J14; J22; J26; J65

1. Introduction

The first year of the COVID-19 pandemic in the United States was characterized by an immediate drop in employment among all workers, followed by a gradual recovery. Older workers between age 50 and 70, who were particularly susceptible to severe illness from COVID-19, were approximately 10% less likely to be employed during the first year of the pandemic (Goda *et al*., 2022). Unlike prior recessions, where older workers have turned to Social Security retirement (SSR) or disability insurance benefits, the drop in employment was accompanied by a decline in applications for disability insurance, and no significant change in retirement applications (Goda *et al*., 2022).

A number of factors could account for this departure from past trends. Rapid public policy responses, including stimulus payments and extended unemployment benefits, likely provided additional financial security in the short term. Higher levels of uncertainty due to changes in availability of vaccines, remote work options, and other factors may have led older adults to adopt 'wait and see' attitudes before making more permanent decisions about work and benefit application.

In this paper, we analyze monthly survey data from the Current Population Survey (CPS) spanning March 2020 to March 2022 to describe patterns in employment, unemployment, and labor force participation for older adults of 50–70. We also analyze Social Security Administration (SSA) data on monthly applications received for retirement and disability applications. In both cases, we compare monthly data in each of the 2 years following the start of the pandemic to their expected patterns had the pandemic not occurred under various sets of assumptions. By the end of our study period, we see recovery in employment and unemployment, with labor force participation remaining depressed relative to pre-pandemic levels. Overall applications for Social Security disability benefits remain depressed through the second year of the pandemic (14% lower than pre-pandemic levels), with the drop driven by applications for Supplemental Security Income (SSI). Application rates for SSR benefits in the first year of the pandemic were overall unchanged, but approximately 3% higher during the second year.

Early in the pandemic, unemployment insurance (UI) was expanded at the Federal level to provide an additional $600 of weekly benefits along with expanded eligibility for job classes that would typically be ineligible for state programs through September 2021. Initially available in all states, termination of these uncharacteristically generous benefits varied as 24 states opted out of these programs during June–August 2021, in advance of the federal end date in September 2021. We test whether the expiration of expanded UI benefits, which led to an estimated 36.3 percentage point drop in UI receipt among customers of a financial services company (Coombs *et al.*, 2022), was associated with changes in Social Security disability applications. We find evidence that applications for concurrent Social Security Disability Insurance (SSDI) and SSI applications reversed earlier declines. Under the assumption that the expiration of expanded UI programs was not driven by differences in factors that affect transitions from UI to disability programs across states and that disability applications would have evolved similarly in the absence of early expiration, these results provide suggestive evidence that the expanded unemployment benefits between March 2020 and September 2021 dissuaded some individuals from applying for disability insurance benefits.

Our paper builds on several strands of literature. A large body of work examines the impacts of the pandemic on labor market outcomes (e.g., Bartik *et al.*, 2020; Cajner *et al.*, 2020; Coibion *et al.*, 2020; Forsythe *et al.*, 2020; Larrimore *et al.*, 2021; Lee *et al.*, 2021; Davis, 2022; Montenovo *et al.*, 2022). Some of this work looks specifically at older workers, the population we examine (e.g., Bui *et al.*, 2020; Quinby *et al.*, 2021; Goda *et al.*, 2022), but only Goda *et al.* (2022) examine SSI and SSDI applications. Analyses of early labor market effects show dramatic declines in employment (Bartik *et al.*, 2020; Cajner *et al.*, 2020; Montenovo *et al.*, 2022), labor force participation (Coibion *et al.*, 2020), and labor demand (Forsythe *et al.*, 2020). In general, this literature finds evidence of considerable labor market disruption from the COVID-19 pandemic that broadly hit populations of all ages, with somewhat more concentrated effects among the youngest (Montenovo *et al.*, 2022) and oldest workers (Bui *et al.*, 2020; Quinby *et al.*, 2021). Lower wage earners, ethnic and racial minorities, and other vulnerable workers were consistently harder hit (Cajner *et al.*, 2020; Larrimore *et al.*, 2021; Davis, 2022; Montenovo *et al.*, 2022).

A smaller literature has explored the effects of the pandemic on retirement and disability benefit claiming. Evidence supports at least a small increase in retirement (Cortes and Forsythe, 2022; Goda *et al.*, 2022; McEntarfer, 2022) and sustained levels of retirement savings (Derby *et al.*, 2022), but no effect on SSR benefit claims (Quinby *et al.*, 2021; Goda *et al.*, 2022). Goda *et al.* (2022) also find that the widely documented labor market exits following the onset of COVID-19 were not matched by major changes in the likelihood of individuals reporting not being in the labor force due to disability. In addition, disability applications declined rather than increased during the first year following the onset of COVID-19, and this reduction was driven by SSI, a program targeting low- to no-wage earners.

Prior to the Great Recession, it was thought that older workers were generally less likely to be displaced than younger workers during economic downturns due to the larger losses from laying off older workers that firms had invested in over many years (Farber *et al.*, 2005). More recently, evidence shows that older workers are particularly vulnerable to recessions, and are more likely to leave the labor force and collect SSR benefits sooner (Coile and Levine, 2007; Munnell *et al.*, 2009; Coile, 2011; Johnson, 2012). It is thought that this shift is related to reductions in tenure among older workers and higher displacement of older workers employed in manufacturing (Munnell *et al.*, 2009). Other work has found that older workers delay retirement in an effort to recover lost earnings and wealth (Chan and Stevens, 1999; Gustman *et al.*, 2010; Goda *et al.*, 2011; McFall, 2011).

A large existing literature has found that disability claiming through SSI and SSDI is sensitive to economic conditions (Stapleton *et al.*, 1998; Black *et al.*, 2002; Autor and Duggan, 2003; Coe *et al.*, 2010; Cutler *et al.*, 2012; Schmidt, 2012; Munnell and Rutledge, 2013; Maestas *et al.*, 2015; 2018; Charles *et al.*, 2018). These studies generally find that higher rates of unemployment lead to larger numbers of applications for SSI and SSDI, increasing both processing costs and benefit obligations substantially. Carey *et al.* (2022) find that a 1 percentage point increase in unemployment rates increases SSDI receipt by 4.2%. The additional benefit claimants induced to apply during times of higher unemployment use less healthcare after entering Medicare, suggesting that the marginal applicants during recessions are healthier and that these applications may partly reflect the need for income support when fewer jobs are available.

Prior work suggests that generous UI benefits are also associated with reduced SSDI claiming (Rutledge, 2011; Lindner and Nichols, 2014; Lindner, 2016). Although the expiration of UI benefits did not lead to meaningful increases in SSDI applications during the Great Recession (Mueller *et al.*, 2016), there is evidence that it led to increases in self-reported disability (Rothstein and Valletta, 2017). In addition, evidence from Austria shows that extended UI benefits increased the probability of future disability insurance (DI) take up while decreasing use concurrently (Inderbitzin *et al.*, 2016), and Couch *et al.* (2014) find that extended jobless spells are associated with a higher likelihood of DI benefits 20 years later.

Finally, a small amount of prior work has examined the effects of UI generosity on older workers retirement decisions (Hamermesh, 1980; Coile and Levine, 2007; Inderbitzin *et al.*, 2016; Rothstein and Valletta, 2017). In general, the evidence is mixed with some studies showing a positive correlation between UI benefits and retirement (Hamermesh, 1980; Inderbitzin *et al.*, 2016; Rothstein and Valletta, 2017), and others finding no consistent evidence of UI generosity affecting retirement decisions (Coile and Levine, 2007).

Our study adds to this literature by examining how work and benefit application decisions are being made by older workers during the second year of the pandemic, a period where vaccine availability, new coronavirus variants, pandemic-induced restrictions, and the availability of other social insurance programs like UI were rapidly changing. This period is especially interesting to study given the high level of uncertainty during the first year of the pandemic, when many older workers appeared to be taking a 'wait and see' approach to retirement and Social Security application decisions (Goda *et al.*, 2022). In addition, several other features of the 2021–22 period differ from prior periods of economic recovery, such as relatively low unemployment rates, supply shortages, the continuation of SSA office closures, and climbing inflation.

The rest of our paper proceeds as follows. Section 2 summarizes the data sources used in our analysis and provides summary statistics. We describe the empirical methods in Section 3. Section 4 reports our results, and Section 5 concludes.

2. Data

We use three primary datasets to assess the effect of COVID-19 on labor market outcomes among older adults and associated spillovers to Social Security – the CPS, SSA's State Monthly Workload Data, and SSA's Monthly Data for Retirement Insurance Applications. Our sample period begins in January 2015, to allow a sufficient pre-period to establish pre-existing trends in our outcome variables that likely would have continued but for the COVID-19 pandemic. Our sample ends in March 2022, 2 years after the onset of COVID-19 pandemic.

2.1 CPS data and variables

The labor market outcome variables we analyze come from the CPS fielded by the U.S. Census Bureau. We source these data from IPUMS (Flood *et al.*, 2020). The CPS surveys 60,000 households, using a probability selected sampling approach. The data include individual-level survey weights, which roughly correlate with the number of individuals in the population represented by the sampled individual. The survey weights adjust for sub-sampling, in which a small area may be significantly over-represented in terms of the number of households; non-interview adjustment to account for households for which no information was obtained (e.g., due to absence, refusal, or impassable roads); and distributional weights based on characteristics such as sex, age, race, and state of residence, which are derived from the known distribution of these characteristics in the population, as extrapolated from the decennial U.S. Census.

The survey is fielded the week of the 19th of each month and the questions refer to activities during the prior week.[1] Households are surveyed for four consecutive months, then not surveyed for the next 8 months, before being surveyed again for a final 4 consecutive months, after which they exit the sample. Surveys are conducted via telephone and in-person interviews with a single 'reference' household member answering questions for all eligible household members. Eligible individuals are age 15 or older, in the civilian population, and not institutionalized (United States Census Bureau, 2019). We use the unharmonized labor force outcome variable created by IPUMS, which directly reflects the underlying CPS variables obtained from the Census Bureau and Bureau of Labor Statistics. Unharmonized IPUMS variables differ only from the underlying data in that IPUMS applies consistent naming conventions across multiple samples (IPUMS, 2022). From this variable, we generate {0,1} dichotomous variables for *Employed, Employed-Absent*, *Unemployed*, and *Not In Labor Force* (*NILF*).[2] For those not in the labor force, we create {0,1} dichotomous variables breaking out the reasons reported for being *NILF* into *Retired*, *Disabled*, and *Other*.[3] We also obtained demographic controls for the households in our sample, including age, sex, race, ethnicity, education, marital status, household size, metro area, and state.

Non-response bias is a known issue with the CPS, likely leading to underestimation of poverty rates (Hokayem *et al.*, 2015). This issue appears to have been significantly exacerbated by a pause in in-person interviews starting March 20, 2020, with in-person interviews partially resuming in July but still remaining below historical levels even as late as October 2020. The change in survey method appears to have skewed the non-response rates such that unemployed and those not participating in the labor force were less likely to participate. This may have led to oversampling of non-Hispanic whites, older respondents, and more educated respondents (Ward and Edwards, 2021), as well as higher income respondents (Rothbaum and Bee, 2021). The underrepresentation of low-income respondents may affect our results since these individuals may be more likely to move in and out of unemployment and the labor force.

We restrict our sample to civilian individuals aged 50–70, to focus on the sub-population with a high likelihood of applying for Social Security disability or retirement benefits. The average SSI and SSDI applicants were aged 40 and 50 between January 2015 and December 2020, respectively (Goda *et al.*, 2022). SSDI rates among insured workers increase significantly with age with the highest claiming rates among those 60–66 (Center for Budget and Policy Priorities, 2021), and SSA retirement benefits are only available to those 62 or older. For our analyses, we further split this age group into 50–61-year-olds and 62–70-year-olds due to differing access to SSA retirement benefits and different baseline employment levels. Our analysis sample includes 2,847,633 observations, 1,701,077 from individuals between 50 and 61 and 1,146,556 from individuals between 62 and 70.[4]

[1]This is usually, but not always, the week including the 12th of the month.

[2]The CPS categorizes anyone temporarily away from work, regardless of the reason as *Employed-Absent*. However, during the pandemic, the employed-absent response may include measurement error, as many workers were furloughed and some furloughed workers may have been recorded as *Employed-Absent* rather than *Unemployed* in the March and April 2020 CPS. Coding errors resulted in individuals out of work due to the pandemic in some cases being coded as 'employed-absent' rather than unemployed (Montenovo *et al.*, 2022).

[3]Reasons for *NILF – Other* include gainful activities such as education and training, as well as what the American Time Use Survey categorizes as 'socializing, relaxing, and leisure' (Eberstadt, 2022).

[4]These numbers reflect the raw number of observations in our sample. All of our analyses utilize individual-level survey weights. The corresponding weighted observations are 7,210,386,432.36, of which 4,422,889,675.123 are between 50 and 61 and 2,787,496,757.235 are between 62 and 70.

Table 1. CPS demographic summary statistics

	Ages 50–61		Ages 62–70	
	Pre-Covid	Post-Covid	Pre-Covid	Post-Covid
Age	55.50	55.56	65.75	65.77
	(3.42)	(3.47)	(2.57)	(2.57)
Female	0.51	0.51	0.53	0.53
	(0.50)	(0.50)	(0.50)	(0.50)
White	0.80	0.79	0.82	0.81
	(0.40)	(0.41)	(0.38)	(0.39)
Black	0.12	0.12	0.11	0.11
	(0.33)	(0.33)	(0.31)	(0.32)
Other	0.08	0.09	0.07	0.07
	(0.27)	(0.28)	(0.25)	(0.26)
Hispanic	0.13	0.15	0.09	0.10
	(0.34)	(0.36)	(0.29)	(0.30)
⩽High school	0.10	0.09	0.10	0.09
	(0.30)	(0.29)	(0.30)	(0.28)
High school	0.30	0.29	0.30	0.30
	(0.46)	(0.46)	(0.46)	(0.46)
Some college	0.16	0.15	0.17	0.16
	(0.37)	(0.35)	(0.38)	(0.37)
College+	0.33	0.36	0.33	0.34
	(0.47)	(0.48)	(0.47)	(0.47)
Associates	0.11	0.11	0.10	0.11
	(0.31)	(0.31)	(0.30)	(0.31)
Disabled	0.13	0.12	0.18	0.17
	(0.33)	(0.32)	(0.39)	(0.38)
Married	0.65	0.65	0.65	0.64
	(0.48)	(0.48)	(0.48)	(0.48)
Divorced/separated	0.19	0.19	0.18	0.18
	(0.39)	(0.39)	(0.38)	(0.38)
Widowed	0.04	0.03	0.09	0.09
	(0.19)	(0.18)	(0.29)	(0.29)
Single	0.12	0.13	0.08	0.09
	(0.32)	(0.34)	(0.27)	(0.29)
Household size	2.61	2.64	2.16	2.17
	(1.36)	(1.37)	(1.13)	(1.14)
Observations	1,286,653	414,424	838,723	307,833

Notes: Sample contains civilians aged 50–61 and 62–70 from the January 2015–March 2022 CPS living in the United States. Share of each relevant demographic is listed and weighted using survey weights. Pre-Covid captures the mean outcome in the pre-period January 2015–February 2020. Post-Covid captures the mean outcome in the post-period March 2020–March 2022.

Tables 1 and 2 report descriptive statistics for our demographic and outcome variables. Although the sample does not differ much across age groups in Table 1, clear differences in labor market outcomes exist, as shown in Table 2. In the pre-COVID period, the average age in the younger group is 56 and 66 in the older group. The remaining demographics are relatively similar across age groups. A few small differences of note include: the older cohort is slightly more likely to be female (53% vs. 51%), less likely to be Hispanic (9% vs. 13%), and more likely to be disabled (18% vs. 13%).

Prior to COVID-19 the older cohort is much less likely to be employed (36% vs. 69%) or unemployed (1% vs. 2%). This is not surprising and these differences are offset by reporting higher levels of not being in the labor force (60% vs. 26%). Retirement is the primary driver of the much higher rate of labor force non-participation in the older cohort and accounts for 81% of individuals not in the labor force, followed by 13% due to disability, and 6% for other reasons. Among the younger cohort, disability is the primary reason for individuals reporting labor force non-participation and accounts for 35–40% of this group. About 31% of this group considered themselves retired, and 29% report reasons other than disability or retirement.

We graph the raw data on the CPS outcomes over time in Figures 1 and 2. Figure 1a shows that the share of the population reporting being employed dropped with the onset of the COVID-19 pandemic, but has been trending upward ever since, subject to seasonality throughout the sample period from

Table 2. CPS employment summary statistics

	Ages 50–61		Ages 62–70	
	Pre-Covid	Post-Covid	Pre-Covid	Post-Covid
Employed	0.688	0.669	0.363	0.353
	(0.463)	(0.471)	(0.481)	(0.478)
Employed-absent	0.026	0.030	0.019	0.020
	(0.160)	(0.169)	(0.136)	(0.142)
Unemployed	0.024	0.039	0.013	0.022
	(0.152)	(0.194)	(0.112)	(0.147)
Not in Labor Force: Retired, Disabled, and Other	0.262	0.262	0.606	0.605
	(0.440)	(0.440)	(0.489)	(0.489)
Retired	0.080	0.083	0.491	0.490
	(0.271)	(0.276)	(0.500)	(0.500)
Disabled	0.105	0.092	0.079	0.074
	(0.306)	(0.289)	(0.270)	(0.261)
NILF-Other	0.078	0.087	0.036	0.042
	(0.268)	(0.282)	(0.186)	(0.200)
Observations	1,286,653	414,424	838,723	307,833

Notes: Sample contains civilians aged 50–61 and 62–70 from the January 2015–March 2022 CPS living in the United States. Share of each employment status is listed and weighted using survey weights. An individual is classified as employed-absent if they are absent from their job for a temporary reason during the survey reference week. Pre-Covid captures the mean outcome in the pre-period January 2015–February 2020. Post-Covid captures the mean outcome in the post-period March 2020–March 2022.

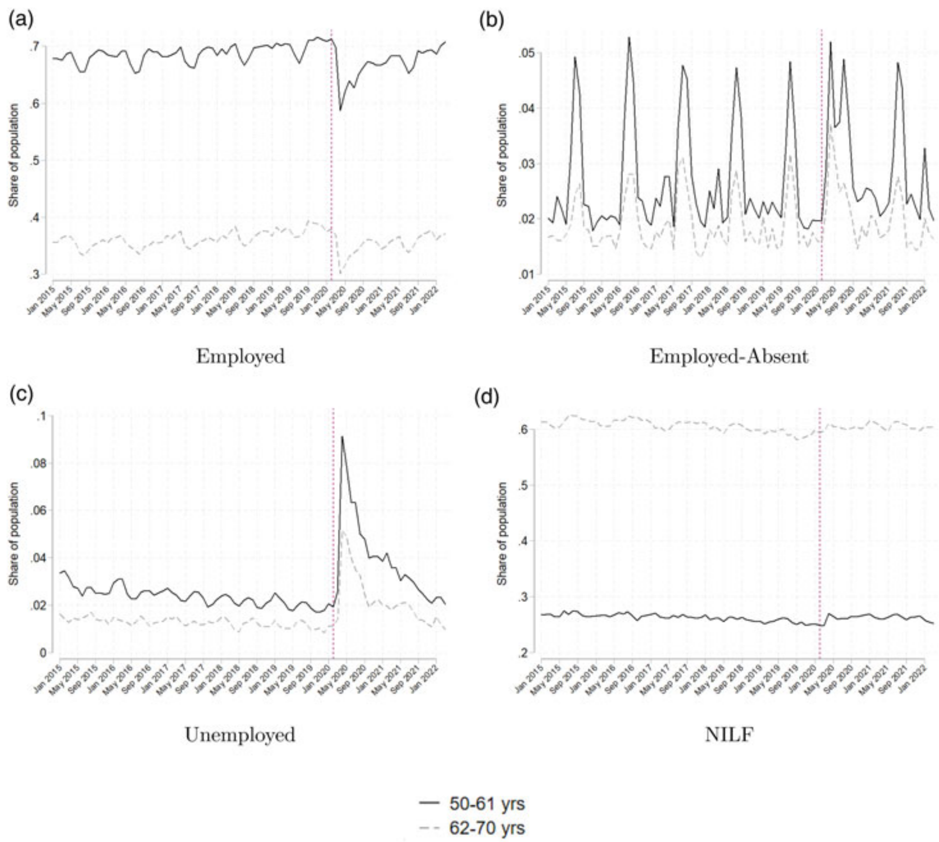

Figure 1. Employment outcomes for ages 50–61 and 62–70, 2015–22.
Notes: Sample contains civilians aged 50–70 from the January 2015–March 2022 CPS living in the United States. Figures depict the share of individuals in an employment category in each month. Estimates are weighted using survey weights.

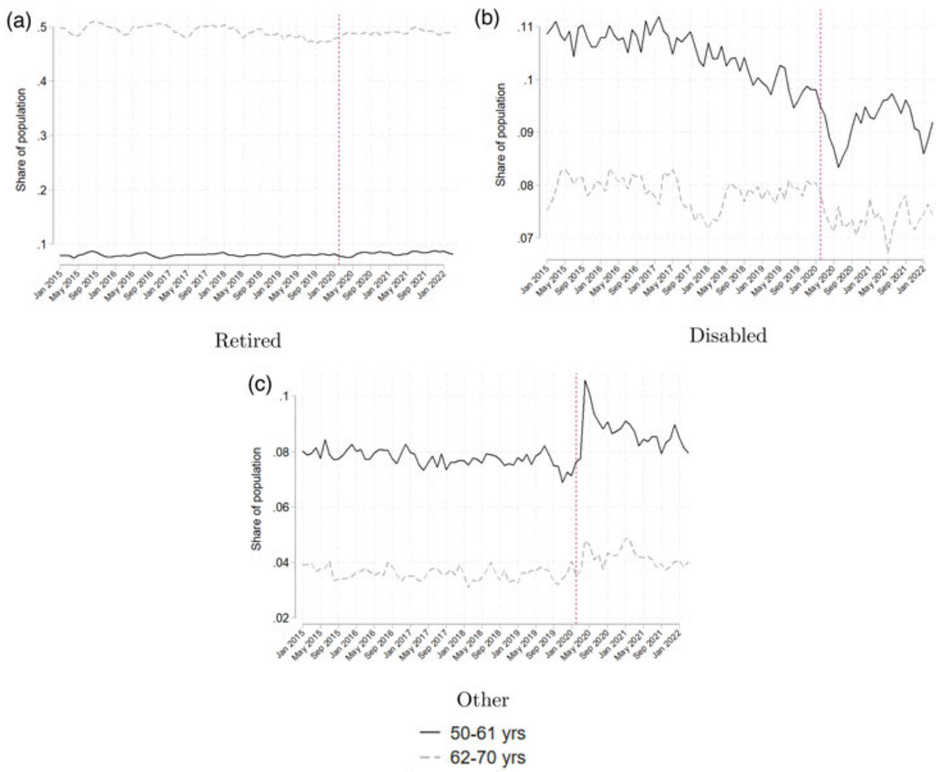

Figure 2. NILF outcomes for ages 50–61 and 62–70, 2015–22.
Notes: Sample contains civilians aged 50–70 from the January 2015–March 2022 CPS living in the United States. Figures depict the share of individuals in an employment category in each month. Estimates are weighted using survey weights.

January 2015 to March 2022. *Employed-Absent* exhibited an uptick early on in the pandemic, depicted in Figure 1b, but fluctuations in 2021 are similar to those in pre-pandemic years. As graphed in Figure 1c, following a large spike in response to the COVID-19 shock, *Unemployed* has steadily trended downward. Figure 1d shows that *NILF* generally has been flat with possibly a slight increase among 50–61-year-olds immediately after COVID-19 that then plateaued higher than the average level in 2019, but in line with earlier years in the sample period. Changes in outcomes over time were similar across age groups, although baseline levels differ significantly across the two age cohorts – the share of the population age 62–70 *Employed*, *Employed-Absent*, and *Unemployed* is smaller than for the 51–60 cohort, while *NILF* is significantly higher.

Figure 2 splits out *NILF* into the three categories: *Retired*, *Disabled*, or *Other*. *Retired* as a share of the population was flat over time, but much larger for the 62–70 age group. Both *Disabled* (Figure 2b) and *Other* (Figure 2c) show much sharper responses to the COVID-19 shock among 50–61-year-olds than among 62–70-year-olds. Despite a larger initial COVID shock, *Disabled* as a share of the population rebounded to a trend comparable to the several months prior to the pandemic for the younger cohort, while it has remained lower than trend post-COVID-19 for the older cohort. Similarly, the share reporting reasons for not participating in the labor force other than disability and retirement jumped in the 50–61-year-old cohort before declining to levels slightly higher than pre-pandemic with a more muted response in the 62–70 cohort.

2.2 SSA administrative claims data

Although the CPS outcomes *Retired* and *Disabled* offer some insight into labor market dynamics affecting Social Security claiming, we turn to the SSA's administrative claims databases to more directly

Table 3. Social security disability application summary statistics

	Pre-Covid	Post-Covid
All	25.49	22.37
	(8.348)	(8.133)
SSDI	9.549	9.527
	(2.788)	(2.947)
SSI	9.539	7.585
	(3.793)	(3.417)
Concurrent	6.406	5.256
	(2.430)	(2.289)
Observations	3,100	1,250

Notes: Sample comes from the SSA State Agency Monthly Workload data from January 2015 to March 2022. Variables denote weekly applications per 100,000 people aged 20–64. Pre-Covid captures the mean outcome in the pre-period January 2015–February 2020. Post-Covid captures the mean outcome in the post-period March 2020–March 2022.

measure these changes (Social Security Administration, 2022*a*, 2022*b*). In particular, we assess changes in applications for SSI, SSDI, Concurrent SSI and SSDI, and SSR. Both the SSI and SSDI programs have the same medical requirements, but target different subgroups. The SSI program focuses on low-income individuals below age 65 with disabilities regardless of work history as well as low-income adults 65 and older without disabilities. The SSDI program supports individuals with disabilities with a sufficient work history, i.e., approximately 10 years of work history with at least five within the last 10 years, although the precise amount of work history varies somewhat over time (Social Security Administration, 2023*a*). Individuals who are attempting to qualify for both programs are captured by the Concurrent SSI and SSDI applications data. Individuals at least 62 years of age are eligible for SSR with the monthly payment amount dependent upon work history and age of claiming (Social Security Administration, 2023*b*).

We focus on applications as a leading indicator of labor market changes that affect SSA, because factors such as administrative processing time and a potentially lengthy appeals process can create a significant, even multi-year, lag from when an individual decides to apply for benefits until actual receipt of benefits. The SSA data are provided at a monthly frequency and follow the federal fiscal calendar from October 1st through September 30th, with all ‘months’ ending on a Friday, leading to 4- and 5-week months that do not directly correspond to actual months.[5] Using this information, we first calculate the average weekly number of claims for each SSA month. We then transform the SSI, SSDI, and Concurrent SSI and SSDI into weekly rates per 100,000 population aged 20–64, and the SSR data into weekly rates per 100,000 population aged 60–69.[6] In addition to total applications for retirement benefits, SSA also provides information on the quantity of applications filed online. These data allow us to examine potential substitution from in-person to online applications in the context of SSA field office closures during the pandemic, providing insight into mechanisms behind changes in disability applications.

The State Average Monthly Workload Data capture all SSI, SSDI, and concurrent SSI and SSDI applications and are available at the state-month level, yielding 4,350 observations between January 2015 and March 2022. The SSA Monthly Data for Retirement Insurance Applications are provided at the national level and distinguish between applications filed via the internet and those filed offline (phone and in-person). The lack of state information in the SSR data leaves us with only 87 observations for analysis. Tables 3 and 4 show pre- and post-COVID means for these variables. In an average week, 25.5 SSI, SSDI, and concurrent applications were received per 100,000 people aged 20–64 prior

[5]Exceptions to this rule exist, but the only exception during our sample period occurred in September 2016 and we adjusted accordingly. More details are available at https://www.ssa.gov/disability/data/ssa-sa-mowl.htm#TimePeriodDescription.

[6]While the disability application data represent data for all ages, direct communication with SSA indicates that the correlation between applications for ages 50+ and overall applications were highly correlated over the study period, with correlation coefficients above 0.90.

Table 4. Retirement application summary statistics

	Pre-Covid	Post-Covid
Total retirement applications	145.2	147.6
	(7.891)	(9.262)
Retirement application filed via internet	74.69	83.04
	(6.673)	(8.672)
Retirement application filed non-internet	70.53	64.56
	(5.740)	(4.640)
Observations	62	25

Notes: Sample comes from the SSA Monthly Data for Retirement Insurance Applications from the January 2015–March 2022. Variables denote weekly applications per 100,000 people aged 60–69. Retirement Application Filed non-Internet denotes all retirement applications filed not through internet, including filing by phone. Pre-Covid captures the mean outcome in the pre-period January 2015–February 2020. Post-Covid captures the mean outcome in the post-period March 2020–March 2022.

to the pandemic; in March 2020 and later, the rate declined to 22.4 applications. Approximately 40% of these applications were for SSDI only, while applications for SSI only constitute about a third of all applications and concurrent SSI and SSDI applications account for the remainder. Prior to March 2020, approximately 145.2 SSR applications were received per 100,000 population aged 60–69; this rate increased slightly to 147.6 during the first 2 years after the pandemic as shown in Table 4. While approximately half of applications were filed via the internet prior to the pandemic, this rate increased slightly to 56% in the 2 years after the onset of the pandemic.

Figures 3a and 3b display SSA disability applications over time. The raw data in Figure 3a suggest that the seasonal pattern exhibited in SSI, SSDI, and concurrent SSI and SSDI applications prior to COVID-19 became less regular post-COVID-19 with reduced seasonality in the first year, but a return to historical seasonality patterns by 2021. SSR data graphed over time in Figure 3b exhibit a noisy but generally flat rate of retirement applications over time. Shifts in application methods from offline to online have occurred, both prior to and following the onset of the COVID-19 pandemic. Online applications appear to be trending upward toward the end of the sample period with offline applications dropping further.

2.3 Expanded UI benefits

We augment our data with information on the availability of expanded UI benefits. The Coronavirus Aid, Relief, and Economic Security (CARES) Act was passed by Congress on March 25, 2020 and signed into law on March 27, 2020. The CARES Act provided fast and direct economic assistance through several programs, some of which expanded the eligibility and generosity of UI benefits. Specifically, the Federal Pandemic Unemployment Compensation (FPUC) provided unemployed workers with expanded weekly benefits, and the Pandemic Unemployment Assistance (PUA) program provided income to unemployed workers ineligible for regular unemployment benefits, such as the self-employed, and those who had already exhausted their state UI benefits. The exact nature of the expanded UI benefits changed over the course of the pandemic. For example, the $600 weekly supplement amount was available between March and July 2020, absent for a period of time, and then reduced to $300 weekly between January and September 2021.[7]

All of the federal programs expired on September 6, 2021, but some states opted to end programs prior to that date. Expiration reduced benefit generosity in terms of the dollar amounts claimants would receive and the types of workers eligible for UI. We construct two state-level, time-varying binary variables: *UI Expiration Month*$_{st}$, which equals 1 during the month where these expanded programs expired in state s, and 0 otherwise; and *Post UI Expiration*$_{st}$, which equals 1 in months after expanded UI programs were expired in state s, and 0 otherwise. This allows us to examine the month during which the regime changed separately from months where expanded UI programs were never in place.

[7]A $300 weekly supplement was also available in Lost Wages Assistance in September and October 2020 as an FEMA disbursement authorized through executive order.

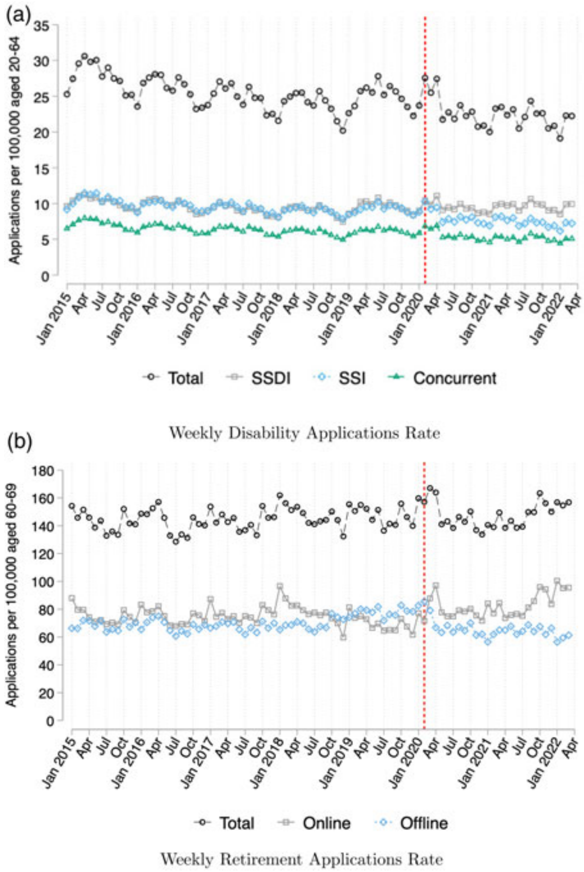

Figure 3. Social security disability and retirement application rates, 2015–22.
Notes: Panel (a) displays aggregated SSA State Agency Monthly Workload data and ranges from January 2015 to March 2022. Application rates are number of weekly applications per 100,000 people aged 20–64. Panel (b) displays aggregated SSA Monthly Data for Retirement Insurance Applications data and ranges from January 2015 to March 2022. Application rates are number of weekly applications per 100,000 people aged 60–69.

Figure 4 shows the month of UI expiration for each state. As shown in the figure, 22 states opted out of at least one program in June 2021, and four in July. The remaining states kept both FPUC and PUA in effect until September 6, 2021.

3. Empirical methods

We estimate the evolution of labor market outcomes for older workers and SSA applications over the COVID-19 pandemic using an event study framework similar to that used in recent work (Bacher-Hicks *et al.*, 2021; Goda *et al.*, 2022). Given the different levels of aggregation across our data sets, we use the three specifications below for our CPS, SSI, and SSDI, and SSR analyses, respectively:

$$Y_{ist} = \sum_{k=-5}^{-1} \beta_k \times 1[e(t) = k] + \sum_{k=1}^{25} \beta_k \times 1[e(t) = k] + \gamma \times 1[e(t) < -5] + \theta_{m(t)} + \tau t + \omega_s + \xi X_{ist} + \varepsilon_{ist} \tag{1a}$$

$$Y_{st} = \sum_{k=-5}^{-1} \beta_k \times 1[e(t) = k] + \sum_{k=1}^{25} \beta_k \times 1[e(t) = k] + \gamma \times 1[e(t) < -5] + \theta_{m(t)} + \omega_s + \varepsilon_{st} \tag{1b}$$

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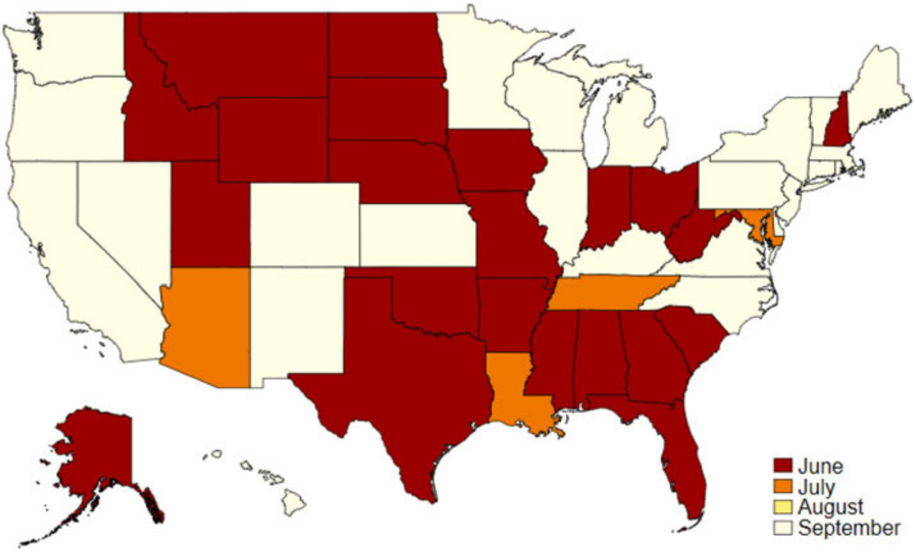

Figure 4. Federal pandemic UI expiration month by state.
Notes: The Federal Pandemic Unemployment Compensation (FPUC) and the Pandemic Unemployment Assistance (PUA) programs were established through the Coronavirus Aid, Relief, and Economic Security (CARES) Act and signed into law on March 27, 2020. All benefits under the FPUC expired on September 6, 2021. The FPUC provided workers with an extra $600 per week in addition to regular state UI benefits or PUA benefits. PUA provided income to unemployed workers who are otherwise ineligible for regular state UI or have previously run out of state UI benefits. Various states opted to allow these programs to expire prior to their initial date. This figure depicts the month in which a state opted out of at least one of the two federal UI programs.

$$
\begin{aligned}
Y_t = \sum_{k=-5}^{-1} \beta_k \times 1[e(t) = k] + \sum_{k=1}^{25} \beta_k \times 1[e(t) = k] \\
+ \gamma \times 1[e(t) < -5] + \theta_{m(t)} + \varepsilon_t
\end{aligned}
\tag{1c}
$$

To assess the effects of COVID-19 on employment outcomes using the CPS data, we employ equation (1a), regressing our outcome variables Y_{ist}, on a series of event-time dummy variables, with $e(t)$ representing the time relative to February 2020 and ranging from −5 to 25, where −5 refers to time periods 5 months or more before February 2020. We further control for month-level indicators $\omega_{m(t)}$. to control for seasonality, a time trend denoted by τ to capture pre-existing trends in our outcome variables, and demographic variables X_{ist}, which include single-year-of-age fixed effects, race, Hispanic ethnicity, education, metro area, and household family size, to reduce the risk that changes in population composition may be affecting our results.

In measuring the effects of COVID-19 on Social Security applications, we use two specifications. For disability applications, we employ equation (1b), using the same strategy for our event-time variables. We further control for month and state fixed effects. Equation (1c) details our analysis for SSR data and is the same as equation (1b) except that state fixed effects are not included because the data are at the national level.

In all three specifications, our coefficients of interest are represented by the β_k.'s. These coefficients measure the deviation between observed outcomes and what we would have expected after controlling for seasonality, changes in the demographic composition, and time-invariant state characteristics, and in our CPS analyses, prior trends.

We further assess changes in our outcome variables using a difference-in-differences approach. This approach collapses the event-time dummies into two aggregated measures, *Post-Covid 1*, representing the time period from March 2020 to March 2021, which overlaps with our prior analysis of initial COVID-19-related changes in labor market outcomes and SSA claiming among older adults

(Goda *et al.*, 2022), and *Post-Covid 2*, which corresponds to the period from April 2021 through March 2022, roughly representing the second year after the onset of the COVID-19 pandemic. The first year is dominated by the initial effects of the pandemic with generally increasing case counts and vaccines only first becoming available to older adults in December 2020. The second period begins in April 2021, when most individuals became eligible for COVID-19 vaccines and COVID-19 cases were declining. This period also includes the rise of variants that led to significant increases in COVID-19 case counts, such as the Delta variant in fall 2021 and the Omicron variant in late 2021 and early 2022. Equations (2a)–(2c) detail our difference-in-differences approach:

$$Y_{ist} = \alpha_1 PostCovid1_{ist} + \alpha_2 PostCovid2_{ist} + \theta_{m(t)} + \tau t + \omega_s + \xi X_{ist} + \varepsilon_{st} \tag{2a}$$

$$Y_{st} = \alpha_1 PostCovid1_{st} + \alpha_2 PostCovid2_{st} + \theta_{m(t)} + \omega_s + \varepsilon_{st} \tag{2b}$$

$$Y_{t} = \alpha_1 PostCovid1_{t} + \alpha_2 PostCovid2_{t} + \theta_{m(t)} + \varepsilon_{st} \tag{2c}$$

Equations (2a)–(2c) include the same set of controls as equations (1a)–(1c). For all specifications using the CPS and disability insurance outcomes, we cluster our standard errors at the state-level to control for heteroskedasticity and arbitrary correlation across observations within a state. For regressions using the SSR data, for which we do not have state identifiers, we include heteroskedasticity-robust standard errors.

Our analysis of CPS data includes time trends to reflect the fact that our outcomes were changing prior to the pandemic, with employment at older ages on a steady upward trajectory and unemployment and labor force non-participation trending down. The inclusion of time trends means that the counterfactual levels of our outcomes in the absence of the pandemic assume the continuation of these trends. However, given the ongoing recovery from the Great Recession occurring over this period, a more conservative benchmark would be to assume that labor force outcomes would have been at the average during the pre-pandemic period. We therefore investigate alternative benchmarks where we omit time trends and define the pre-pandemic period as the average in the 2015–19 period as well as the 2 years prior to the start of the pandemic.

Our last set of analyses assesses whether the expiration of expanded UI programs resulted in changes in disability insurance application outcomes. A causal interpretation relies on the assumption that, conditional on controls, outcomes in states that ended expanded UI programs early would have evolved similarly to states that did not end them early. We examine how trends in our outcomes evolved in the months preceding UI program expiration, and conclude that there is more support for UI expiration decisions being unrelated to claiming Federal disability benefits than state-level employment outcomes; thus, we restrict these analyses to our disability applications data.[8]

To conduct these analyses, we limit our focus to the post-pandemic period from March 2020 onward and estimate a version of equation (2b) that includes $UIExpirationMonth_{st}$, a binary variable with a value of 1 in the month t in which state s allowed one or more of their expanded UI benefits to expire, and $PostUIExpiration_{st}$, a binary variable that equals 1 for all months following the expiration of expanded UI benefits in state s. We differentiate between these two variables because $UIExpirationMonth_{st}$ represents a partially treated month while subsequent months are fully treated. As these specifications are limited to only the post-pandemic period, a time when seasonality patterns were less of a concern than other time-varying factors such as Covid surges from new variants, we include month of year (month × year) fixed effects rather than month fixed effects. These controls allow more flexibility than month fixed effects but were not possible in our main specifications because our Post Covid variables do not have temporal variation across states. The coefficient on $PostUIExpiration_{st}$ summarizes the change in the outcome variable in months where the state no

[8]We cannot conduct a similar analysis with the SSA Retirement applications as our data are only at the national-level data, and so we cannot leverage state-level differences in month of expiration.

longer had special pandemic UI programs in place relative to average values of the outcome during the pandemic period prior to the program expiration.

To further explore the effect of UI expiration on disability claiming in particular, we estimate an event study with the month prior to UI expiration as the omitted period ($t = -1$), tracking the periods 5 months prior and 5 months after UI expiration. Months outside this window are grouped into the $t = -5$ and $t = +5$ periods. These figures show the evolution of disability applications both before and after the expanded UI programs expired.

4. Results

4.1 Labor market outcomes

We first estimate the effect of the COVID-19 pandemic on labor market outcomes for older workers. In Figure 5, we present coefficients from our event study estimation in equation (1a). Beginning with Figure 5a, we examine how the probability of being employed has evolved compared to what would have been expected if prior trends and seasonality had continued, after controlling for changes in demographic composition. February 2020 is assumed to be the period prior to the pandemic, and all prior and following months are shown relative to this baseline. We present the coefficients for the 50–61-year-olds in the black line and with a gray line for 62–70-year-olds.

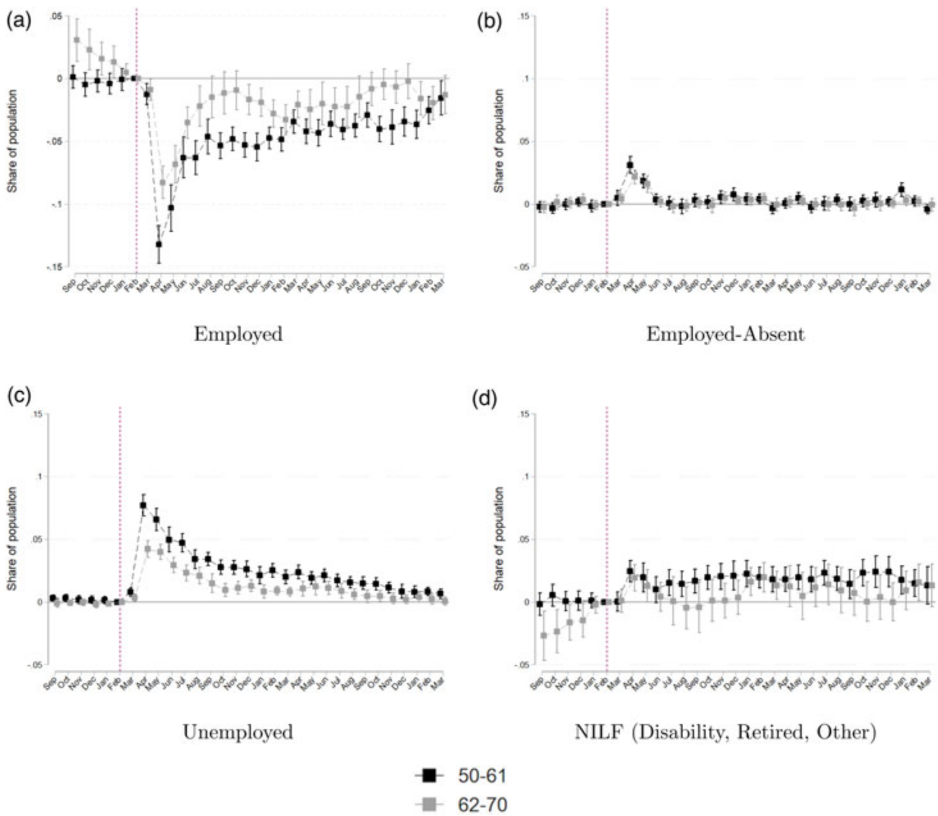

Figure 5. Event studies of employment outcomes from the CPS among 50–70-year-olds.
Notes: Sample contains civilians aged 50–70 from the January 2015–March 2022 CPS living in the United States. Outcome variable is whether or not an individual is employed, employed but absent, unemployed, or not in the labor force. An individual is classified as employed-absent if they are absent from their job for a temporary reason during the survey reference week. Standard errors are robust and clustered at the state level. Estimates are weighted using survey weights and 95% confidence intervals are shown. The event time is relative to February 2020. Regressions include a time trend, month and state fixed effects and adjust for age, sex, race, Hispanic ethnicity, education, and household family size.

When comparing the overall dynamics in the second year of the pandemic to the first year, we see the deviation in employment steadily trending back toward zero, indicating a recovery of employment from the sharp drop and depressed levels seen in year one. By March 2022, the results suggest that employment is returning to what would have expected given pre-pandemic patterns. In fact, the deviations in employment levels for 62–70-year-olds are not statistically different from zero in most months in the latter portion of year two. As seen in Figure 5b, employed but absent only deviated from expectations in the beginning of year one and did not exhibit any unexpected patterns from June 2020 through the second year of COVID-19.

Deviations in unemployment, as seen in Figure 5c, generally display inverse dynamics to those seen with employment above in Figure 5a. While initially peaking around 4–7 percentage points higher than would have been predicted in April 2020, the deviations in unemployment have declined throughout the second year of the pandemic. For 62–70-year-olds, our monthly estimates for deviations in unemployment are no longer statistically different from zero starting in September 2021, suggesting that unemployment rates are not significantly different from what would have been predicted given trends, seasonality, and changes in demographic composition since February 2020.

Finally, we examine the dynamics of individuals classified as not in the labor force (NILF). The dynamics of labor force non-participation differ from that of unemployment and employment. In particular, for the 50–61-year-olds, we do not see a continual reduction in labor force non-participation throughout the second year of the pandemic. Instead, we observe a steady and higher level of labor force non-participation than we would have expected. By the beginning of 2022, the point estimates begin to suggest a slight, mild trend of recovery toward what we would have expected, but the coefficients are not statistically different from earlier in year two. Results for the 62–70-year-olds are noisier; however, relative to February 2020, labor force non-participation is slightly higher for this group in March 2022.

Next we collapse our event study estimates into two post-COVID-19 indicators, one for the first year and one for the second year of the pandemic. These results are presented in Table 5, with the estimates for 50–61-year-olds in panel A and 62–70-year-olds in panel B. Starting with column (1) of panel A, comparing the coefficient estimates for year one and year two, we observe an estimate almost half as large in the second year as the first year of the pandemic. In year two, employment was about 3.1 and 2.5 percentage points lower than predicted levels for 50–61-year-olds and 62–70-year-olds, respectively. These differences amount to a 4.5% and 7% reduction relative to the

Table 5. Changes in employment outcomes following the COVID-19 pandemic

	(1) Employed	(2) Employed-Absent	(3) Unemployed	(4) NILF
(A) 50–61-year-olds				
Post-Covid 1	−0.055*** (0.003)	0.006*** (0.001)	0.034*** (0.002)	0.014*** (0.003)
Post-Covid 2	−0.031*** (0.003)	0.002** (0.001)	0.013*** (0.002)	0.016*** (0.004)
Observations	1,701,077	1,701,077	1,701,077	1,701,077
Pre-Covid mean	0.688	0.026	0.024	0.262
T-test PC1 = PC2	0.000	0.000	0.000	0.488
(B) 62–70-year-olds				
Post-Covid 1	−0.038*** (0.004)	0.003*** (0.001)	0.019*** (0.002)	0.016*** (0.003)
Post-Covid 2	−0.025*** (0.004)	−0.000 (0.001)	0.007*** (0.002)	0.018*** (0.004)
Observations	1,146,556	1,146,556	1,146,556	1,146,556
Pre-Covid mean	0.363	0.019	0.013	0.606
T-test PC1 = PC2	0.000	0.000	0.000	0.459

Standard errors in parentheses.
Notes: Samples contain civilians aged 50–61 and 62–70 from the January 2015–March 2022 CPS living in the United States. Outcome variable is whether or not an individual is employed, unemployed, or not in the labor force due to disability, retirement, or another reason respectively. An individual is classified as employed-absent if they are absent from their job for a temporary reason during the survey reference week. Standard errors are robust and clustered at the state level. Estimates are weighted using survey weights. *Post-Covid 1* equals 1 between March 2020 and March 2021, and *Post-Covid 2* equals 1 between April 2021 and March 2022. Regressions include a time trend, and month and state fixed effects, and adjust for age, sex, race, Hispanic ethnicity, education, and household family size. Pre-Covid means captures the mean of the dependent variable in the pre-period January 2015–February 2020.
*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Table 6. Changes in NILF following the COVID-19 pandemic

	(1) NILF	(2) Retired	(3) Disabled	(4) Other
(A) 50–61-year-olds				
Post-Covid 1	0.014*** (0.003)	0.003* (0.002)	−0.005*** (0.002)	0.017*** (0.001)
Post-Covid 2	0.016*** (0.004)	0.006** (0.003)	0.000 (0.003)	0.010*** (0.002)
Observations	1,701,077	1,701,077	1,701,077	1,701,077
Pre-Covid mean	0.262	0.080	0.105	0.078
T-test PC1 = PC2	0.488	0.086	0.041	0.000
(B) 62–70-year-olds				
Post-Covid 1	0.016*** (0.003)	0.012*** (0.004)	−0.004* (0.002)	0.008*** (0.001)
Post-Covid 2	0.018*** (0.004)	0.018*** (0.006)	−0.005* (0.002)	0.005*** (0.002)
Observations	1,146,556	1,146,556	1,146,556	1,146,556
Pre-Covid mean	0.606	0.491	0.079	0.036
T-test PC1 = PC2	0.459	0.075	0.694	0.031

Standard errors in parentheses.
Notes: Samples contain civilians aged 50–61 and 62–70 from the January 2015–March 2022 CPS living in the United States. Outcome variable is whether or not an individual is not in the labor force as well as each subcategory of NILF: disability, retirement, or another reason. Standard errors are robust and clustered at the state level. Estimates are weighted using survey weights. *Post-Covid 1* equals 1 between March 2020 and March 2021, and *Post-Covid 2* equals 1 between April 2021 and March 2022. Regressions include a time trend, and month and state fixed effects, and adjust for age, sex, race, Hispanic ethnicity, education, and household family size. Pre-Covid means captures the mean of the dependent variable in the pre-period January 2015–February 2020.
*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

pre-pandemic mean. The magnitude of the deviation in year two is significantly smaller than the deviation in year one for both age groups.

The lower levels of employment are due to both increases in unemployment and increases in labor force non-participation. While the increase in unemployment was approximately half of the reduction in employment during year one, unemployment constituted approximately 30–40% of the reduction in employment in the second year.

By contrast, the increase in labor force non-participation accounts for the majority of the reduction in employment for both age groups. This increase is consistent with some individuals who were previously unemployed and looking for work subsequently choosing to leave the labor force all together in the second year of the pandemic.

We now turn to Table 6 where we separate the labor force non-participation by the reason the respondent noted, namely that they were out of the labor force due to being retired, disabled, or for reasons other than retirement or disability. The results in Table 6 show a shift between year one and two of the pandemic. In the first year of the pandemic, there was a significant portion not looking for work for other reasons. By the second year of the pandemic, the deviation in non-participation due to reasons other than retirement or disability declined, while the deviation in non-participation due to retirement increased.[9] Non-participation for disability reasons returned to predicted levels for 50–61-year-olds, eliminating the slight reduction seen during the first year in the pandemic, and held steady during the second year of the pandemic for 62–70-year-olds. Together, these results indicate a transition toward retirement and away from exits due to other reasons. We note, however, that differential non-response during the pandemic among low-income populations discussed earlier may affect our results by understating labor force exits, as the

[9]It is possible that a component of the reduction in disability as a reason for labor force nonparticipation among 50–61-year-olds in Table 6 comes from individuals who received a negative determination from SSA, and therefore, changed their disability status. However, in general, SSI and SSDI receipt is reported more frequently than are work limitations or affirmative answers to the six-part question on difficulties with daily activities, the two primary measures of self-reported disability in the CPS. Burkhauser *et al.* (2012) show that, among those reporting SSI and SSDI receipt, only 84.1% reported a work limitation and only 63.3% reported a difficulty with hearing, vision, memory, physical difficulty, mobility limitations or personal care; 92% of those reporting SSI or SSDI receipt answer affirmatively to either the work limitation question or one of the parts of the six-part difficulty question. These percentages suggest that the factors driving SSI and SSDI disability determinations may differ from those leading to self-determined disabilities.

populations who were more affected by non-response may be those who are more likely to move along the employment and participation margin.

We also conduct two additional versions of our analysis with alternative counterfactual benchmarks. The first omits time trends from the specification and thus compares outcomes during the pandemic to the average for the 2015–19 period. The second is similar but shortens the pre-pandemic period to the same number of months as in the post-pandemic period, resulting in a sample period of February 2018–March 2022, with 25 months in each of the pre- and post-pandemic era.

The results are included in Appendix A. We present results for the first alternative in Figure A.1 and Tables A.1 and A.2. The results are qualitatively similar though smaller in magnitude owing to the fact that the counterfactual employment rate is lower and counterfactual unemployment and non-participation rates are higher in the 2015–19 period on average relative to what the continuation of the trend over those years would imply. In Figure A.2 and Tables A.3 and A.4, we present the results for the second alternative benchmark. When we shorten our pre-pandemic period to be the same number of months in the post-pandemic period, the results are both qualitatively and quantitatively in line with our baseline results.

4.2 SSA applications

We now examine changes in applications for SSI, SSDI, and SSR. We first estimate equation (1b) to evaluate the month by month deviations relative to February 2020 in disability applications. Starting with Figure 6a, we observe a sharp reduction in total SSI and SSDI applications that levels off in the

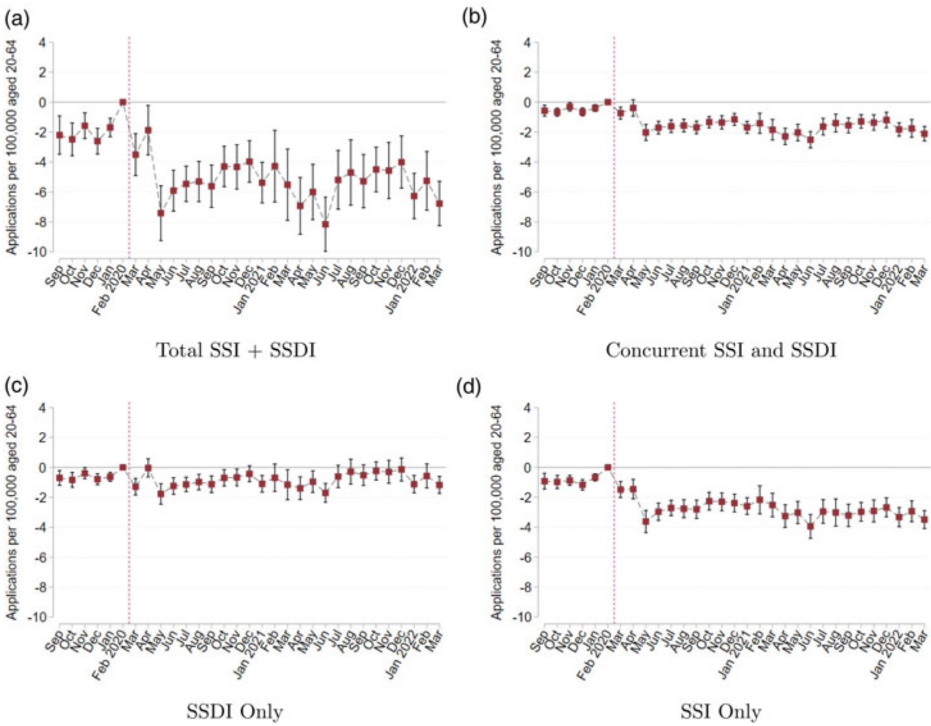

Figure 6. Event study of social security disability applications.
Notes: Sample comes from the SSA State Agency Monthly Workload and ranges from January 2015 to March 2022. Outcome variable is weekly applications per 100,000 people aged 20–64. Standard errors are robust and clustered at the state level. The 95% confidence intervals are shown. Regressions include month and state fixed effects and event time relative to February 2020.

Table 7. Changes in disability applications during the COVID-19 pandemic

	(1) All	(2) SSDI	(3) SSI	(4) Concurrent
Post-Covid 1	−2.82∗∗∗	−0.15	−1.66∗∗∗	−1.02∗∗∗
	(0.466)	(0.180)	(0.186)	(0.141)
Post-Covid 2	−3.63∗∗∗	0.04	−2.33∗∗∗	−1.34∗∗∗
	(0.482)	(0.187)	(0.199)	(0.148)
Observations	4,350	4,350	4,350	4,350
Pre-Covid mean	25.49	9.55	9.54	6.41
T-test PC1 = PC2	0.09	0.33	0.00	0.02

Robust and clustered (at state level) standard errors in parentheses.
Notes: Sample comes from the SSA State Agency Monthly Workload and ranges from January 2015 to March 2022. Outcome variable is weekly applications per 100,000 people aged 20–64. Standard errors are robust and clustered at the state level. Regressions include month and state fixed effects. *Post-Covid 1* equals 1 between March 2020 and March 2021, and *Post-Covid 2* equals 1 between April 2021 and March 2022.
∗p < 0.10, ∗∗p < 0.05, ∗∗∗p < 0.01.

end of year one around five fewer applications per 100,000 individuals aged 20–64 than would have been predicted. In the second year of the pandemic, we continue to see a depressed level of applications for SSI and/or SSDI relative to predicted levels that is similar in magnitude.

Next, we decompose total disability applications into three subgroups: concurrent SSI and SSDI applications (Figure 6b), SSDI only applications (Figure 6c), and SSI only applications (Figure 6d). There are several patterns of note when examining the decomposition. First, the dynamics in Figures 6b and 6d follow closely to that of total applications, and drive the majority of the total effect. Both stay at a depressed level of applications relative to what pre-pandemic patterns would have anticipated. Second, as seen in Figure 6c, applications for SSDI only follow a different pattern from applications for SSI or concurrent applications. We do not observe a significant decline in SSDI only applications relative to the pre-pandemic levels.

In Table 7, we estimate the changes in the outcomes during the COVID-19 pandemic relative to the pre-pandemic period and compare the coefficients for Post-Covid 1 and Post-Covid 2 to differentiate the magnitude of the effects in year one and year two. The results in column (1) show that the deviation in total applications in year two is 3.63 fewer applications per 100,000 people aged 20–64, and this coefficient is significantly different (at the 10% level) from the 2.82 reduction estimated in year one. Column (2) shows that SSDI only applications were not significantly lower than predicted in either post-Covid period. However, deviations in SSI only (column 3) and concurrent SSI and SSDI applications (column 4) both grew in magnitude during the second year of the pandemic remaining significantly lower than pre-pandemic levels. Column (3) indicates that there were 2.33 fewer SSI only applications in year two, a significant decrease from year one which saw 1.66 fewer applications. Column (4) indicates that there were 1.34 fewer concurrent SSI and SSDI applications in year two, a significant decrease from 1.02 fewer applications in year one. These results reinforce findings from the first year of the pandemic, during which time SSI represented a significant share of ‘missing’ applications for disability insurance (Goda *et al.*, 2022).

Turning to Figure 7, we evaluate deviations in applications for SSR benefits. In year one, we found no evidence of a statistically significant change in total SSR applications, but some evidence that applications filed via the internet substituted for applications filed offline. While results in Figure 7 are noisy given the national level data, the estimates suggest a slightly higher level of applications in late 2021 and early 2022 relative to earlier in the pandemic. This pattern is more noticeable in Figure 7b, where we see higher levels of applications filed via the internet in late 2021 compared with late 2020. In Figure 7c, we see persistently lower levels of applications filed offline through March 2022. These patterns across mode of application likely result from the fact that Social Security offices did not reopen until April 7, 2022.

In Table 8, column (1), when we collapse the monthly coefficients into Post-Covid 1 and Post-Covid 2, we find that while in the first year of the pandemic, applications shifted from online to offline with no change in the overall total, in the second year, there was a statistically significant

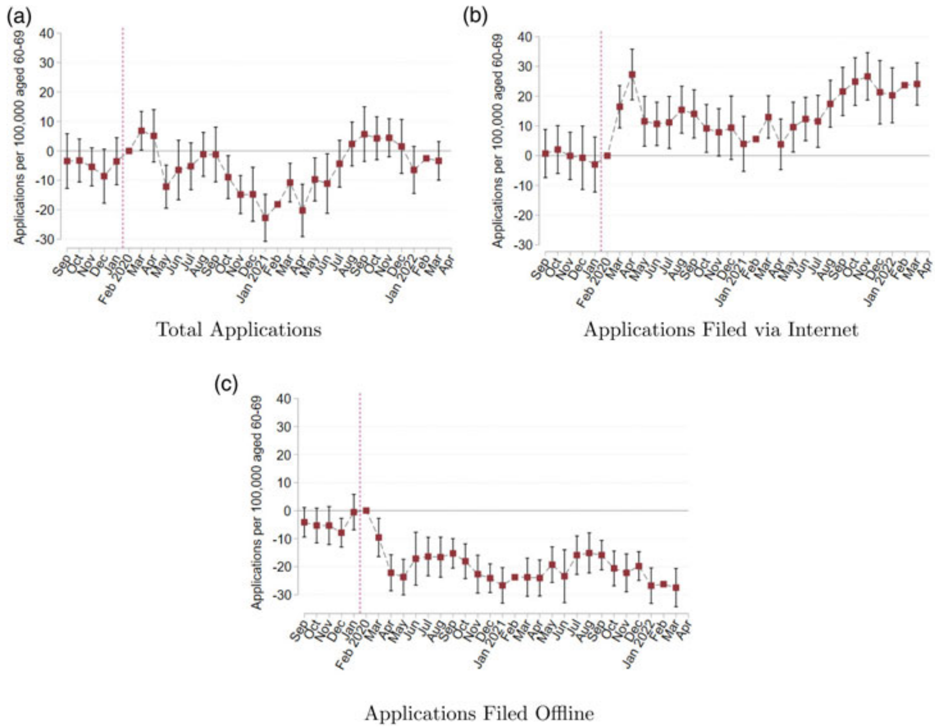

Figure 7. Event study of SSR applications.
Notes: Sample comes from the SSA Monthly Data for Retirement Insurance Applications and ranges from January 2015 to March 2022. Outcome variable is weekly applications per 100,000 people aged 60–69. Standard errors are robust. The 95% confidence intervals are shown. Regressions include month fixed effects and event time relative to February 2020.

increase in total applications. Specifically, in the second year there are 4.75 more applications per 100,000 individuals aged 60–69 relative to predicted levels. The total effect in column (1) is almost entirely driven by increases in applications filed via the internet. These results are consistent with a larger share of older individuals reporting labor force non-participation due to retirement in Table 6.

The fact that SSA offices remained closed until April 2022 and applications for SSR shifted from online to offline during the pandemic provides another possible mechanism for the decline in SSI and

Table 8. Changes in retirement applications during the COVID-19 pandemic

	(1) Total	(2) Filed via Internet	(3) Filed offline
Post-Covid 1	−0.09	5.33***	−5.43***
	(2.457)	(1.699)	(1.453)
Post-Covid 2	4.75**	11.62***	−6.87***
	(2.138)	(2.227)	(1.351)
Observations	87	87	87
Pre-Covid mean	145.23	74.69	70.53
T-test PC1 = PC2	0.13	0.02	0.41

Robust and clustered (at state level) standard errors in parentheses.
Notes: Sample comes from the SSA Monthly Data for Retirement Insurance Applications and ranges from January 2015 to March 2022. Outcome variables represent weekly applications per 100,000 people aged 60–69. Standard errors are robust. Regressions include month fixed effects. *Post-Covid 1* equals 1 between March 2020 and March 2021, and *Post-Covid 2* equals 1 between April 2021 and March 2022.
*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Table 9. Changes in disability applications during the COVID-19 pandemic: UI expiration

	(1) All	(2) SSDI	(3) SSI	(4) Concurrent
UI expiration month	0.28	0.34	−0.10	0.03
	(0.746)	(0.336)	(0.270)	(0.206)
Post UI expiration	1.62	0.78	0.23	0.62**
	(1.123)	(0.472)	(0.399)	(0.296)
Observations	1,250	1,250	1,250	1,250
Pre-Covid mean	25.49	9.55	9.54	6.41

Robust and clustered (at state level) standard errors in parentheses.
Notes: Sample comes from the SSA State Agency Monthly Workload and ranges from March 2020 to March 2022. Outcome variable is weekly applications per 100,000 people aged 20–64. Standard errors are robust and clustered at the state level. Regressions include month of year and state fixed effects. *UI Expiration Month* equals 1 if expanded UI programs expired during the month; *Post UI Expiration* equals 1 in months following expanded UI program expiration.
*p < 0.10, **p < 0.05, ***p < 0.01.

concurrent applications shown in the previous section. Specifically, if applicants for SSI and concurrent benefits face barriers in applying for benefits online, office closures could instead lead to reduced applications overall.

4.3 Expiration of expanded UI benefits

As explained in Section 2.3, while federal programs expanding UI expired in September 2021, there were several states that allowed one or both of their UI programs to expire in June, July, or August 2021. We estimate a version of equation (2b) that limits our sample period to only include the pandemic period from March 2020 onward and incorporates the state-level variation in when expanded UI benefit expired to assess whether there were associated changes in disability insurance applications. As described in Section 3, $UIExpirationMonth_{st}$ has a value of 1 in the month t in which state s allowed one or both of their expanded UI benefits to expire. $PostUIExpiration_{st}$ has a value of 1 for all months following the expiration of expanded UI benefits in state s. The specifications also include state fixed effects and month-of-year fixed effects to control for fixed differences across states and time patterns during the pandemic that may have resulted in overall higher or lower applications in any given month.

In Table 9 we evaluate the relationship between UI expiration and deviations in applications for disability. During the month of program expiration, which represents a period where expanded UI programs were partially in place, there is no evidence that application rates differ from earlier in the pandemic. During the months following program expiration, concurrent SSI and SSDI application rates are statistically significantly higher (without correction for multiple comparisons). The magnitude of the increase, 0.62 applications per 100,000 individuals aged 20–64, represents a reversal of approximately half of the decline that was seen over the course of the pandemic in Table 7. While the corresponding coefficients in the other columns are positive and suggestive of a behavioral response, they are not statistically significant. Decomposing the post-UI expiration effect in line with Goodman-Bacon (2021) indicates that, while most of the effects of UI expiration on applications are positive, substantial heterogeneity exists and negative effects cannot be ruled out for SSDI only and SSI only applications.

In Figure 8, we plot event study figures that show the evolution of Social Security disability applications before and after UI expiration that come from modified versions of our main specification that include event time binary variables for 5 months before and after UI expiration, where time −5(+5) include all periods earlier (later) than 5 months before (after) UI expiration, and 0 represents the month during which the programs first expired. Consistent with the results in Table 9, we see that applications are slightly elevated in the months following UI expiration. These effects appear to be concentrated in the first few months after expanded UI programs expire. In general, these figures do not show evidence that application rates were evolving differently in the months preceding the expiration of the expanded UI programs.

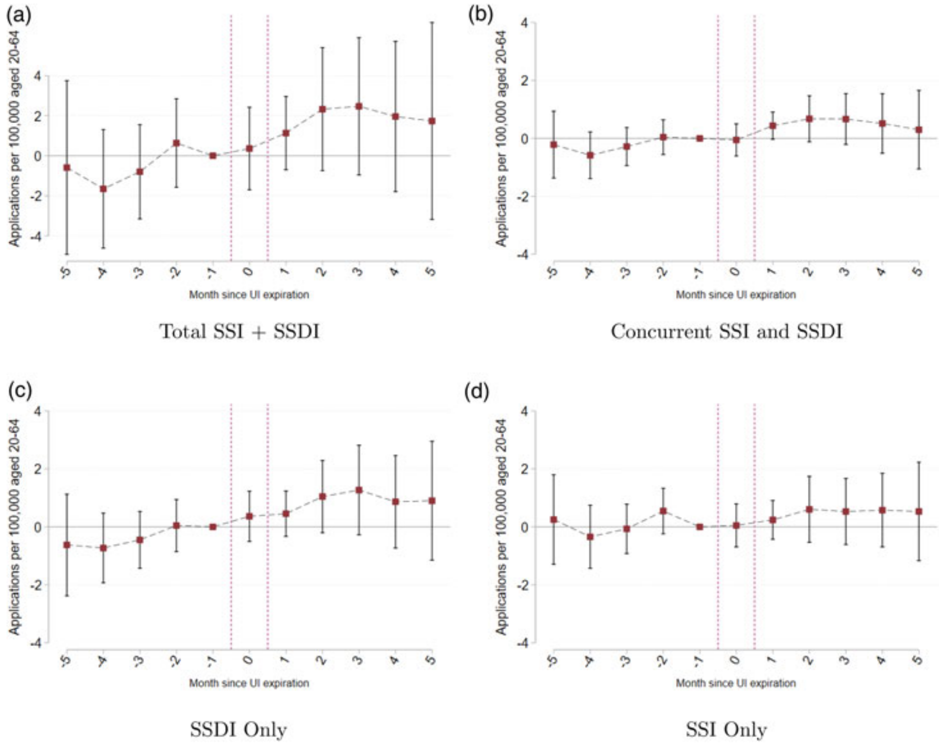

Figure 8. Event study of social security disability applications: UI expiration.
Notes: Sample comes from the SSA State Agency Monthly Workload and ranges from March 2020 to March 2022. Outcome variable is weekly applications per 100,000 people aged 20–64. Standard errors are robust and clustered at the state level. The 95% confidence intervals are shown. Regressions include month of year and state fixed effects. Months since UI expiration is equal to zero in the month that expanded UI programs expired; −5 denotes five or more months prior to expiration; 5 denotes five or more months after expiration.

5. Conclusion

The COVID-19 pandemic that began in March 2020 led to unprecedented disruption in the economy. Employment levels dropped dramatically in the 2 months after its onset before a rapid, partial recovery toward pre-pandemic levels.

The prevalence of labor force non-participation remained elevated throughout both years and reasons for non-participation remained fairly constant for ages 50–61 and 62–70, with some evidence of a shift from non-participation due to reasons other than retirement and disability toward non-participation due to retirement. Reductions in non-participation due to disability persisted in the second year for the 62- to 70-year-old age group, but reverted to pre-pandemic levels among the 50- to 61-year-old age group. Consistent with the idea that some who had left the labor force during the first year were waiting some time before reporting retirement, we see no change in retirement applications in the first year of the pandemic followed by a statistically significant increase in retirement applications of approximately 3% during the second year.

Applications for disability benefits remained depressed during the first 2 years of the pandemic, driven by SSI and concurrent SSI and SSDI applications. SSDI applications appear largely unaffected by the pandemic. The distributional shift toward online rather than offline retirement applications and the fact that SSA offices did not reopen for in-person appointments until April 2022, after the end of our sample period, suggest some of the reduction in applications for SSI and concurrent SSI and SSDI applications may reverse with increased access to in-person SSA application services.

We also examine the role of expanded UI benefits in the labor market recovery during the second year of the pandemic. While UI expansions were in place during the full first year of the pandemic in some capacity, these enhanced benefits began to expire in the summer of 2021. We find evidence that concurrent SSI and SSDI applications increased after these programs expired, reversing approximately half of their decline during the pandemic.

The pandemic recession differs in many ways from prior recessions, and the second year of the pandemic came with widespread vaccine availability, new coronavirus variants that generated large increases in infections, and policy changes. As the COVID-19 pandemic continues to evolve, it will be important to continue to monitor how labor market outcomes among older workers and spillovers to Social Security change as the COVID-19 pandemic transitions to an endemic state.

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Appendix A: Alternative benchmarks

A.1 Counterfactual: 2015–19 average

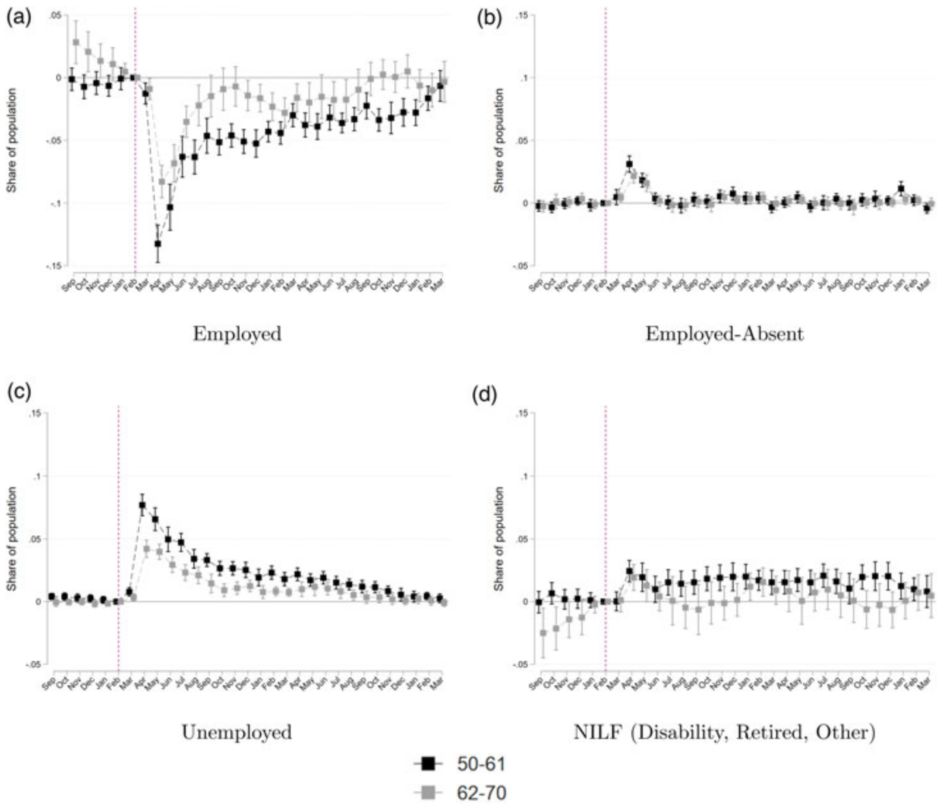

Figure A.1. Event studies of employment outcomes from the CPS among 50–70-year-olds.
Notes: Sample contains civilians aged 50–70 from the January 2015–March 2022 CPS living in the United States. Outcome variable is whether or not an individual is employed, employed but absent, unemployed, or not in the labor force. An individual is classified as employed-absent if they are absent from their job for a temporary reason during the survey reference week. Standard errors are robust and clustered at the state level. Estimates are weighted using survey weights and 95% confidence intervals are shown. The event time is relative to February 2020. Regressions include month and state fixed effects and adjust for year of age fixed effects, sex, race, Hispanic ethnicity, education, and household family size.

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Table A.1. Changes in employment outcomes following the COVID-19 pandemic

	(1) Employed	(2) Employed-Absent	(3) Unemployed	(4) NILF
(A) 50–61-year-olds				
Post-Covid 1	−0.038*** (0.003)	0.005*** (0.001)	0.027*** (0.002)	0.005** (0.002)
Post-Covid 2	−0.009*** (0.003)	0.001 (0.001)	0.003** (0.001)	0.005 (0.003)
Observations	1,701,077	1,701,077	1,701,077	1,701,077
Pre-Covid mean	0.688	0.026	0.024	0.262
T-test PC1 = PC2	0.000	0.000	0.000	0.793
(B) 62–70-year-olds				
Post-Covid 1	−0.021*** (0.003)	0.003*** (0.001)	0.016*** (0.001)	0.002 (0.002)
Post-Covid 2	−0.002 (0.003)	−0.000 (0.001)	0.003** (0.001)	−0.001 (0.003)
Observations	1,146,556	1,146,556	1,146,556	1,146,556
Pre-Covid mean	0.363	0.019	0.013	0.606
T-test PC1 = PC2	0.000	0.000	0.000	0.448

Standard errors in parentheses.

Notes: Samples contain civilians aged 50–61 and 62–70 from the January 2015–March 2022 CPS living in the United States. Outcome variable is whether or not an individual is employed, unemployed, or not in the labor force due to disability, retirement, or another reason respectively. An individual is classified as employed-absent if they are absent from their job for a temporary reason during the survey reference week. Standard errors are robust and clustered at the state level. Estimates are weighted using survey weights. The Post-Covid estimate captures the change in employment outcome using January 2015–February 2020 as the pre-period and March 2020–March 2021 as the first post-period and April 2021–March 2022 as the second post-period. Regressions include month and state fixed effects, and adjust for year of age fixed effects, sex, race, Hispanic ethnicity, education, and household family size. Pre-Covid means captures the mean of the dependent variable in the pre-period January 2015–February 2020.

$*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

Table A.2. Changes in NILF following the COVID-19 pandemic

	(1) NILF	(2) Retired	(3) Disabled	(4) Other
(A) 50–61-year-olds				
Post-Covid 1	0.005** (0.002)	0.001 (0.001)	−0.010*** (0.001)	0.014*** (0.001)
Post-Covid 2	0.005 (0.003)	0.004*** (0.001)	−0.006*** (0.002)	0.007*** (0.001)
Observations	1,701,077	1,701,077	1,701,077	1,701,077
Pre-Covid mean	0.262	0.080	0.105	0.078
T-test PC1 = PC2	0.793	0.080	0.129	0.000
(B) 62–70-year-olds				
Post-Covid 1	0.002 (0.002)	−0.003 (0.003)	−0.003** (0.002)	0.008*** (0.001)
Post-Covid 2	−0.001 (0.003)	−0.001 (0.003)	−0.004 (0.002)	0.004*** (0.001)
Observations	1,146,556	1,146,556	1,146,556	1,146,556
Pre-Covid Mean	0.606	0.491	0.079	0.036
T-test PC1 = PC2	0.448	0.550	0.868	0.016

Standard errors in parentheses.

Notes: Samples contain civilians aged 50–61 and 62–70 from the January 2015–March 2022 CPS living in the United States. Outcome variable is whether or not an individual is not in the labor force as well as each subcategory of NILF: disability, retirement, or another reason. Standard errors are robust and clustered at the state level. Estimates are weighted using survey weights. The Post-Covid estimate captures the change in employment outcome using January 2015–February 2020 as the pre-period and March 2020–March 2021 as the first post-period and April 2021–March 2022 as the second post-period. Regressions include month and state fixed effects, and adjust for age, sex, race, Hispanic ethnicity, education, and household family size. Pre-Covid means captures the mean of the dependent variable in the pre-period January 2015–February 2020.

$*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

A.2 Counterfactual: February 2018–February 2020 average

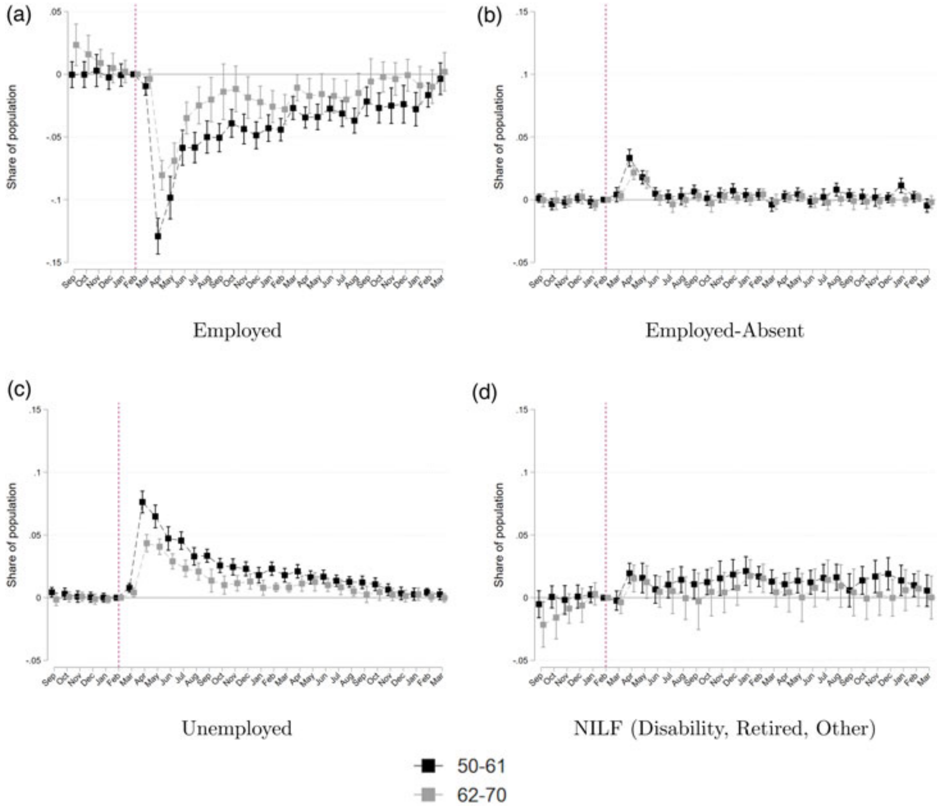

Figure A.2. Event studies of employment outcomes from the CPS among 50–70-year-olds.
Notes: Sample contains civilians aged 50–70 from the February 2018–March 2022 CPS living in the United States. Outcome variable is whether or not an individual is employed, employed but absent, unemployed, or not in the labor force. An individual is classified as employed-absent if they are absent from their job for a temporary reason during the survey reference week. Standard errors are robust and clustered at the state level. Estimates are weighted using survey weights and 95% confidence intervals are shown. The event time is relative to February 2020. Regressions include month and state fixed effects and adjust for age, sex, race, Hispanic ethnicity, education, and household family size.

Table A.3. Changes in employment outcomes following the COVID-19 pandemic

	(1) Employed	(2) Employed-Absent	(3) Unemployed	(4) NILF
(A) 50–61-year-olds				
Post-Covid 1	−0.047*** (0.003)	0.006*** (0.001)	0.031*** (0.002)	0.010*** (0.002)
Post-Covid 2	−0.017*** (0.003)	0.002** (0.001)	0.006*** (0.001)	0.010*** (0.003)
Observations	901,574	901,574	901,574	901,574
Pre-Covid mean	0.688	0.026	0.024	0.262
T-test PC1 = PC2	0.000	0.000	0.000	0.774
(B) 62–70-year-olds				
Post-Covid 1	−0.030*** (0.003)	0.004*** (0.001)	0.017*** (0.002)	0.010*** (0.003)
Post-Covid 2	−0.011*** (0.003)	−0.000 (0.001)	0.004*** (0.001)	0.007** (0.003)
Observations	644,848	644,848	644,848	644,848
Pre-Covid mean	0.363	0.019	0.013	0.606
T-test PC1 = PC2	0.000	0.000	0.000	0.481

Standard errors in parentheses.
Notes: Samples contain civilians aged 50–61 and 62–70 from the February 2018–March 2022 CPS living in the United States. Outcome variable is whether or not an individual is employed, unemployed, or not in the labor force due to disability, retirement, or another reason respectively. An individual is classified as employed-absent if they are absent from their job for a temporary reason during the survey reference week. Standard errors are robust and clustered at the state level. Estimates are weighted using survey weights. The Post-Covid estimate captures the change in employment outcome using February 2018–February 2020 as the pre-period and March 2020–March 2021 as the first post-period and April 2021–March 2022 as the second post-period. Regressions include month and state fixed effects, and adjust for year of age fixed effects, sex, race, Hispanic ethnicity, education, and household family size. Pre-Covid means captures the mean of the dependent variable in the pre-period February 2018–February 2020.
*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Table A.4. Changes in NILF following the COVID-19 pandemic

	(1) NILF	(2) Retired	(3) Disabled	(4) Other
(A) 50–61-year-olds				
Post-Covid 1	0.010*** (0.002)	0.002* (0.001)	−0.007*** (0.001)	0.015*** (0.001)
Post-Covid 2	0.010*** (0.003)	0.005*** (0.002)	−0.003 (0.002)	0.008*** (0.001)
Observations	901,574	901,574	901,574	901,574
Pre-Covid mean	0.262	0.080	0.105	0.078
T-test PC1 = PC2	0.774	0.087	0.131	0.000
(B) 62–70-year-olds				
Post-Covid 1	0.010*** (0.003)	0.005 (0.003)	−0.003** (0.002)	0.008*** (0.001)
Post-Covid 2	0.007** (0.003)	0.007* (0.004)	−0.004** (0.002)	0.005*** (0.001)
Observations	644,848	644,848	644,848	644,848
Pre-Covid mean	0.606	0.491	0.079	0.036
T-test PC1 = PC2	0.481	0.473	0.827	0.014

Standard errors in parentheses.
Notes: Samples contain civilians aged 50–61 and 62–70 from the February 2018–March 2022 CPS living in the United States. Outcome variable is whether or not an individual is not in the labor force as well as each subcategory of NILF: disability, retirement, or another reason. Standard errors are robust and clustered at the state level. Estimates are weighted using survey weights. The Post-Covid estimate captures the change in employment outcome using January 2018–February 2020 as the pre-period and March 2020–March 2021 as the first post-period and April 2021–March 2022 as the second post-period. Regressions include month and state fixed effects, and adjust for year of age fixed effects, sex, race, Hispanic ethnicity, education, and household family size. Pre-Covid means captures the mean of the dependent variable in the pre-period February 2018–February 2020.
*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

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