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Gopi Shah Goda
Emilie Jackson
Lauren Hersch Nicholas
Sarah Stith

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ABSTRACT

The COVID-19 pandemic triggered a large and immediate drop in employment among US workers, along with major expansions of unemployment insurance 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 unemployment insurance, we find that the loss of these additional financial supports is associated with a drop in older adult unemployment rates and an increase in Social Security Disability Insurance claiming. Social Security retirement benefit claiming has rebounded to pre-pandemic levels, but has shifted from offline to online applications.

Gopi Shah Goda
Stanford University
SIEPR
366 Galvez St.
Stanford, CA 94305
and NBER
gopi@stanford.edu

Emilie Jackson
Michigan State University
486 W. Circle Dr
25D Marshall-Adams Hall
East Lansing, MI 48824
emiliej@msu.edu

Lauren Hersch Nicholas
Colorado School of Public Health
CU Anschutz Fitzsimons Building
13001 East 17th Place
3rd Floor, Mail Stop B119
Aurora, CO 80045
lauren.h.nicholas@cuanschutz.edu

Sarah Stith
University of New Mexico
Department of Economics
1915 Roma Ave. NE 1019
Albuquerque, NM 87131
sss1000000@gmail.com

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 percent 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 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 50-70. We also analyze Social Security Administration (SSA) administrative data on monthly applications received for retirement and disability applications. In both cases, we compare monthly data in each of the two years following the start of the pandemic to their expected patterns had the pandemic not occurred. 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. Applications for Social Security disability benefits remain depressed through the second year of the pandemic (17 percent lower than pre-pandemic levels), with the drop more pronounced in applications for Supplemental Security Income (SSI) relative to Social Security Disability Insurance (SSDI) benefits.

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 twenty-four 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 nationally (Coombs et al., 2022), was associated with changes in labor market outcomes and Social Security disability applications. Among older adults, we find that unemployment dropped by 0.5 percentage points in state-months where expanded UI benefits had expired. In addition, applications for Social Security Disability Insurance (SSDI) increased by 5.2 percent and applications for concurrent SSDI and Supplemental Security Insurance (SSI) by 8.8 percent. While these results cannot be interpreted causally since program expiration was not random, they provide suggestive evidence that the expanded unemployment benefits between March 2020 and September 2021 dissuaded some individuals from working or 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); Montenovo et al. (2022); Davis (2022); Larrimore et al. (2021); Lee et al. (2021)). 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) examines SSI and SSDI applications. Analyses of early labor market effects show dramatic declines in unemployment (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; Montenovo et al., 2022; Davis, 2022; Larrimore et al., 2021).

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 (Goda et al., 2022; Cortes and Forsythe, 2022; McEntarfer, 2022) and sustained levels of retirement savings (Derby et al., 2022), but no effect on Social Security retirement (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 larger for SSI, a program targeting low- to no-wage earners, than for SSDI, which requires some work history for eligibility.

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 and Levine, 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 (Helppie McFall, 2011; Chan and Stevens, 1999; Gustman et al., 2010; Goda et al., 2011).

A large existing literature has found that disability claiming through SSI and SSDI is sensitive to economic conditions (Stapleton et al., 1998; Autor and Duggan, 2003; Coe et al., 2010; Cutler et al., 2012; Maestas et al., 2015, 2018; Schmidt, 2012; Black et al., 2002; Charles et al., 2018; Munnell and Rutledge, 2013). 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 percent. 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 DI takeup 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 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 Current Population Survey (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, two 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 subsampling, 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, i.e., the week including the 12th of the month. Households are surveyed for four consecutive months, then not surveyed for the next eight months, before being surveyed again for a final four 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 $Not\ In\ Labor\ Force$ ($NILF$).[1] 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*. 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), and potentially affected by COVID-19 and COVID-19-related policies. 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

[1] The employed-absent response may include measurement error, particularly between February and May 2020—many workers were furloughed and some furloughed workers may have been recorded as $Employed-Absent$ rather than $Unemployed$ (Montenovo et al., 2022)

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).

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 2,871,418 observations, 1,724,862 from individuals between 50 and 61 and 1,146,556 from individuals between 62 and 70.

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 are 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 $NILF$ 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 $NILF$ and accounts for 40% of this group, followed by 31% who considered themselves retired, and finally 29% report reasons other than disability or retirement.

We graph the raw data on the CPS outcomes over time in Figure 1 and Figure 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 January 2015–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 represented by the 62–70 cohort is smaller than that represented by the 51–60 cohort for *Employed*, $Employed - Absent$, and *Unemployed*, but is larger for $NILF$.

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. However, *Disabled* as a share of the population appears to have somewhat rebounded for the younger cohort, while it has remained lower 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 measure these changes (Social Security Administration, 2022a,b). In particular, we assess changes in applications for Supplemental Security Income (SSI), Social Security Disability Insurance (SSDI), Concurrent SSI and SSDI, and Social Security Retirement (SSR). 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 four- and five-week months that do not directly correspond to actual months.[2] 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.

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 age 20 to 64 prior to the pandemic; in March 2020 and later, the rate declined to 22.4 applications. Approximately 40 percent of these

[2] 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.

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 two 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 percent in the two years after the onset of the pandemic.

Figure 3a and 3b displays SSA disability applications over time. The raw data in 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 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 Unemployment Insurance Benefits

We augment our data with information on the availability of expanded Unemployment Insurance (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 workers an extra $600 per week in 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 federal programs expired on September 6, 2021, but some states opted to allow these programs to expire prior to that date. We construct a state-level, time-varying binary variable, $UI\ Expiration_{st}$, that equals 1 in states and months where these expanded programs were no longer in effect, and 0 otherwise.[3] In order to harmonize these data with the timing of the CPS reference week, we code a state's expanded UI programs as expired in a given month if the expiration date was prior to the 12th of that month.[4]

Figure 7 shows the month of UI expiration for each state. As shown in the figure, 18 states opted out of at least one program in June 2021, five in July, and one in August. 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.

$$Y_{ist} = \sum_{k=-5}^{-1} \beta_k \times 1[e(t) = k] + \sum_{k=1}^{10} \beta_k \times 1[e(t) = k] + \gamma \times 1[e(t) < -5] + \theta_{m(t)} + \tau t + \omega_s + \xi X_{ist} + \varepsilon_{ist} \quad (1a)$$

$$Y_{st} = \sum_{k=-5}^{-1} \beta_k \times 1[e(t) = k] + \sum_{k=1}^{10} \beta_k \times 1[e(t) = k] + \gamma \times 1[e(t) < -5] + \theta_{m(t)} + \psi_{y(t)} + \omega_s + \varepsilon_{st} \quad (1b)$$

[3] There are four states that terminated one of the two federal programs early – we group these states into the month where they ended at least one federal unemployment insurance program.

[4] For example, Tennessee ended both FPUC and PUA on July 3, 2021. Because expiration occurred prior to the 12th of the month, $UI\ Expiration_{st}$ is equal to 1 in July 2021 and later months. However, Alaska terminated the FPUC on June 19, 2021. Therefore, $UI\ Expiration_{st}$ for Alaska is 0 in June 2021, but 1 for July 2021 and later months.

$$Y_t = \sum_{k=-5}^{-1} \beta_k \times 1[e(t) = k] + \sum_{k=1}^{10} \beta_k \times 1[e(t) = k] + \gamma \times 1[e(t) < -5]$$
$$+ \theta_{m(t)} + \psi_{y(t)} + \varepsilon_{st} \tag{1c}$$

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 month-level time trend τ_t to capture pre-existing trends in our outcome variables, and demographic variables X_{ist}, which include age, 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, state, and year fixed effects [5] 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 based on a continuation of prior trends, after controlling for seasonality, changes in the demographic composition, and time-invariant state characteristics.

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

[5] We include year fixed effects rather than a month-level time trend because we adjust our applications data by population, which is measured annually. Demographic information is not available for these data.

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 below detail our difference-in-differences approach.

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

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

$$Y_t = \alpha_1 PostCovid1_t + \alpha_2 PostCovid2_t + \theta_{m(t)} + \psi_{y(t)} + \varepsilon_{st} \tag{2c}$$

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 last set of analyses assesses whether the expiration of expanded unemployment insurance programs was associated with changes in both labor market and disability insurance application outcomes. To do so, we first augment Equations 2a, 2b and 2c by including *UI* $Expiration_{st}$, a binary variable that equals 1 if expanded UI benefits were expired in a given month in a given state as described earlier. As all of the expanded UI programs expired in 2021, the UI coefficient effectively divides the second year after the onset of the pandemic *Post-Covid 2* period into pre- and post-UI expiration. Months during the second year when expanded UI benefits were available are captured by the coefficient on *Post-Covid 2*, and the total effect during months when expanded UI benefits had expired are given by the sum of the coefficients for *Post-Covid 2* and *UI Expiration*. To further explore the effect of UI expiration on disability claiming in particular, we generate an event study framework with the month of UI expiration as the omitted period (t=0), tracking the periods five months prior and five months after UI expiration. Months outside this window are grouped into the t=-5 and t=+5 periods. We adjust for state, year and month fixed effects.

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 4, we present coefficients from our event study estimation in equation 1a. Beginning with Figure 4a, 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.

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 4b, 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 4c, generally display inverse dynamics to those seen with employment above in Figure 4a. 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 percent reduction relative to the 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 percent 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. 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 towards retirement and away from exits due to other reasons.

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 5a, we observe a sharp decrease in total SSI and SSDI applications that levels off in the end of year one around four 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 5b), SSDI only applications (Figure 5c), and SSI only applications (Figure 5d). There are several patterns of note when examining the decomposition. First, the dynamics in Figure 5b and 5d 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 5c, applications for SSDI only follow a diverging pattern from applications for SSI or concurrent applications in year two and begin to recover slowly. In fact, from July 2021 onwards, most coefficients are statistically indistinguishable from zero, suggesting that SSDI only applications are similar to what would have been predicted for this time period.

In Table 7, we 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 4.09 fewer applications per 100,000 people aged 20 to 64, and this coefficient is not significantly different from that estimated in year one.

Column (2) shows that SSDI only applications have recovered to predicted levels; however, the deviations in SSI and concurrent SSI and SSDI applications have slightly increased during the second year of the pandemic and remain significantly lower. 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 6, 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 6 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 6b, where we see higher levels of applications filed via the internet in late 2021 compared with late 2020. In Figure 6c, 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 a statistically significant increase in total applications in the second year of the pandemic. We find that in the second year there are 10.61 more applications per 100,000 individuals age 60 to 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.

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 versions of Equations 2a and 2b that incorporate $UI\ Expiration_{st}$ to differentiate between months during the second year of the pandemic with and without expanded UI benefits available. We caution that because the expiration of expanded UI benefits occurred non-randomly, these coefficients should not be interpreted causally.

First, we estimate a modified version of Equation 2a to examine the association between UI expiration and labor market outcomes. In Table 9, we see that the expiration of expanded UI benefits is associated with lower levels of unemployment. More precisely, in the months after UI expiration unemployment is 0.5pp (panel A) and 0.4pp (panel B) lower, accounting for about one-third to one-half of the year two deviation. While employment appears to increase somewhat during months when expanded UI benefits were not available, the differences are not statistically different, and in general, the other labor market outcomes we examine do not vary during these months.

Second, in Table 10 we evaluate the association between UI expiration and deviations in applications for disability. Starting with Column (1), the coefficient on $UI\ Expiration_{st}$ indicates that in state-months during which expanded UI benefits have expired, we observe 1.9 more applications per 100,000. This effect reverses about 37 percent (1.9/5.13) of the year two effect on total applications. When breaking down the types of applications, this effect is largely driven by SSDI and concurrent applications. We see 0.86 more SSDI applications per 100,000 individuals age 20 to 64 in months after expanded UI benefits expired in a state. In magnitude, this is a reversal of the entire deviation in SSDI applications in year two (0.86/0.81). We see a similar magnitude change in concurrent applications, 0.75 more applications per 100,000 individuals, which offsets half of the second year deviation in concurrent applications (0.75/1.50). By contrast, only one tenth of SSI applications (0.30/2.83) are offset by UI expiration. Overall, Table 10 suggests a significant rebound in applications for SSDI and concurrent SSDI and SSI in months after expanded UI benefits have expired.

Finally, 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 five months before and after UI expiration, where time -5(+5) include all periods earlier (later) than five months before (after) UI expiration. Consistent with the results in Table 10, 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.

5 Conclusion

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

Older workers experienced many of these patterns during the first year of the pandemic, but unlike previous recessions, Social Security applications for retirement and disability did not significantly increase. Our analysis extends earlier work into the second year of the pandemic to determine whether labor market outcomes exhibited changes or more people turned to Social Security as COVID-19 persisted.

We find evidence that while employment and unemployment rates for older workers have largely recovered to predicted levels by March 2022, labor force non-participation remains elevated. Further, we see a compositional shift among respondents towards reporting retirement as the reason for not participating in the labor force rather than reasons other than disability or retirement. 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 a small increase in retirement applications during the second year of the pandemic. However, applications for disability benefits remain depressed relative to pre-pandemic levels. The distributional shift towards online rather than offline retirement applications and the fact that SSA offices did not reopen to in-person appointments until April 2022, after the end of our sample period, suggest some of the reduction in 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. Leveraging variation in when states chose to allow these benefits to expire, we find that months after the expiration of expanded UI benefits are associated with a small reduction in unemployment and a partial reversal of the reduction in SSDI applications. However, these results cannot be interpreted causally due to the non-random variation driving benefit expiration.

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 result in more than 100,000 confirmed cases of COVID-19 each day as of June 2022, it will be important to continue to monitor how labor market outcomes among older workers and spillovers to Social Security continue to evolve as the COVID-19 pandemic transitions to an endemic state.

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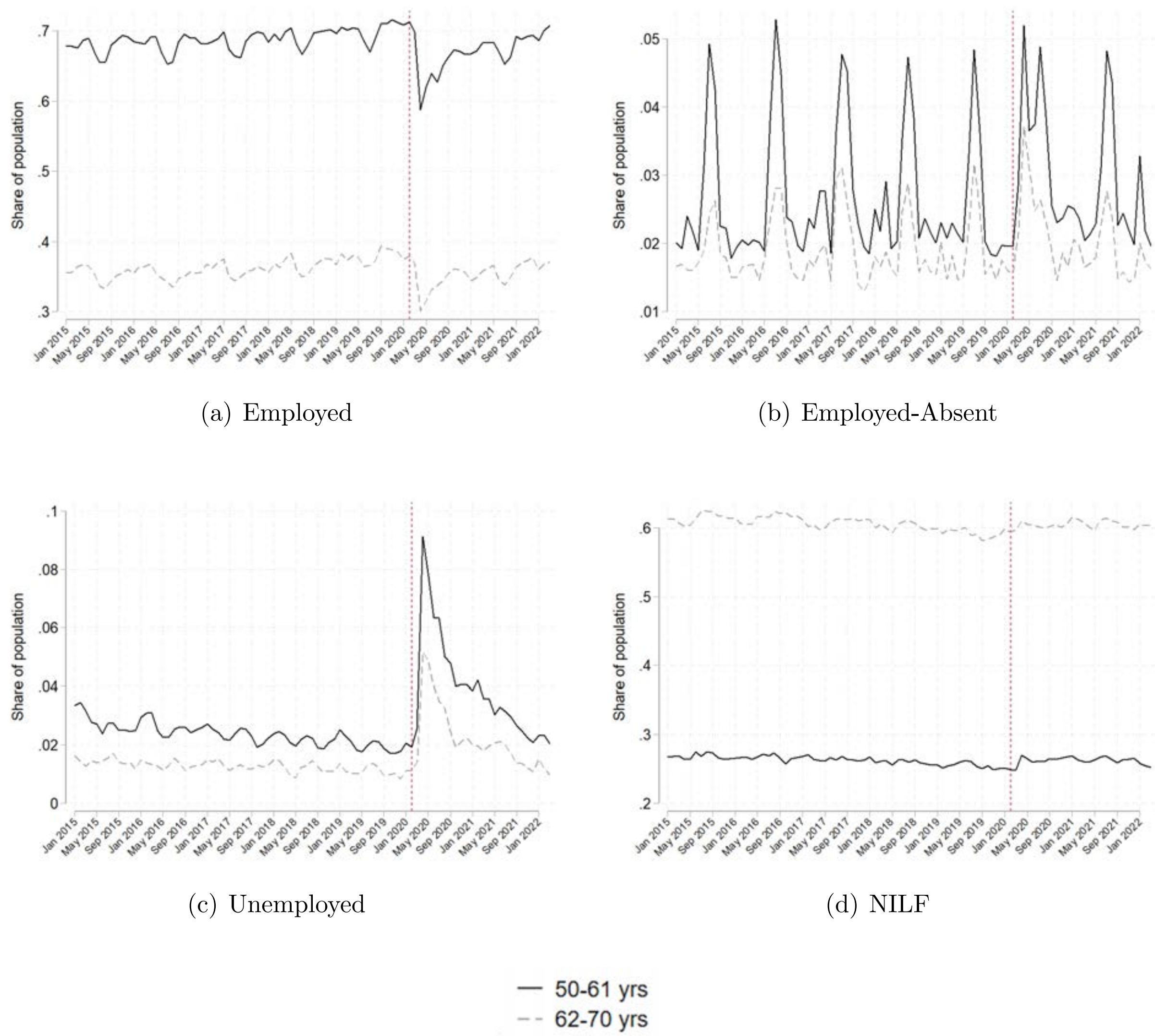
A Figures

Figure 1: Employment Outcomes for Ages 50-61 and 62-70, 2015-2022



(a) Employed

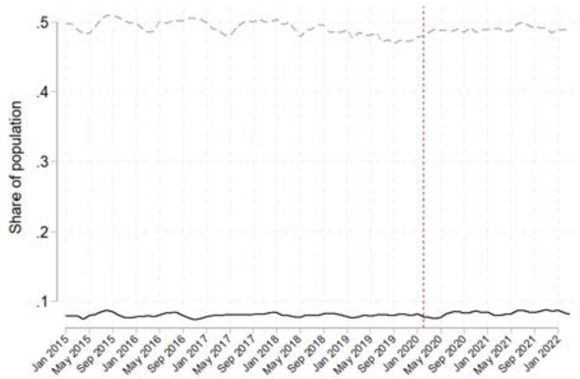
(b) Employed-Absent

(c) Unemployed

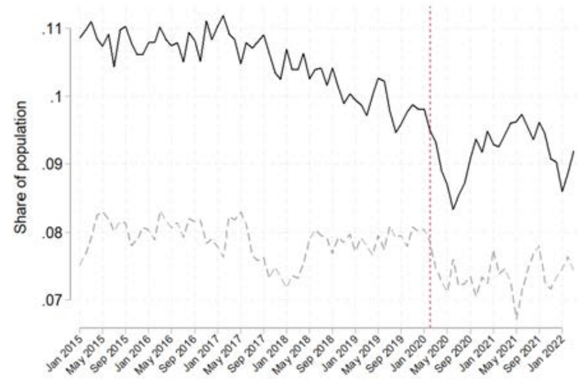
(d) NILF

Notes: Sample contains civilians ages 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.

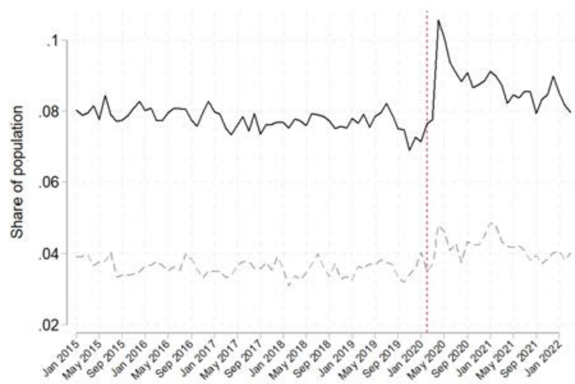
Figure 2: NILF Outcomes for Ages 50-61 and 62-70, 2015-2022



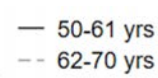
(a) Retired



(b) Disabled

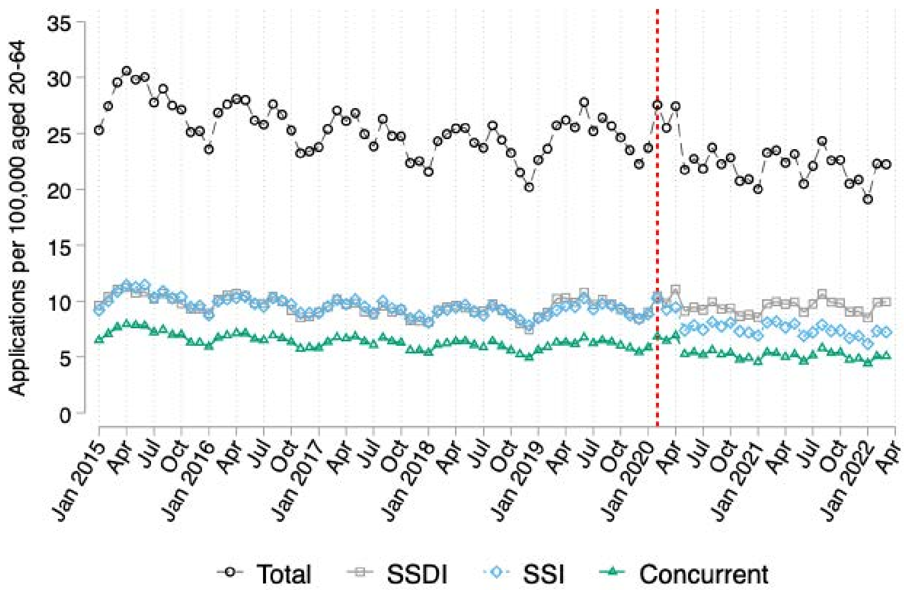


(c) Other

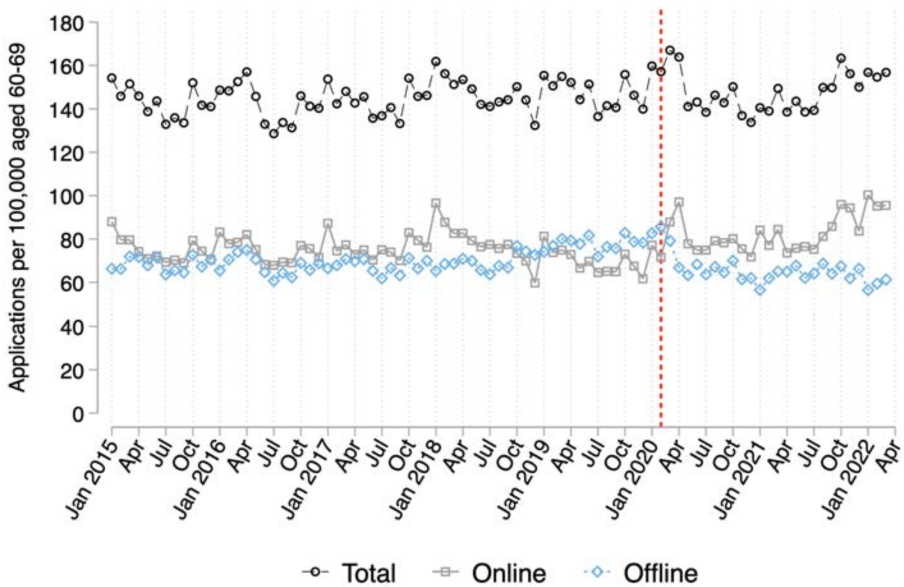


Notes: Sample contains civilians ages 50-70 from the January 2015-March 2022 CPS living in the United States. Figures depict the share of individuals in an employment category in each month. Estimates are weighted using survey weights.

Figure 3: Social Security Disability and Retirement Application Rates, 2015-2022



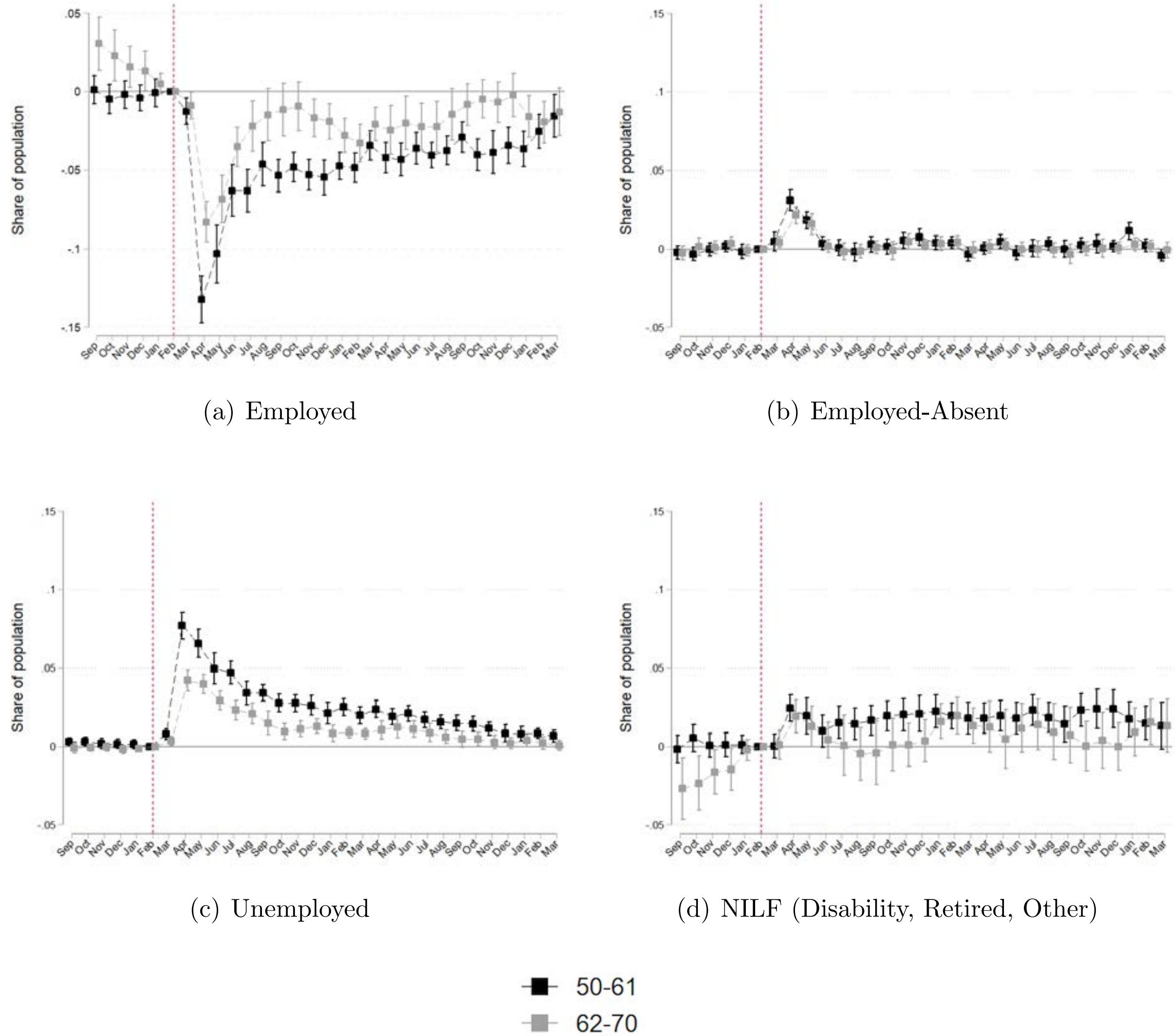
(a) Weekly Disability Applications Rate



(b) Weekly Retirement Applications Rate

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 to 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: Event Studies of Employment Outcomes from the CPS Among 50-70 Year Olds



(a) Employed

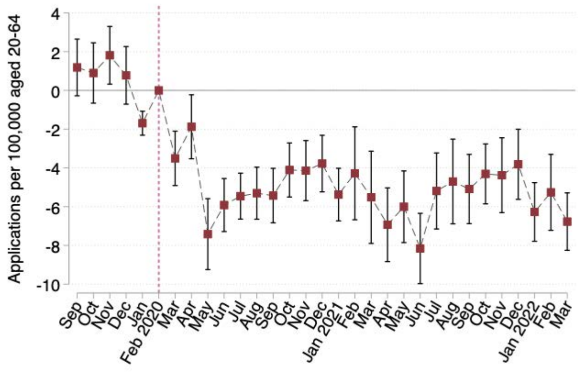
(b) Employed-Absent

(c) Unemployed

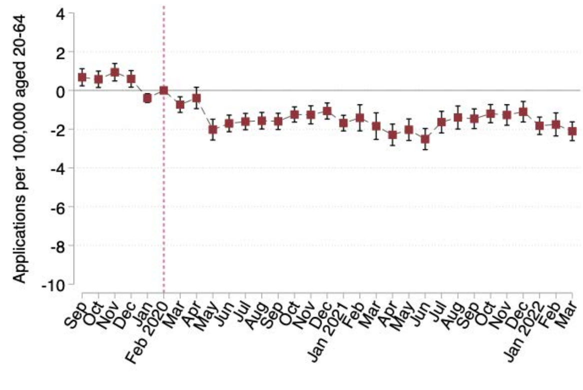
(d) NILF (Disability, Retired, Other)

Notes: Sample contains civilians ages 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.

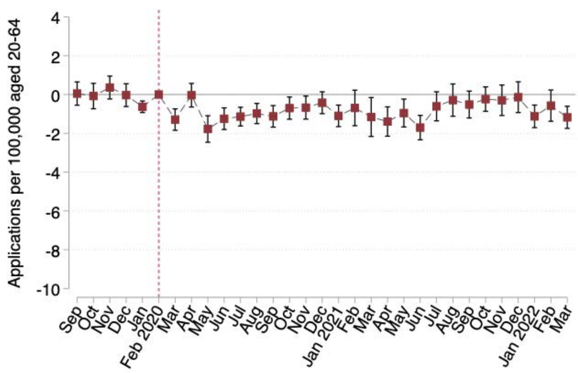
Figure 5: Event Study of Social Security Disability Applications



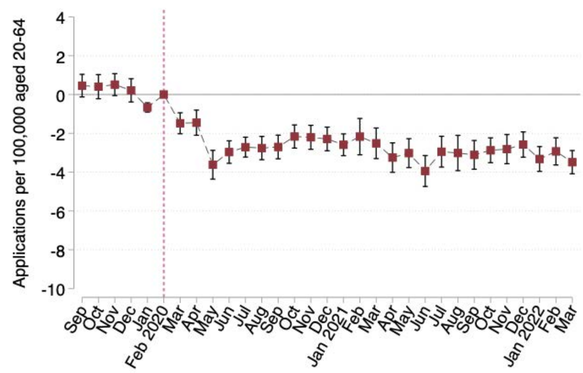
(a) Total SSI + SSDI



(b) Concurrent SSI and SSDI



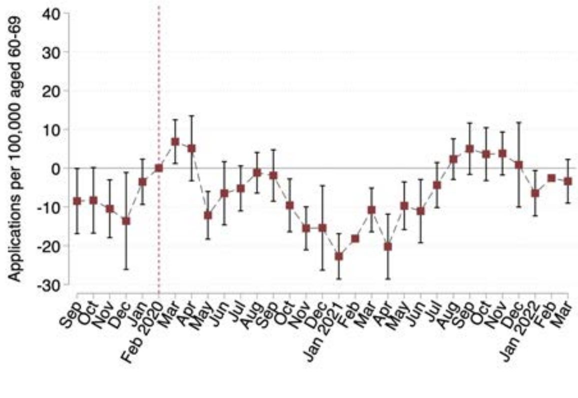
(c) SSDI Only



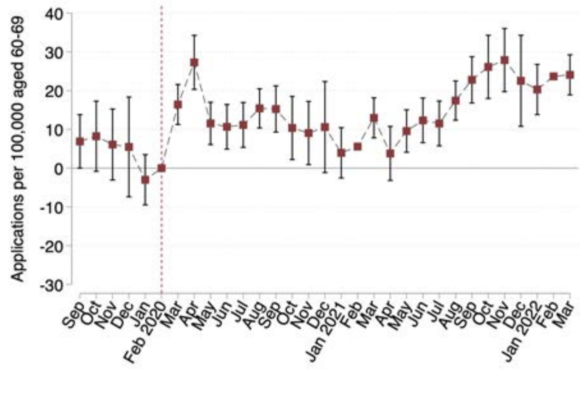
(d) SSI Only

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 to 64. Standard errors are robust and clustered at the state level. 95% confidence intervals are shown. Regressions include month, year, and state fixed effects and event time relative to February 2020.

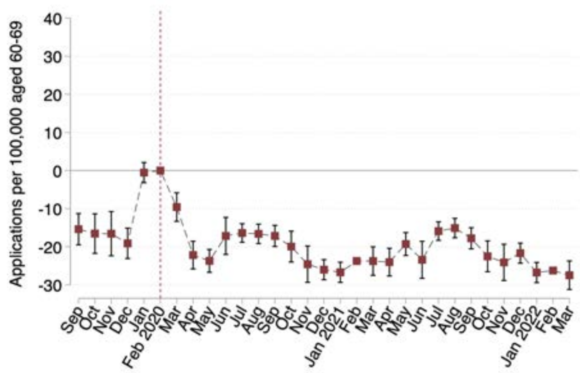
Figure 6: Event Study of Social Security Retirement Applications



(a) Total Applications



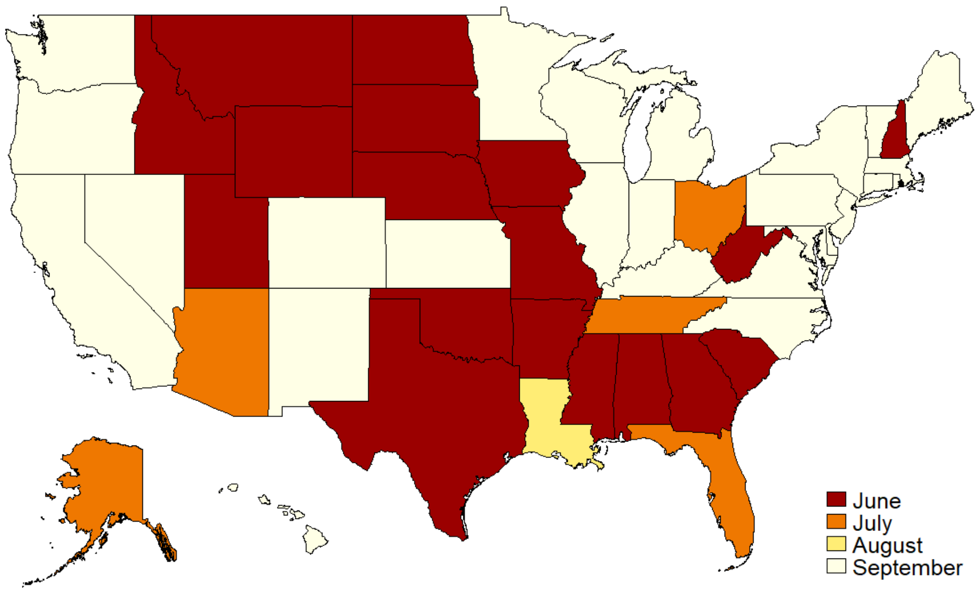
(b) Applications Filed via Internet



(c) Applications Filed Offline

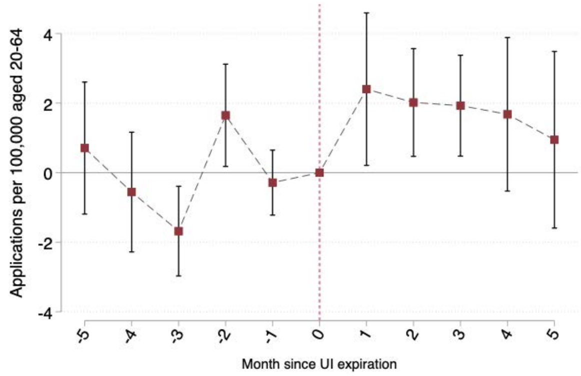
Notes: Sample comes from the SSA Monthly Data for Retirement Insurance Applications and ranges from January 2015 to March 2022. Outcome variable is weekly applications per 100,000 people aged 60 to 69. Standard errors are robust. 95% confidence intervals are shown. Regressions include month and year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

Figure 7: Federal Pandemic Unemployment Insurance Expiration Month by State

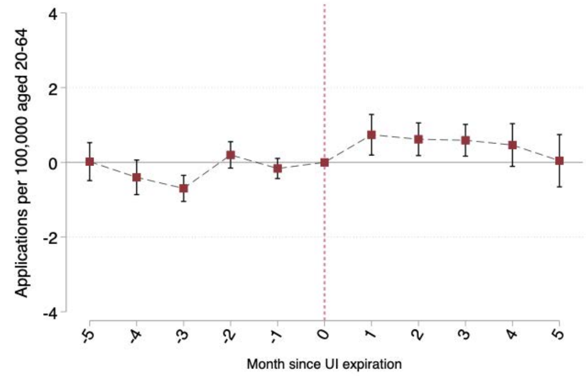


Notes: The Federal Pandemic Unemployment Compensation (FPUC) and the Pandemic Unemployment Assistance (PUA) programs were established through the Coronavirus Aid, Relief, and Economic Security (CARES) Act and signed into law on March 27, 2020. All benefits under the FPUC expired on September 6, 2021. 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.

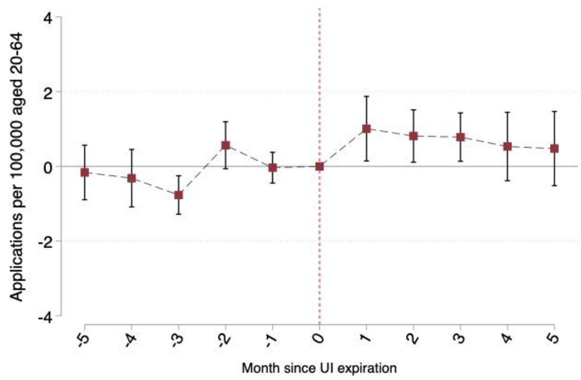
Figure 8: Event Study of Social Security Disability Applications: UI Expiration



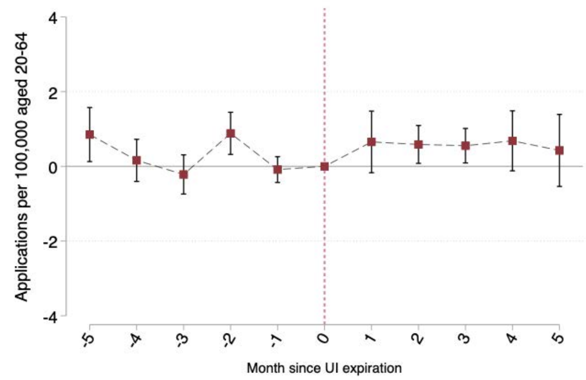
(a) Total SSI + SSDI



(b) Concurrent SSI and SSDI



(c) SSDI Only



(d) SSI Only

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 to 64. Standard errors are robust and clustered at the state level. 95% confidence intervals are shown. Regressions include month, year, and state fixed effects, relative to the month of UI expiration. Months since UI expiration that are $\mp$ 5, inclusive, are grouped together.

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)
$\leq$ 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	1286653	414424	838723	307833

Notes: Sample contains civilians ages 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.

Table 2: CPS Employment Summary Statistics

	Ages 50-61		Ages 62-70	
	Pre-Covid	Post-Covid	Pre-Covid	Post-Covid
Employed	0.688	0.670	0.363	0.353
	(0.463)	(0.470)	(0.481)	(0.478)
Employed-Absent	0.026	0.030	0.019	0.020
	(0.160)	(0.171)	(0.136)	(0.142)
Unemployed	0.024	0.035	0.013	0.022
	(0.152)	(0.184)	(0.112)	(0.147)
Not in Labor Force-Retired, Disabled, and Other	0.262	0.249	0.606	0.605
	(0.440)	(0.432)	(0.489)	(0.489)
Retired	0.080	0.085	0.491	0.490
	(0.271)	(0.279)	(0.500)	(0.500)
Disabled	0.105	0.095	0.079	0.074
	(0.306)	(0.294)	(0.270)	(0.261)
NILF-Other	0.078	0.082	0.036	0.042
	(0.268)	(0.275)	(0.186)	(0.200)
Observations	1286653	438209	838723	307833

Notes: Sample contains civilians ages 25-49, 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.

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	3100	1250

Notes: Sample comes from the SSA State Agency Monthly Workload, and contains civilians ages 20-64 from the January 2015-March 2022 living in the United States who applied for social security disability benefits on the state level. Outcome variable is weekly applications per 100,000 people aged 20 to 64. 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.

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, and contains civilians ages 60-69 from the January 2015-March 2022 living in the United States who applied for retirement insurance on the country level. Outcome variable is weekly applications per 100,000 people aged 60 to 69. Retirement Application Filed non-Internet stands for 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.

Table 5: Changes in Employment Outcomes Following COVID-19 Pandemic

A. 50-61-Year-Olds

	(1) Employed	(2) Employed-Absent	(3) Unemployed	(4) NILF
Post-Covid 1	-0.055***	0.006***	0.034***	0.014***
	(0.003)	(0.001)	(0.002)	(0.003)
Post-Covid 2	-0.031***	0.002**	0.013***	0.016***
	(0.003)	(0.001)	(0.002)	(0.004)
Observations	1701077	1701077	1701077	1701077
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

	(1) Employed	(2) Employed-Absent	(3) Unemployed	(4) NILF
Post-Covid 1	-0.038***	0.003***	0.019***	0.016***
	(0.004)	(0.001)	(0.002)	(0.003)
Post-Covid 2	-0.025***	-0.000	0.007***	0.018***
	(0.004)	(0.001)	(0.002)	(0.004)
Observations	1146556	1146556	1146556	1146556
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

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

Notes: Samples contains civilians ages 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 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.

Table 6: Changes in NILF Following COVID-19 Pandemic

A. 50-61-Year-Olds

	(1) NILF	(2) Retired	(3) Disabled	(4) Other
Post-Covid 1	0.014***	0.003*	-0.005***	0.017***
	(0.003)	(0.002)	(0.002)	(0.001)
Post-Covid 2	0.016***	0.006**	0.000	0.010***
	(0.004)	(0.003)	(0.003)	(0.002)
Observations	1701077	1701077	1701077	1701077
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

	(1) NILF	(2) Retired	(3) Disabled	(4) Other
Post-Covid 1	0.016***	0.012***	-0.004*	0.008***
	(0.003)	(0.004)	(0.002)	(0.001)
Post-Covid 2	0.018***	0.018***	-0.005*	0.005***
	(0.004)	(0.006)	(0.002)	(0.002)
Observations	1146556	1146556	1146556	1146556
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

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

Notes: Samples contains civilians ages 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 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.

Table 7: Changes in Disability Applications During COVID-19 Pandemic

	(1) All	(2) SSDI	(3) SSI	(4) Concurrent
Post-Covid 1	-3.78***	-0.61***	-2.08***	-1.10***
	(0.513)	(0.196)	(0.219)	(0.156)
Post-Covid 2	-4.09***	-0.34	-2.66***	-1.08***
	(0.861)	(0.313)	(0.376)	(0.235)
Observations	4350	4350	4350	4350
Pre-Covid Mean	25.49	9.55	9.54	6.41
T-test PC1 = PC2	0.63	0.28	0.02	0.92

Robust and clustered (at state level) standard errors in parentheses

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

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 to 64. Standard errors are robust and clustered at the state level. 95% confidence intervals are shown. Regressions include month, year, 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.

Table 8: Changes in Retirement Applications During COVID-19 Pandemic

	(1) Total	(2) Filed via Internet	(3) Filed offline
Post-Covid 1	-4.18	14.76***	-18.94***
	(2.904)	(2.345)	(1.602)
Post-Covid 2	10.61**	24.54***	-13.93***
	(5.299)	(4.609)	(2.564)
Observations	87	87	87
Pre-Covid Mean	145.23	74.69	70.53
T-test PC1 = PC2	0.00	0.01	0.00

Robust and clustered (at state level) standard errors in parentheses

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

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 to 69. Standard errors are robust. Regressions include month and year 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.

Table 9: Changes in Employment Outcomes Following COVID-19 Pandemic: UI Expiration

A. 50-61-Year-Olds

	(1) Employed	(2) Employed-Absent	(3) Unemployed	(4) NILF
Post-Covid 1	-0.055***	0.006***	0.034***	0.014***
	(0.003)	(0.001)	(0.002)	(0.003)
Post-Covid 2	-0.033***	0.001	0.016***	0.017***
	(0.003)	(0.001)	(0.002)	(0.004)
UI Expiration	0.003	0.002**	-0.005***	-0.000
	(0.004)	(0.001)	(0.001)	(0.004)
Observations	1701077	1701077	1701077	1701077
Pre-Covid Mean	0.688	0.026	0.024	0.262
T-test PC1 = PC2	0.000	0.000	0.000	0.491

B. 62-70-Year-Olds

	(1) Employed	(2) Employed-Absent	(3) Unemployed	(4) NILF
Post-Covid 1	-0.038***	0.003***	0.019***	0.016***
	(0.004)	(0.001)	(0.002)	(0.003)
Post-Covid 2	-0.028***	-0.001	0.009***	0.020***
	(0.006)	(0.001)	(0.002)	(0.006)
UI Expiration	0.005	0.000	-0.004**	-0.002
	(0.005)	(0.001)	(0.001)	(0.005)
Observations	1146556	1146556	1146556	1146556
Pre-Covid Mean	0.363	0.019	0.013	0.606
T-test PC1 = PC2	0.069	0.002	0.000	0.482

Standard errors in parentheses

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

Notes: Samples contains civilians ages 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. The unemployment insurance (UI) regressor represents when an individual state opted-out of extended benefits (June through August for early opt-out states and September for other states). 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.

Table 10: Changes in Disability Applications During COVID-19 Pandemic: UI Expiration

	(1) All	(2) SSDI	(3) SSI	(4) Concurrent
Post-Covid 1	-3.78***	-0.61***	-2.08***	-1.10***
	(0.513)	(0.196)	(0.219)	(0.156)
Post-Covid 2	-5.13***	-0.81**	-2.83***	-1.50***
	(0.857)	(0.306)	(0.378)	(0.230)
UI Expiration	1.90***	0.86***	0.30**	0.75***
	(0.380)	(0.158)	(0.145)	(0.114)
Observations	4350	4350	4350	4350
Pre-Covid Mean	25.49	9.55	9.54	6.41
T-test PC1 = PC2	0.04	0.42	0.01	0.02

Robust and clustered (at state level) standard errors in parentheses

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

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 to 64. Standard errors are robust and clustered at the state level. 95% confidence intervals are shown. Regressions include month, year, and state fixed effects. *Post Covid 1* equals 1 between March 2020 and March 2021, *Post Covid 2* equals 1 between April 2021 and March 2022, and *UI Expiration* equals 1 if the UI status is expired in a state in a given month.