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The COVID-19 Pandemic and Older Adults' Employment and Economic Security: Insights from Earnings and Credit Panel Data

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Abstract

This study examines the relationship between reductions in labor force participation and earnings during the first 15 months of the COVID-19 pandemic and older adults' economic security. Our particular focus is on consumer credit and debt. We construct a unique panel dataset, combining individual-level administrative data on quarterly labor force participation, unemployment claims, and earnings and detailed financial information from credit report data for adults ages 50 and older in Ohio from January 2018 through June 2021. Our findings indicate that financially vulnerable older adults—including those who were older, from Black neighborhoods, with lower credit scores, and with less available credit – were more likely to exit the labor force during the COVID-19 pandemic than the pre-COVID-19 periods. They were also more likely to miss debt payments after an exit. However, labor force exits were associated with an increase in creditor forbearances during the COVID-19 pandemic, thereby mitigating the typical negative effects of labor force exits on credit outcomes observed in pre-COVID-19 periods in Ohio. With regard to Social Security retirement benefit claiming, we find that Ohio counties with older adults carrying more non-housing debt and with lower credit scores had a higher share of eligible older adults claiming Social Security retirement benefits early during the COVID-19 pandemic—with indicators of financial vulnerability in a county's older population being more predictive of early claiming than exits from the labor force. These findings offer important insights for public policies targeting the economic security of current and future Social Security beneficiaries.

Keywords: older adults, unemployment, retirement, economic security

JEL Codes: D14; G51; J26; J64

1. Introduction

The net effect of the COVID-19 pandemic on older adults' economic security is theoretically ambiguous. For many older adults, Social Security retirement benefits and private retirement funds provided a stable source of income during the COVID-19 pandemic (Munnell and Chen 2021). Combined with reduced consumption during the pandemic (Chetty et al. 2020; Horvath, Kay, and Wix 2021) and generous COVID-19 era government benefits, many older households actually paid down their debt and thus increased net wealth during the pandemic (Horvath, Kay, and Wix 2021). Yet, some older adults were working prior to the pandemic, either pre-retirement or to supplement retirement benefits (Purcell 2020). Those in the labor force who experienced a loss of earned income may have had difficulty keeping up with their expenses (Clark, Lusardi, and Mitchell 2020; Moen, Pedtke, and Flood 2020). Among adults age 65 and older in the labor force, the unemployment rate rose from an annual average of three percent in 2019 to a peak of 15.6 percent in April 2020 (Johnson 2020), with an additional 11 percent of households age 65 and older exiting the labor force in 2020. Our prior research indicates that 16 percent of adults ages 50 to 61 and nine percent of adults ages 62 to 66 had debt placed in forbearance in 2020 during the COVID-19 pandemic due to a financial hardship (Brown, Collins, and Moulton 2022). Our primary research question asks how reductions in labor force participation and earnings during the COVID-19 pandemic associate with older adults' economic security, with a particular focus on changes in consumer credit and debt.

To inform this question, we construct a unique panel dataset combining individual-level administrative data on quarterly labor force participation, earnings, unemployment claims, and detailed financial information from credit report data for a random sample of more than 900,000 adults ages 50 and older in Ohio from 2018 through the end of the second quarter of 2021. Using these panel data, we identify older adults who were working in the first quarter of 2020 (prior to the onset of the pandemic) and trace their employment and credit outcomes quarterly through the end of June 2021. To net out COVID-19 era differences, we construct a comparison sample of older adults working in the first quarter of 2018 and follow their employment and credit outcomes quarterly through the end of the second quarter of 2019. We also aggregate the employment and credit data to the county level and merge in administrative records on social security retirement and disability claims by age group, county, and quarter from January 1, 2018, through June 30, 2021. We exploit geographic and temporal variation in labor and credit characteristics of older adults to examine heterogeneous effects of labor force exits on social-security-claiming activity before and after the onset of the COVID-19 pandemic.

For our first aim, we describe how pre-pandemic indicators of financial vulnerability from credit data associate with COVID-related changes in labor force participation and wage earnings among older adults (age 50 and older). We define financial vulnerability based on pre-pandemic credit scores, access to credit, debt levels, and wages. We also include demographic characteristics such as age, gender, the majority race of the ZIP code, and whether the ZIP code is urban or rural. While labor force studies of the COVID-19 pandemic document that older workers were more likely to exit the labor force and had significantly lower re-employment probabilities than younger workers (Powell 2022; Montes, Smith, and Dajon 2022), they do not identify if affected older adults were prepared for unemployment spells and retirement, as measured by indicators of financial vulnerability—which has important implications for the economic security of Social Security beneficiaries. For example, prior to the pandemic, studies indicate that older adults increasingly carried more debt than earlier cohorts (Brown et al. 2020; Lusardi, Mitchell, and Oggero 2020), and that those with higher debt levels and financial stress tended to delay Social Security retirement claiming and worked longer (Butrica and Karamcheva 2018; Haurin, Moulton, and Loibl 2022).

We estimate a series of difference in difference models, identifying the differential association of baseline demographic and financial characteristics on labor force exits after the onset of the COVID-19 pandemic compared to their association in pre-pandemic periods. We find evidence of heterogeneous effects by age, gender, income, race, and location in Ohio, where the oldest working adults as of the baseline quarter (ages 67-71 and 72+), females, those from Ohio ZIP codes with a majority Black population, and those from urban Ohio ZIP codes, were significantly more likely to exit the labor force during the COVID-19 quarters than during pre-COVID-19 quarters. Older adults with lower wage income, in ZIP codes with a majority Black population, and in urban Ohio ZIP codes were also significantly more likely to have an active Unemployment Insurance (UI) benefit claim. By contrast, the oldest workers and female workers were less likely to claim unemployment insurance benefits despite being more likely to exit the labor force during the COVID-19 quarters.

Unique to our study, we also find differential effects based on credit characteristics of working older adults. While we find that the older adults whom we observe with lower credit scores in the baseline quarter (Q1 of 2018 or Q1 of 2020) were always more likely to exit the labor force the following year, this effect was nearly 10 times larger after the initial onset of the COVID-19 pandemic in Q2 of 2020. Older adults with lower credit scores were also much more likely to claim unemployment insurance benefits during the pandemic in Ohio. We find that working older adults without access to revolving credit prior to the onset of COVID-19 were more likely to exit the labor force and more likely to have a UI claim relative to pre-pandemic periods. We find that higher baseline wages prior to the pandemic were also associated with a reduced likelihood of COVID-19-era unemployment benefit claims among older adults.

Our second aim identifies how labor force exits, active unemployment claims, and changes in wage earnings during the COVID-19 periods relative to the pre-COVID-19 periods are related to changes in financial well-being as measured in credit data—including nonpayment on debts and the use of forbearance. Our results indicate that in pre-COVID-19 periods, leaving the labor force was typically associated with an increase in financial distress for older adults, as evidenced by a reduction in credit score and increase in payment delinquencies. However, this effect was muted for labor force exits that occurred immediately after the COVID-19 pandemic. While nonpayment of debt increased for older adults with COVID-19-era labor force exits relative to pre-COVID-19 periods, nonpayment was completely offset by an increase in having debt in forbearance and subsequently a decrease in being severely delinquent on debt relative to pre-COVID-19 labor exits. Thus, the generous payment forbearance offered during the pandemic likely prevented older adults from experiencing severe financial distress (Cherry et al. 2021; Horvath, Kay, and Wix 2021).

We find a nuanced relationship between COVID-19-period labor force exits and changes in household debt levels. In pre-COVID-19 quarters, there is a significant negative relationship, where leaving the labor force was associated with a *reduction* in total debt, mortgage debt, and credit card debt. This negative relationship is greater for credit card debt during the COVID-19 quarters, where leaving the labor force or having a UI claim during COVID-19 was associated with even larger reductions in credit card debt than in pre-COVID-19 quarters. In general, changes in debt levels reflect changes in current consumption as well as repayment of debt, and thus decreases in debt could reflect older adults consuming less or paying down debt more quickly. In line with debt representing a form of consumption, we find evidence that *increases* in wages during the pre-COVID-19 quarters were associated with a significant *increase* in total debt, mortgage debt, and credit card debt. This positive relationship is larger during the COVID-19 quarters. This raises caution for studies that use increasing debt levels as an indication of financial distress, as increases in debt can also occur with increased consumption, and reductions in debt could occur due to reduced consumption or credit constraints.

Our third aim investigates the relationship between COVID-19-era exits from the labor force, indicators of financial vulnerability, and early Social Security retirement (Old-Age and Survivors Insurance (OASI)) claims for older adults. The focal outcome is the share of adults ages 62 to 66 claiming early Social Security retirement benefits in an Ohio county over a four-quarter period beginning in the second quarter of 2020, relative to similar pre-COVID-19 four-quarter periods beginning in 2018 and 2019. We find that in pre-COVID-19 periods, an increase in the county share of working older adults who leave the labor force was associated with a large and significant increase in the share of the same-age older adults in the county who began claiming Social Security retirement benefits early. However, this relationship was weaker during COVID-19. Instead, during COVID-19 periods, we find that lower average credit scores and higher average non-housing debt among adults ages 62 to 66 in a county were associated with a significant increase in early Social-Security-retirement-benefits-claiming rates. Thus, indicators of financial distress as measured in credit data correlate more strongly with early claiming during COVID-19 periods than non-COVID-19 periods. Taken together, the findings from our study provide detailed new insights into the changes in the economic security of current and future Social Security beneficiaries.

2. Literature Review

2.1 Older Adults' Labor Force Participation During the COVID-19 Pandemic

A growing literature examines the effects of the COVID-19 pandemic on labor outcomes. Studies document the marked increase in unemployment immediately after the onset of the pandemic in March 2020 and how it dissipated over time, with heterogeneity by age, gender, race, geography (urban or rural), and education (Cheng et al. 2020; Gupta et al. 2020; Lee, Park, and Shin 2021; Moen, Pedtke, and Flood 2020; Brooks, Mueller, and Thiede 2021). Older adults experienced an increase in labor force exits following the onset of the COVID-19 pandemic relative to pre-pandemic periods (Bui, Button, and Picciotti 2020; Goda et al. 2022a; Quinby, Rutledge, and Wettstein 2021). For example, Quinby, Rutledge, and Wettstein (2021) find an average eight percentage points—or 50 percent—increase in the annual rate of labor force exits among working adults ages 55 and older from March 2020 to March 2021, relative to labor force exits in prior periods.

Findings are mixed on whether older adults were more or less adversely affected than younger age groups, with some studies finding that increases in labor force exits during the COVID-19 pandemic were larger for older adults than prime-age workers (Bui, Button, and Picciotti 2020; Cheng et al. 2020; Goda et al. 2022a; Gupta et al. 2020), and other studies finding older adults were not disproportionately affected relative to younger adults (Munnell and Chen 2021; Polyakova et al. 2020; Quinby, Rutledge, and Wettstein 2021). Part of the discrepancy is due to the definition and measurement of labor force exits for older workers. Most studies use data from the U.S. Census Current Population Survey (CPS) to analyze the flow of labor force exits among individuals working in a prior period (Quinby, Rutledge, and Wettstein 2021), while others examine changes in the stock of individuals in the labor force (Polyakova et al. 2020; Goda et al. 2022a, 2022b). Because older adults are much less likely than younger adults to be in the labor force, stock measures may mask factors that predict exits among older adults previously working.

Studies also vary in the age categories included, with the oldest working adults found to be more adversely affected than working adults under age 70 (Cheng et al. 2020; Quinby, Rutledge, and Wettstein 2021). Finally, studies vary in the timing of observed exits, with the most pronounced increase in labor exits among older adults occurring immediately after the onset of the pandemic (Montenovo et al. 2020). However, studies through March 2021 continued to observe elevated rates of exits for older adults—even if not more pronounced than for younger adults (Goda et al. 2022a; Quinby, Rutledge, and Wettstein 2021). The most recent data from the Federal Reserve through October 2022 find that while self-reported unemployment of older adults returned to pre-pandemic levels, labor force participation of older adults remained depressed relative to pre-pandemic periods, pointing to "accelerated retirements" (Powell 2022; Montes, Smith, and Dajon 2022).

Aside from differences by age, a few prior studies explore other demographic factors that are associated with increased labor force exits among older adults. Gender is consistently found to be significant, with older women experiencing higher increases in labor force exits after the onset of COVID-19 than older men (Andrea et al. 2022; Bui, Button, and Picciotti 2020; Goda et al. 2022a; Tamborini and Kim 2022)—a finding also observed in the general population (Albanesi and Kim 2021). While in the general population there is consistent evidence that Black workers were more likely to experience persistent declines in labor force participation due to the COVID-19 pandemic than White workers (Lee, Park, and Shin 2021; Montenovo et al. 2020), there is mixed evidence of racial differences in labor force exits among older adults. For example, Quinby, Rutledge, and Wettstein (2021) find no significant differences in COVID-19 era labor force exits of older adults by race, ethnicity, or indicators of the local severity of the COVID-19 pandemic, while Moen, Pedtke, and Flood (2022) find a particularly large decline for Black men. Lower levels of education are significantly associated with increased COVID-19 labor exits for older adults (Goda et al. 2022a; Quinby, Rutledge, and Wettstein 2021). This is in line with studies in the general population that not only find differences by level of education, but also by type of job and the extent to which jobs could be performed remotely (Montenovo et al. 2020).

Relatively few studies examine financial measures and indicators of financial vulnerability that correlate with COVID-19 labor force exits among older adults. Using CPS data, Sanzenbacher (2021) finds that a larger share (38 percent) of lower-income older adults (age 62+) who were working immediately prior to the COVID-19 pandemic (October-December of 2019) shift to not working one year later, relative to higher-income adults during the same period (22 percent). This 16-percentage point gap in labor exits among low-income workers is larger than the 10-percentage point gap observed in pre-COVID-19 periods. While this offers descriptive insight, CPS data is limited in its ability to capture more complete financial detail given the structure of the panel and limited set of indicators.

Our unique panel dataset of quarterly wage and credit data allows us to advance the understanding of labor force exits of older adults during the COVID-19 pandemic in three important ways. First, our study defines labor force exits using administrative panel data on wages earned in a quarter, allowing for more granular measurement of quarter-to-quarter changes in labor force activity before and after the onset of the pandemic. Second, we observe labor force exits at more frequent, quarterly intervals, allowing for a highly detailed examination of labor force participation. Third, in addition to standard demographic factors, we identify a rich set of indicators of financial vulnerability prior to the onset of the pandemic—including income, debt, and credit score—that associate with increased labor force exits among older adults after the onset of the pandemic relative to pre-COVID-19 periods.

2.2 Changes in Older Adults' Retirement Behavior During COVID

For older adults, decisions about retirement must be considered alongside labor force exits and the extent to which the onset of the COVID-19 pandemic sped up the timeline by which older adults entered retirement and claimed Social Security benefits. Research finds that in previous economic recessions, working older adults near retirement age exited the labor force and began claiming Social Security retirement benefits earlier than they would have absent the recession (Coile and Levine 2007, 2011). However, the onset of the COVID-19 pandemic was different than past economic recessions. To the extent that older adults viewed the pandemic as temporary and short-lived, we may not expect to observe increases in retirement and Social Security claiming, despite increases in labor exits. Instead, we may expect to observe increases in Unemployment Insurance (UI) claims among older adults as was observed in the general population immediately following the onset of the COVID-19 pandemic (Lozano and Rojas et al. 2020). Hedin, Schnorr, and Wachter (2020) find that older workers in California filed UI claims at a similar rate to mid-career workers, while workers in their 20s showed substantially higher claiming rates during the early months of the pandemic.

The CPS, as well as other household surveys, includes self-reported retirement behaviors, and a few prior studies indicate an increase in self-reported retirement during the COVID-19 pandemic—albeit at a lower rate than the increase in labor exits among older adults (Quinby, Rutledge, and Wettstein 2021; Coibion, Gorodnichenko, and Weber 2020; Kaplan et al. 2021; Sanzenbacher 2021). For example, in an analysis of Nielsen survey data, Coibion, Gorodnichenko, and Weber (2020) find that 59.5 percent of people who reported being out of the labor force and not looking for work in April 2020 indicated being retired, compared to 52.7 percent of the same group prior to the onset of the pandemic. Using CPS data, Kaplan et al. (2021) find that the US retirement rate rose from 18.5 percent in February 2020 to 19.5 percent in April 2021—of which only 0.4 percentage points can be explained by expected historic trends pre-COVID-19. Despite increases in self-reported retirement, analyses of aggregate Social Security data through March 2021 do not find evidence of an immediate increase in Social Security Old-Age and Survivors Insurance (OASI) applications in response to the COVID-19 pandemic (Goda et al. 2022a; Quinby, Rutledge, and Wettstein 2021). However, longer-term effects on the timing of social security claiming are still unclear.

Studies using average Social-Security-retirement-benefits-claiming rates at the national level can mask important heterogeneity, as the COVID-19 pandemic may have sped up claiming for certain groups and slowed claiming for others. Prior studies find evidence of differences in retirement timing and Social-Security-retirement-benefits-claiming behaviors based on the financial position of the working older adult. Exogenous decreases in wealth, such as due to house price decreases or poor stock market performance, are found to delay retirement and Social Security benefit claiming (Begley and Chan 2018; Goda, Shoven, and Slavov 2012; Ondrich and Falevich 2014). Consistently, Brown, Coile, and Weisbenner (2010) find increases in wealth through inheritance increase the likelihood of retiring. Butrica and Karamcheva (2018, 2020) find that higher levels of debt are associated with increased probability of working and delaying retirement and Social Security claiming. Haurin, Moulton, and Loibl (2022) identify higher levels of financial stress as a mechanism explaining decreased probability of claiming Social Security benefits early—particularly for those with higher wage income before retirement eligibility.

Taken together, studies prior to the onset of the COVID-19 pandemic suggest that older adults experiencing financial vulnerability—either due to lower levels of wealth or higher levels of debt—were less likely to claim Social Security retirement benefits if they were in the labor force and could continue working. It is unclear how this response may differ during the COVID-19 pandemic when the option to continue working was not equally accessible or desirable due to

COVID-19-related layoffs and fear of disease spread. While those with higher debt burdens may desire to continue working, they may be unable to do so—and may be more likely to claim unemployment insurance benefits rather than permanently exiting the workforce by claiming Social Security retirement benefits. The current study contributes new knowledge about Social-Security-retirement-benefits-claiming behavior because we link and aggregate individual-level wage, unemployment insurance, and credit data to the county and quarter-year level to explore how variation in debt burdens and wages of older adults associate with Social Security retirement claims.

2.3 COVID-19 and the Economic Security of Older Adults

The net effect of the COVID-19 pandemic on older adults' economic security is still not well understood. For older adults already out of the labor force prior to the onset of the pandemic, there is no expected reduction in income—and in fact, many experienced short-term increases in income due to the COVID-19 economic stimulus payment.[1] At the same time, shut-downs in the economy between February and April 2020 and fear of COVID-19 spread were associated with reduced consumption—particularly among older adults in the top half of the consumption distribution prior to COVID-19 (Meyer, Murphy, and Sullivan 2022). Thus, for the average healthy older adult, stable or increasing income combined with reduced consumption contributed to increased rates of saving and reductions in debt after the onset of the COVID-19 pandemic (Baker et al. 2020; Brown, Collins, and Moulton 2022; Meyer, Murphy, and Sullivan 2022).

For some older adults, however, there is evidence of a negative impact of the COVID-19 pandemic on economic well-being (Abrams, Finlay, and Kobayashi 2022). Older adults were more susceptible to severe illness from the coronavirus and significant financial consequences—increased health expenditures, reduced ability to work, and unexpected financial strain on a household due to the death of a partner (Gilstrap et al. 2022; Polyakova et al. 2020). For older adults in the labor force prior to the onset of the pandemic—particularly those who were eligible for Social Security retirement benefits but chose to work to supplement their income—COVID-

[1]Older adults receiving Social Security retirement benefits were eligible for the COVID-19 stimulus payment and the payment did not count against the income limit for Social Security, with the $1,400 per person payment typically deposited directly into their monthly benefit account.

19-pandemic-related work disruptions may be detrimental to financial health. Recent studies use survey data to measure self-reported indicators of financial well-being among those experiencing income shocks. For example, Sharma and Babiarz (2022) use the Health and Retirement Study to show that older adults who experienced an income shock during the COVID-19 pandemic reduced their spending. If these older adults received stimulus transfer payments, these payments were used to smooth consumption and repay debt. Using data from the 2020 wave of the Health and Retirement Study (HRS), Andrea et al. (2022) find that COVID-19-era job loss and reductions in income were associated with a greater prevalence of financial hardship, food insecurity, and poor/fair self-rated health than older adults not experiencing job loss or income reductions.

There is limited research that uses administrative data to measure the economic security of older adults after the onset of the pandemic.[2] Using consumer credit data, Brown, Collins, and Moulton (2022) analyze trends in credit and debt before and after the onset of the COVID-19 pandemic among older adults. While adults ages 50 and older experienced larger reductions in household debt after the start of the COVID-19 pandemic relative to adults ages 18-49, household debt levels increased for particular vulnerable segments of older adults: those with lower incomes, lower credit scores, and from single-person households. These vulnerable households were also less likely to be making payments on their debts and more likely to have their debts in forbearance or COVID-19-related accommodations. Our present study examines the extent to which these heterogeneous effects in credit and debt outcomes are related to labor-force exits of older adults.

[2] Several papers examine other dimensions of heterogeneity in economic and financial stability during the pandemic, with age heterogeneity being particularly understudied. For example, Mills et al. (2022) trace pandemic-era debt and financial stability changes across pre-pandemic income groups.

3. Data and Methods

3.1 Data and Sample Construction

We construct a unique panel dataset for this analysis, combining data on adults ages 50 and older in Ohio from two sources. The first is credit panel data from Experian, one of three national credit bureaus, with data on the full population with credit records in the state of Ohio (8.2 million individuals). In the Ohio Credit Panel data, we observe account balances (e.g., credit cards, student loans, auto loans, and mortgages), payment delinquency and forbearance, credit score, and ZIP code. We merge in ZIP-code-level data on race and urban areas from the American Community Survey (ACS), as race and neighborhood characteristics are not reported in credit data.[3]

For this study, we select a 20 percent random sample of individuals and their household members in the Ohio Credit Panel dataset in 2019 or 2020.[4] We link this sample to our second data source, administrative data on quarterly employment data for all workers in the state of Ohio through the Ohio Longitudinal Data Archive (OLDA).[5] The quarterly OLDA employment data allow us to observe wage income by employer, weeks worked for each employer, and unemployment-claim activity and benefit amounts.

For our third aim, we aggregate individual credit, wage, and unemployment indicators to the county-quarter level and merge them with quarterly level data on Social-Security-benefit claims in an Ohio county. Aggregate counts of initial Social Security claims by claim type (OASI, SSI, and SSDI), county, quarter, and age group (50-61; 62-66; 67+) are provided by the Social Security Administration for this research project for the years 2018 through 2021 in Ohio.[6] Our primary focus is OASI-retired-worker claims for adults ages 62 to 66, who are eligible to claim retirement benefits early prior to full retirement age.

[3] In alternative specifications that probe the intensive margin of COVID-19 disease exposure, we use data on COVID-19 cases and deaths at the county level, downloaded through a COVID-19 data repository hosted by the New York Times.
[4] The subsample of the full credit panel is required by our data providers to allow matching between our credit panel and state administrative data.
[5] The Ohio Longitudinal Data Archive is a project of the Ohio Education Research Center (oerc.osu.edu) and provides researchers with centralized access to administrative data. The OLDA is managed by The Ohio State University's Center for Human Resource Research (chrr.osu.edu) in collaboration with Ohio's state workforce and education agencies (ohioanalytics.gov), with those agencies providing oversight and funding. For information on OLDA sponsors, see http://chrr.osu.edu/projects/ohio-longitudinal-data-archive .
[6] Cells with fewer than ten claimants in a given county and quarter are omitted from the output.

While our data are limited to one state, Ohio includes diverse urban and rural communities with 16 metropolitan statistical areas and 32 counties in the rural Appalachian region, providing important heterogeneity for this analysis. Ohio mirrors the nation with regard to its age and gender distribution, the percent of individuals who identify as Black, and the percentage of individuals in the labor force.[7]

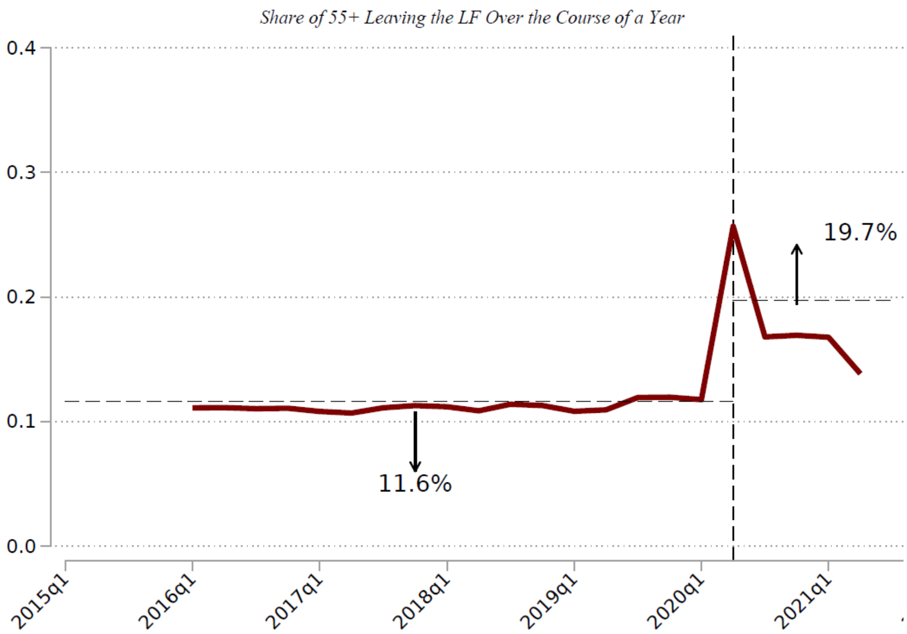
3.2 Labor Force Trends Among Older Adults in the Ohio Sample

To situate our sample of Ohioans in the national context, we compare trends in labor force indicators in our sample data to national trends from the Current Population Survey (CPS) as summarized in prior studies (Goda et al. 2022a; Quinby, Rutledge, and Wettstein 2021). Using the Ohio employment data, we first plot the share of individuals ages 55 and older in our 20 percent random sample who left the labor force over the course of a year.[8] We code individuals as having left the labor force (LF) over the course of a year if any weeks worked were observed four quarters prior to a reference quarter, but there were no weeks worked in the current quarter. Figure 1 below plots trends in this indicator over time.

The share of older Ohioans exiting the labor force increases markedly in Q2 of 2020, from a base of about 11.6 percent in a given quarter to a peak of about 25 percent—then declining slightly with an average exit rate of 19.7 percent through Q2 2021. By comparison, estimates using national CPS data for adults ages 55 and older indicate an average pre-COVID-19 annual exit rate of 15 percent that increases to 23 percent in March through December 2020 (Quinby, Rutledge, and Wettstein 2021). Thus, while our point estimates are slightly lower, the trends and size of the increase in exits during COVID-19 are similar.

[7] U.S. Census Bureau; https://www.census.gov/quickfacts/fact/table/OH,US/PST045219, April 26, 2021
[8] While our sample data includes adults age 50 and older, we limit the sample to adults age 55 and older for this comparison so that our sample is constructed similar to Quinby, Rutledge, and Wettstein (2021)

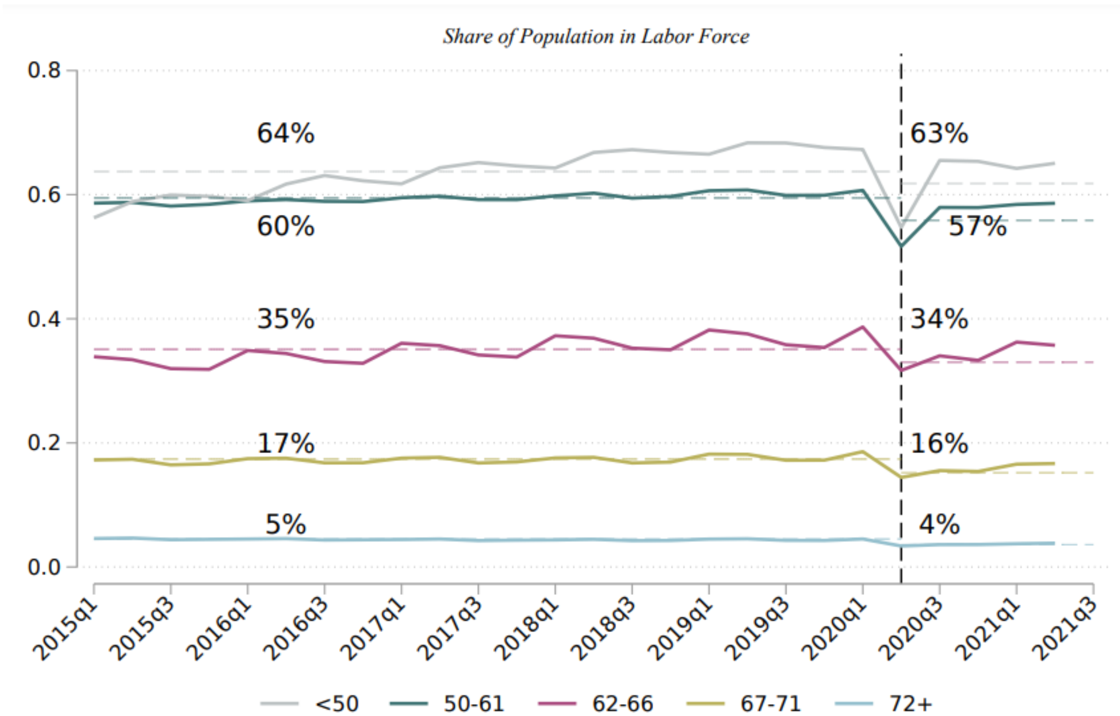
Figure 1: Share of Ohio Population Age 55+ Leaving the Labor Force Over the Course of a Year



Source: OLDA UI Wages Data, 2015-2021

We next examine the share of the older adult population in the labor force, with any weeks worked reported in a quarter in the Ohio employment data ("in labor force"), by age group. Figure 2 reports the trends, including adults younger than 50, for comparison. We report the average percent of people who were in the labor force by age group from January 1, 2015, through March 30, 2020, and then for April 1, 2020, through June 30, 2021 (the COVID-19 period). All age groups experience a large dip in labor force participation in Q2 2020 that rebounds in the following quarters. For adults ages 50 to 61, we observe an average three percentage point decline in labor force participation after the onset of COVID-19 through the end of June 2021 (from 60 percent to 57 percent), whereas we observe a one percentage point decline in average labor force participation for adults ages 62 to 66 (from 35 percent to 34 percent) and for adults ages 67 to 71 (from 17 percent to 16 percent). The overall share in the labor force estimated using Ohio's employment data is lower than estimates using national CPS data. For example, Goda et al. (2022a) report that about 70 percent of older adults ages 50 to 61 were in the labor force pre-COVID-19. This discrepancy is likely due to the Ohio employment data only including taxable wages earned in the state of Ohio, while CPS is self-reported employment from all sources. Important for our analysis, the trends in labor force participation observed using Ohio's employment data pre- and post- the onset of COVID-19 are similar to estimates derived from CPS data.

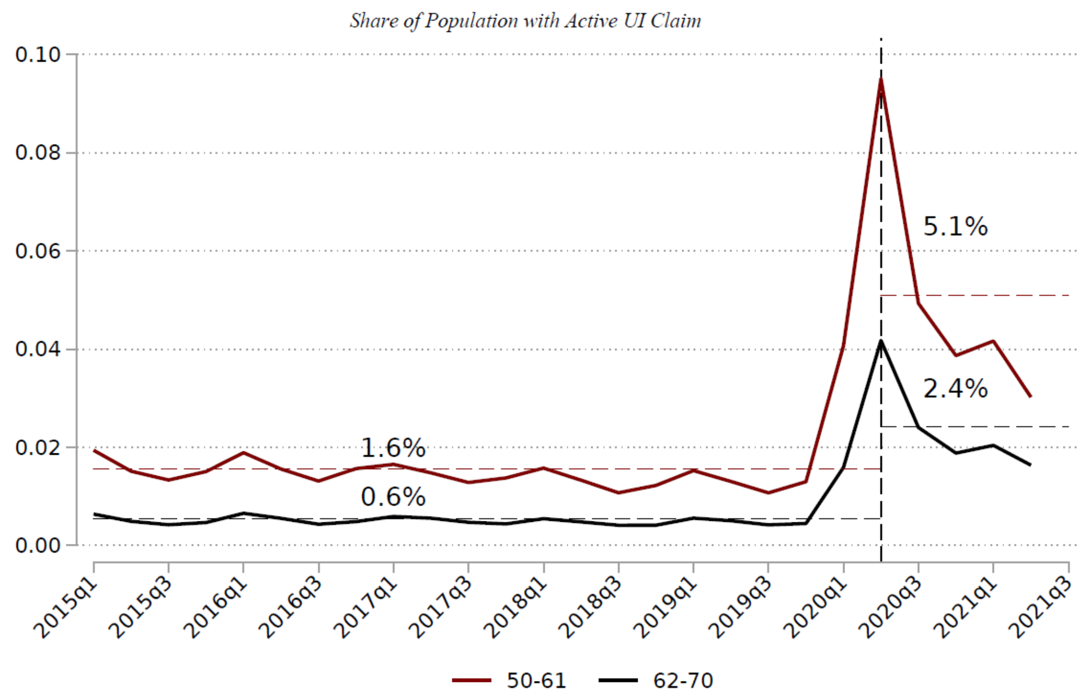
Figure 2: Share of Ohio Population in Labor Force by Age Group



Source: OLDA UI Wages Data, 2015-2021

Finally, we examine the share of the random sample population in Ohio with an active Unemployment Insurance (UI) claim by age group. We infer an active UI claim if an individual is recorded as having an active claim with a positive weekly benefit amount within a given quarter. Figure 3 plots this share over time by quarter for people ages 50 to 61 and 62+. There is a spike in UI claims in Q2, 2020 that subsequently declines but remains higher than pre-pandemic levels. While UI receipt is not reported directly in CPS data, Goda et al. (2022b) summarize the share of respondents who indicate being unemployed for the same age groups—finding similar trends to those observed in the Ohio data.

Figure 3: Share of Ohio Population Age 50+ with Active UI Claim by Age Group



Source: OLDA UI Claims Data, 2015-2020

3.3 Empirical Specifications

3.3.1 Predicting labor force exits.

Our first set of empirical specifications describes the characteristics of older adults who exited the labor force during the COVID-19 pandemic, with a particular focus on baseline indicators of financial vulnerability that differ for COVID-19-period exits relative to pre-COVID-19-period exits.

We define the base quarter as Q1, 2018 for the pre-COVID-19 quarters (Q2, 2018-Q2, 2019) and as Q1, 2020 for the COVID-19 quarters (Q2, 2020-Q2, 2021).[9] We limit our sample to older adults who were in the labor force in a base quarter and estimate separate linear probability regression models for labor force exits as of (n) quarters (n=1-5) following the base quarter, as follows:

[9] We use Q1, 2018 as the baseline quarter for the pre-COVID-19 period rather than Q1, 2019, as it allows us to follow outcomes through five pre-COVID-19 quarters post baseline (through Q2, 2019).

$$Y_{i,t+n} = \beta_0 + \beta_1 Credit_{i,t} + \beta_2 Demog_{i,t} + \beta_3 X_{z,t} + \beta_4 COVID_{t+n} + \beta_5(COVID_{t+n} * Credit_{i,t}) + \beta_6(COVID_{t+n} * Demog_{i,t}) + \beta_7(COVID_{t+n} * X_{z,t}) + e_{i,t} \quad (1)$$

Where $Y_{i,t+n}$ is an indicator for leaving the labor force, coded "1" if an individual was not in the labor force in quarter t+n conditional on being in the labor force in Q1(t). The baseline quarter (t) is defined as Q1 of 2018 for the pre-COVID-19 quarters or Q1 of 2020 for the COVID-19 quarters. In our primary specification, we define out of the labor force to include everyone with $0 in wage earnings in a quarter, which includes both voluntary and involuntary exits. In an alternative specification, we measure involuntary separations with an indicator for having an active unemployment claim in quarter t+n conditional on being in the labor force in quarter t. To better explore the extensive margin of changes in wages, we estimate an alternative specification where the outcome is a continuous measure of the difference in the dollar amount of wages earned in the outcome quarter relative to the baseline quarter.

Financial vulnerability at baseline is measured by a vector of credit variables ($Credit_{i,t}$) that include debt levels by type of debt (mortgage, credit card, student loan, auto loan), credit score, and a dummy indicator for having any available credit on a revolving line of credit. The vector of baseline individual demographic characteristics ($Demog_{i,t}$) includes individual wage income in the base quarter, a dummy indicator for another household member with wage income in the base quarter, the number of adults in the household with credit data, age cohort, and gender. $X_{z,t}$ is a vector of ZIP code characteristics, including a dummy variable coded "1" if the majority of people in a ZIP code are Black and an indicator for being an urban ZIP code z. $COVID_{t+n}$ is a dummy indicator coded "1" if the outcome quarter is in Q2 to Q4, 2020 or Q1 and Q2, 2021. We interact the COVID-19 indicator with the vectors of credit, demographic, and ZIP code covariates. The resulting interaction coefficients can be interpreted as the difference in differences estimates of the association of the baseline covariates with the change in labor force outcomes during the COVID-19 period relative to the pre-COVID-19 period. We cluster standard errors by individual.

3.3.2 Labor force exits and changes in credit outcomes.

For our second aim, we estimate the association of exiting the labor force, receiving active UI during the pandemic, and changes in wages relative to pre-COVID-19 periods, with indicators of economic well-being from credit data. Our regression specification is similar to equation (1); however, we include the full sample of older adults, not limited to those who were in the labor force at baseline. We estimate the following model using OLS regressions:

$$\Delta Y_{i,t+n} = \beta_0 + \beta_1 Credit_{i,t} + \beta_2 Demog_{i,t} + \beta_3 X_{z,t} + \beta_4 COVID_{t+n} + \beta_5 IN\_LF_{i,t} + \beta_6 LEFT\_LF_{i,t+n} + \beta_7 (COVID_{t+n} * LEFT\_LF_{i,t+n}) + e_{i,t} \quad (2)$$

Here, $\Delta Y_{i,t+n}$ represents the change in a credit outcome in quarter t+n, relative to the level of the credit outcome in Q1(t) of 2018 or 2020. We estimate equation (2) separately for the following credit outcomes: change in credit score from baseline, non-payment status,[10] delinquency status, forbearance status (for 2020-2021 quarters), and changes in debt levels since the base quarter by type. Explanatory variables include the same vectors of Credit, Demographic, and ZIP code characteristics at baseline included in Equation (1). We also include an indicator for being in the labor force (IN_LF) as of the baseline quarter (t), as well as an indicator for not being in the labor force (LEFT_LF) in the current quarter (t+n). The key coefficient of interest is the interaction between the COVID-19 period and being out of the labor force (LEFT_LF) in a given quarter. In alternative specifications, we replace LEFT_LF with an indicator for having an active UI claim in the current quarter, and with the change in wages since the baseline quarter.[11]

To consider heterogeneous effects of changes in labor force participation, we estimate a series of triple difference in differences models that interact the LEFT_LF and COVID-19 period indicators with baseline credit and demographic characteristics. We acknowledge that labor force participation may be endogenous, and thus do not claim that our estimates are causal. Nonetheless,

[10] Defined as having a trade with either a forbearance or 60+ delinquency and excludes student loan trades which were largely in forbearance by default during COVID-19.

[11] In alternative specifications, we also include an interaction between IN_LABOR and COVID-19 as a control variable, allowing for differential effects of COVID-19 on outcomes for those who were in and out of the labor force the entire time (i.e., without a labor-force exit). The LEFT_LF and COVID-19 interaction results from our primary specification are substantively similar with and without the additional interaction as a control variable.

our models allow for identification of particular groups of older adults who are at higher risk of economic insecurity.

3.3.3 County-level social security claims.

For our third aim, we explore COVID-19-era differences in indicators of financial vulnerability that associate with the share of older adults in a county claiming early Social Security retirement (OASI) benefits. To do this, we estimate the share of adults ages 62 to 66 claiming OASI benefits in a county during a one-year period as a function of the share of workers ages 62 to 66 exiting the labor force in the county over the same one-year period and a vector of credit and demographic characteristics describing older adults in the county as of a baseline quarter. We construct a pooled sample of county-year observations, with year $t \in \{2018, 2019, 2020\}$. We define the base quarters (b(t)) as Q1, 2020 for the COVID-19 period, and as of Q1, 2018 or Q1, 2019 for the pre-COVID-19 periods. We measure outcomes as the share in county c claiming early retirement benefits cumulatively in Q2, 2020 through Q1, 2021 for the COVID-19 period, and cumulatively in Q2, 2018-Q1, 2019 for the 2018 and Q2, 2019-Q1, 2020 for the 2019 pre-COVID-19 periods. We estimate the following model using OLS regression:

$$Y_{c,t} = \beta_0 + \beta_1 Credit_{c,b(t)} + \beta_2 Demog_{c,b(t)} + \beta_3 X_{c,b(t)} + \beta_4 COVID_t + \beta_5 IN\_LF_{c,b(t)} + \beta_6 LEFT\_LF_{c,t} + \beta_7 (COVID_t * LEFT\_LF_{c,t}) + e_{c,t} \quad (3)$$

where $Y_{c,t}$ is the share of adults ages 62-66 in a county filing an OASI claim in a one-year period, measured as the sum of new claims in Q2, Q3, and Q4 of year t, plus those in Q1 of year t+1, divided by the total number of adults age 62 to 66 in the county as of t.[12] Financial vulnerability at baseline is measured by the same vector of credit variables ($Credit_{c,b(t)}$) and demographic variables ($Demog_{c,b(t)}$) described in equation (1) but aggregated to the county level for adults ages 62 to 66 in a county. $X_{c,b(t)}$ is the average house value in the county as of the baseline quarter, a proxy for the amount of wealth in the county. $COVID_t$ is a dummy indicator coded "1"

[12] We calculate the total number of older adults in a county at time t based on the number of adults ages 62 to 66 with a credit file at time t, weighted by the estimated share of older adults in a county with credit data, with weights generated using Census data.

if the outcome period is measured during COVID-19 (Q2, 2020-Q1, 2021), and "0" otherwise. We include a variable controlling for the share of adults ages 62 to 66 who were in the labor force ($IN\_LF_{c,b(t)}$) as of the baseline quarter (b in year t), as well as a variable measuring the share of older adults who left the labor force between Q2 of year t and Q1 of year t+1 ($LEFT\_LF_{c,t}$). The key coefficient of interest is the interaction between the COVID-19 period and the share leaving the labor force (LEFT_LF) in a given year. In alternative specifications, we replace LEFT_LF with a variable measuring the share having an active UI claim in t. To further explore COVID-19-era differences in indicators of financial vulnerability, we interact the COVID-19 indicator with the vectors of credit and demographic covariates. We cluster standard errors by county.

3.4 Variable Construction and Sample Characteristics

3.4.1 Labor force exits, unemployment claims, and changes in wages.

Table 1 summarizes labor force exits (or being out of the labor force), active unemployment claims, and changes in wages as of one to five quarters after the Q1 baseline quarter of a given year (2018 or 2020). Thus, Q2, Q3, and Q4 correspond to quarters in the baseline year (2018 or 2020), and Q5 and Q6 correspond to the first and second quarters of the following year (2019 or 2021). Panel A limits the sample to older adults in the labor force as of Q1 following Equation (1), where the labor force indicator is an outcome. Panel B includes all older adults regardless of labor force status as of Q1 following Equation (2), where the labor force indicator is an explanatory variable.

As indicated in Panel A, there is a marked increase in labor force exits between Q1 and Q2 of 2020 (18.9 percent) which is much higher than the share of labor force exits between Q1 and Q2 of 2019 (3.5 percent). The share who left the labor force declines in subsequent quarters of 2020 and 2021 but remains elevated compared to the same quarter in 2018. Similarly, the share of previously working older adults with an active UI claim peaks in Q2, 2020 (14.2 percent) and then declines but remains elevated through 2021 relative to 2018. Finally, average quarterly wages among those working in Q1 (Panel A) decline by $3,680 from Q1 to Q2 of 2020—a much larger decline than the $1,070 decline from Q1 to Q2 of 2018. The difference in pre- and during COVID-19 wage trends is smaller in subsequent quarters. The trends are similar for Panel B; however, the overall levels are much smaller because the labor force indicators are, as a share of all older adults in a given quarter, not limited to those in the labor force in Q1 (thus, the overall sample is also larger in Panel B).

Table 1: Summary Statistics for Labor Force Indicators, by Aim

Panel A: Aim 1 (In Labor Force as of Q1)	Mean	Mean	Mean	Mean	Mean
Baseline Quarter = Q1 2018					
	Q2	Q3	Q4	Q5	Q6
Left LF	0.035	0.070	0.079	0.095	0.108
Active UI Claim	0.015	0.016	0.016	0.018	0.016
Change Wages ($10k)	-0.107	-0.144	-0.110	-0.101	-0.178
N	293,564	297,660	301,874	306,192	309,836
Baseline Quarter = Q1 2020					
	Q2	Q3	Q4	Q5	Q6
Left LF	0.189	0.109	0.120	0.140	0.148
Active UI Claim	0.142	0.075	0.057	0.059	0.045
Change Wages ($10k)	-0.368	-0.194	-0.085	-0.197	-0.212
N	302,728	306,662	310,233	314,069	317,817
Panel B: Aim 2 (Full Sample Regardless of Labor Force in Q1)					
Baseline Quarter = Q1 2018					
	Q2	Q3	Q4	Q5	Q6
Left LF	0.012	0.024	0.028	0.034	0.039
Active UI Claim	0.007	0.006	0.007	0.008	0.007
Change Wages ($10k)	-0.034	-0.044	-0.029	-0.029	-0.054
N	843,913	849,033	854,242	861,566	857,779
Baseline Quarter = Q1 2020					
	Q2	Q3	Q4	Q5	Q6
Left LF	0.065	0.038	0.042	0.050	0.054
Active UI Claim	0.053	0.029	0.023	0.023	0.018
Change Wages ($10k)	-0.127	-0.066	-0.025	-0.066	-0.070
N	881,576	881,322	879,776	878,550	878,406

Notes: Summary statistics are means. Labor force (LF) outcomes as of a given quarter are relative to Q1 of the baseline year.

3.4.2 Changes in economic well-being from credit data.

Table 2 summarizes the credit outcomes modeled in Equation (2) as of one to five quarters after the Q1 baseline quarter of a given year (2018 or 2020). The credit outcomes include those measuring credit score, debt repayment, and debt levels. Credit score is the Experian VantageScore 4.0, with values ranging from 300 to 850. We observe an average increase in credit scores of three to six points during COVID-19 in Q2, 2020 through Q2 of 2021, relative to the credit score in Q1 of 2020. As indicated elsewhere (Kowalik, Liu, and Wang 2021), the boost in credit scores for the average consumer during COVID-19 is due to a combination of generous forbearance policies that prevented consumers from being reported as delinquent on their debt even if they were not making payments and a general decline in debt levels and increase in liquidity during the period.

The outcome variable non-payment is an indicator that takes the value "1" if an individual is delinquent on any debt payment for 60 or more days (two months of missed payments) or is in forbearance on the debt, which we define following prior studies as having a balance with no required payment due to financial hardship (Cherry et al. 2021). Forbearance is only measured in 2020 and 2021 as it was not widely used by creditors prior to the COVID-19 pandemic. We exclude payment status on student loans, as all federal student loans were in forbearance during COVID-19. We separately measure delinquency and forbearance on debt payments. As indicated in Table 2, rates of non-payment increased substantially in Q2, 2020 to a high of 7.9 percent—the majority of which can be attributed to having debt in forbearance during the same period (6.2 percent). Rates of nonpayment and forbearance decline in Q3, 2020, but non-payment rates remain elevated compared to pre-COVID-19 periods through Q6. Total household debt includes mortgages, credit cards, auto loans, personal installment loans, student loans, and collections. We also separately measure credit card and mortgage debt. There is a larger decline in debt during the COVID-19 periods relative to the pre-COVID-19 periods, with an average decline in total debt of about $2,300 from Q1, 2020 to Q2, 2021, compared to an average decline of $1,700 from Q1, 2018 to Q2, 2019. The primary difference is credit card debt, which declined by an average of about $1,000 from Q1 to Q6 during COVID-19 compared to no real change from Q1 to Q6 of the pre-COVID-19 quarters.

Table 2: Summary Statistics for Credit Outcomes, Aim 2

Baseline Quarter = Q1 2018	Mean (SD) Q2	Mean (SD) Q3	Mean (SD) Q4	Mean (SD) Q5	Mean (SD) Q6
Change in Credit Score	0.201	-0.396	-0.916	0.177	0.371
	(23.09)	(29.84)	(34.19)	(37.46)	(40.27)
Non-Payment	0.024	0.025	0.026	0.025	0.023
	(0.15)	(0.16)	(0.16)	(0.16)	(0.15)
Delinquency 60+ Days	0.024	0.025	0.026	0.025	0.023
	(0.15)	(0.16)	(0.16)	(0.16)	(0.15)
Change in Total Debt (100ks)	-0.004	-0.006	-0.007	-0.016	-0.017
	(0.32)	(0.42)	(0.48)	(0.52)	(0.56)
Change in Mortgage Debt (100ks)	-0.006	-0.009	-0.014	-0.017	-0.02
	(0.26)	(0.33)	(0.38)	(0.41)	(0.44)
Change in Credit Card Debt (100ks)	0.001	0.001	0.003	0.000	0.001
	(0.04)	(0.05)	(0.06)	(0.07)	(0.07)
N	843,913	849,033	854,242	861,566	857,779

Baseline Quarter = Q1 2020	Mean (SD) Q2	Mean (SD) Q3	Mean (SD) Q4	Mean (SD) Q5	Mean (SD) Q6
Change in Credit Score	2.896	3.255	3.139	4.81	5.918
	(22.91)	(29.24)	(33.44)	(36.82)	(39.29)
Non-Payment	0.079	0.06	0.064	0.05	0.046
	(0.27)	(0.24)	(0.25)	(0.22)	(0.21)
Delinquency 60+ Days	0.021	0.018	0.019	0.018	0.015
	(0.14)	(0.13)	(0.14)	(0.13)	(0.12)
Forbearance	0.062	0.045	0.048	0.034	0.033
	(0.24)	(0.21)	(0.21)	(0.18)	(0.18)
Change in Total Debt (100ks)	-0.011	-0.015	-0.013	-0.021	-0.023
	(0.33)	(0.45)	(0.53)	(0.58)	(0.62)
Change in Mortgage Debt (100ks)	-0.006	-0.015	-0.016	-0.017	-0.021
	(0.26)	(0.36)	(0.42)	(0.45)	(0.49)
Change in Credit Card Debt (100ks)	-0.005	-0.007	-0.006	-0.011	-0.01
	(0.04)	(0.05)	(0.06)	(0.07)	(0.07)
N	881,576	881,322	879,776	878,550	878,406

Notes: Summary statistics are means, with standard deviations in parentheses. All changes are as of a given quarter relative to Q1 in the same year. Forbearance is only measured beginning in 2020 as it was not common prior to the COVID-19 pandemic.

3.4.3 Baseline indicators of financial vulnerability and demographic characteristics.

Appendices A and B summarize the baseline (Q1) levels of the demographic, credit, wage, and ZIP code level variables included in Equation (1) and (2), respectively. The means of the demographic and credit variables at baseline in years 2018 and 2020 are largely similar—indicating that the baseline periods (both prior to the COVID-19 pandemic) are comparable on key covariates. Summary statistics for the samples from Equation (1) and Equation (2) differ expectedly. The sample that conditions on being in the labor force in Q1 (Appendix A) is nearly eight years younger than the full sample (Appendix B), and has more debt (e.g., higher baseline Debt-to-Income ratio, higher levels of debt types, and higher rates of credit utilization). Household sizes, gender makeup, and geographic characteristics are similar between the two samples.

3.4.4 County-level social security claims.

Appendix C summarizes the county-level variables modeled in Equation (3) by year (2018, 2019, and 2020). The outcome is the number of OASI claims in a county and year (Q2, Q3, Q4 of year t, and Q1 of year t+1) for adults ages 62 to 66, divided by the census-adjusted population in the county ages 62 to 66. The average share across Ohio counties decreases slightly in 2020 to 16.4 percent, from 17.7 percent in 2019 and 17.4 percent in 2018. At the same time, the average share of adult workers leaving the labor force over the course of the year increases to 7.7 percent in 2020-21, up from 6.1 percent in 2019 and 6.0 percent in 2018. The share of adults ages 62 to 66 in the labor force as of the baseline quarter (Q1) increases slightly over time, from 34.8 percent in 2018 to 35.9 percent in 2020. Other covariates at baseline are relatively constant over time. Dollars are nominal and thus it is not surprising that levels of variables measured in dollars increase slightly over time.

4. Results

4.1 Financial Vulnerability and Labor Force Outcomes

Our first aim (Equation 1) identifies baseline factors that are associated with (1) the probability of leaving the labor force, or (2) having an Unemployment Insurance (UI) claim, both outcomes conditional on being in the labor force as of Q1 of a given year. We also separately estimate models for (3) changes in wages since Q1. Complete regression results are reported in Appendices D, E, and F. Tables 3.1 and 3.2 report the coefficients for the COVID*baseline covariate interactions, which can be interpreted as the difference in the effect of a particular covariate on labor outcomes during the COVID-19 period, relative to the effect of the covariate on labor outcomes in pre-COVID-19 periods. A positive interaction effect indicates that the baseline factor is associated with a greater probability of labor force exit (Table 3.1) or having an active UI claim during the pandemic (Table 3.2), relative to pre-COVID-19 periods.

We find evidence of heterogeneous effects by age, where the oldest working adults as of the baseline quarter were significantly more likely to exit the labor force during the COVID-19 quarters than during pre-COVID-19 quarters—this effect persisted through the end of our analysis period in Q2, 2021; see Table 3.1. The oldest working adults were initially less likely to have an active UI claim in Q2, 2020 but were significantly more likely to have a UI claim by Q3, 2020 through Q2 of 2021 relative to the same-age adults during the pre-COVID-19 quarters; see Table 3.2. The oldest age groups also saw significant reductions in wage income during COVID-19 relative to pre-COVID-19 wage changes.

Aside from age, we also observe significant heterogenous effects by gender, the majority race of the ZIP code, and whether or not the working adult lived in an urban ZIP code. In our sample, female older workers were more likely to exit the labor force during COVID-19 than female older workers in pre-COVID-19 quarters. However, they were also significantly less likely to have an active UI claim compared to pre-COVID-19 quarters, which may indicate more voluntary exits among older female workers during COVID-19 relative to female older workers in pre-COVID-19 quarters. From Q3 of 2020 through Q2 of 2021, working older adults in majority Black ZIP codes were significantly more likely to exit the labor force compared to pre-COVID-19 quarters, and were significantly more likely to have an active UI claim. Working older adults in urban ZIP codes were significantly more likely to exit the labor force during COVID-19, and by Q3 of 2020 through Q2, 2021, were significantly more likely to have an active UI claim. Older adults in majority-Black ZIP codes also experienced a significant decline in quarterly wages during the COVID-19 period.

Turning to indicators of financial vulnerability, we find that in pre-COVID-19 quarters, working older adults with higher credit scores at baseline were less likely to leave the labor force and less likely to have a UI claim. The relationship between credit score and leaving the labor force is more than seven times larger during the first quarter of the COVID-19 pandemic (Q2), where a 100-point increase in credit score at baseline is associated with a 2.3 percentage point decrease in the probability of exiting the labor force during COVID-19—above the normal 0.3 percentage point decrease for higher credit scores. The size of the COVID*credit score interaction on leaving the labor force decreases but continues to be statistically significant through the end of the study period in Q2, 2021. We also find that higher-credit-score adults were consistently significantly less likely to file a UI claim during all COVID-19 quarters relative to pre-COVID-19 quarters.

We find that older adults having any available credit on credit cards at baseline were less likely to exit the labor force during COVID-19 and were less likely to have an active UI claim in the COVID-19 quarters, relative to older adults with available credit during pre-COVID-19 quarters. We find no consistent relationship between debt levels and exits from the labor force or UI claims during COVID-19, with the exception of auto debt. Holding higher levels of auto debt at baseline is associated with a decreased likelihood of exiting the labor force—with the effect being even greater during the COVID-19 periods. Further, during COVID-19, higher levels of auto debt were associated with a lower likelihood of having an active UI claim compared to pre-COVID-19 quarters.

Turning to wages, higher quarterly wages at baseline in normal pre-COVID-19 periods were associated with a reduced probability of older adults exiting the labor force—an effect that is not significantly different during COVID-19 periods. However, higher quarterly wages at baseline were associated with a reduction in the probability of having an active UI claim during the COVID-19 quarters that is larger than during pre-COVID-19 periods. With regard to other covariates, female older adults and older adults from larger household sizes were also more likely to exit the labor force during COVID than pre-COVID-19 periods.

Table 3.1: Key OLS Regression Coefficients Predicting Left Labor Force Since Q1 (Aim 1)

	Q2 Beta (S.E.)	Q3 Beta (S.E.)	Q4 Beta (S.E.)	Q5 Beta (S.E.)	Q6 Beta (S.E.)
Covid=1	0.309***	0.073***	0.052***	0.063***	0.059***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Covid x Age 62-66	0.011***	0.018***	0.019***	0.021***	0.018***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Covid x Age 67-71	0.060***	0.059***	0.064***	0.067***	0.057***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Covid x Age 72+	0.098***	0.106***	0.102***	0.098***	0.081***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Covid x Female	0.009***	0.005*	0.006***	0.012***	0.009***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Covid x Black Zip	-0.006	0.015***	0.017***	0.010**	0.011**
	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)
Covid x HH Size	0.005***	0.003***	0.003***	0.003**	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Covid x Wages ($10k)	-0.000	-0.002	-0.003	0.000	-0.002
	(0.001)	(0.003)	(0.002)	(0.003)	(0.002)
Covid x Other HH Wages	-0.008***	-0.001	-0.001	0.001	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Covid x Available Credit	-0.013***	-0.007*	-0.008**	-0.011***	-0.011***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Covid x Credit Score	-0.023***	-0.007***	-0.004***	-0.005***	-0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Covid x Mort Debt ($100k)	-0.001	-0.002	-0.001	-0.003*	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Covid x CC Debt ($100k)	-0.017**	-0.007	0.003	-0.002	-0.010
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Covid x Student Debt ($100k)	-0.020***	-0.003	-0.002	0.001	0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Covid x Auto Debt ($100k)	-0.009*	-0.021***	-0.022***	-0.029***	-0.015***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Covid x Urban	0.010***	0.007***	0.010***	0.002	0.006**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Constant	0.081***	0.110***	0.141***	0.170***	0.154***
	(0.017)	(0.017)	(0.018)	(0.019)	(0.019)
N	596292	604322	612107	620261	627653
Mean	0.113	0.090	0.099	0.118	0.128
SD	0.317	0.285	0.299	0.323	0.334
Unique Individuals	358,725	363,276	368,449	373,513	377,543
F-statistic	406	132	157	200	222

***p<.001; **p<.01; *p<.05; Standard errors in parentheses

Notes: Models estimated as linear probability models using OLS. All models include the vector of covariates summarized in Equation 1; Sample is limited to individuals in the labor force (LF) as of Q1 of a given year; full results are shown in Appendix D.

Table 3.2: Key OLS Regression Coefficients Predicting Active UI Claim (Aim 1)

	Q2	Q3	Q4	Q5	Q6
	Beta (S.E.)	Beta (S.E.)	Beta (S.E.)	Beta (S.E.)	Beta (S.E.)
Covid=1	0.305***	0.166***	0.129***	0.118***	0.098***
	(0.006)	(0.005)	(0.005)	(0.005)	(0.004)
Covid x Age 62-66	-0.008***	0.002	0.004**	0.001	0.005***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Covid x Age 67-71	-0.030***	0.003	0.010***	0.007***	0.009***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
Covid x Age 72+	-0.046***	0.004	0.012***	0.008***	0.011***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Covid x Female	-0.008***	-0.005***	-0.003**	-0.003***	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Covid x Black Zip	-0.015***	0.009***	0.006**	0.007**	0.005*
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
Covid x HH Size	-0.002*	-0.000	-0.000	-0.001*	-0.001*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Covid x Wages ($10k)	-0.005***	-0.003***	-0.002***	0.000	-0.001**
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Covid x Other Wages	0.006***	0.002	0.002	0.002*	0.002
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Covid x Available Credit	0.007*	-0.005*	-0.006**	-0.006**	-0.006**
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Covid x Credit Score	-0.019***	-0.014***	-0.012***	-0.011***	-0.009***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Covid x Mort Debt ($100k)	-0.007***	-0.002**	-0.001	0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Covid x CC Debt ($100k)	-0.023***	-0.003	-0.007	-0.002	-0.004
	(0.005)	(0.004)	(0.004)	(0.004)	(0.003)
Covid x Student Debt ($100k)	-0.016***	-0.006***	-0.001	-0.001	-0.002
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Covid x Auto Debt ($100k)	0.009*	-0.007*	-0.005*	-0.008**	-0.006**
	(0.004)	(0.003)	(0.002)	(0.003)	(0.002)
Covid x Urban	-0.022***	0.011***	0.013***	0.012***	0.006***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	0.029*	0.053***	0.060***	0.085***	0.075***
	(0.014)	(0.011)	(0.009)	(0.012)	(0.012)
N	596292	604322	612107	620261	627653
Mean	0.079	0.046	0.036	0.039	0.031
SD	0.270	0.209	0.187	0.194	0.173
Unique Individuals	358,725	363,276	368,449	373,513	377,543
F-statistic	345	133	91	95	66

***p<.001; **p<.01; *p<.05; Standard errors in parentheses

Notes: Models estimated as linear probability models using OLS. All models include the vector of covariates summarized in Equation 1; Sample is limited to individuals in the labor force (LF) as of Q1 of a given year; full results are shown in Appendix E.

4.2 Labor Force Exits and Changes in Credit and Debt

We next turn to the models predicting changes in indicators of financial well-being from credit data. We estimate models separately for changes in credit score (Table 4), indicators of non-payment (Tables 5.1-5.3), and changes in debt levels as of Q_n relative to the base quarter (Tables 6.1-6.3). The key explanatory variable is whether or not the older adult exited the labor force as of a given quarter (Panel A), and in subsequent models, whether or not they had an active UI claim (Panel B), and finally the continuous change in wages from the baseline quarter (Panel C). While we estimate the models with the full vector of baseline covariates described in Equation (2), for ease of interpretation, Tables 4 to 6 report the results of the interaction between the COVID-19 period and the labor force indicator, as well as its components. The interaction term is the key coefficient of interest and can be interpreted as the additional effect of the labor indictor during COVID-19 quarters relative to the effect of the given labor indicator in pre-COVID-19 quarters.

4.2.1 Change in credit score.

Table 4 summarizes the results predicting change in credit score from Q1 to the current quarter. As shown in Panel A, leaving the labor force was typically associated with a reduction in credit score of two to five points for older adults. However, the COVID-19 interaction indicates that leaving the labor force during the pandemic associated with a 2.5 to 3.2 point increase in credit score relative to pre-COVID-19 periods. Similarly, having an active UI claim (Panel B) was typically associated with a 2.5 to 5.3 point reduction in credit score—an effect that is more than offset during the COVID-19 period, as indicated by the positive interaction coefficients. Finally, increases in quarterly earned income (Panel C) were typically associated with an increase in credit score (thus decreases in earned were income associated with decreases in credit score). We observe no difference in the relationship during COVID-19. These results are in line with the increased generosity of unemployment benefits, stimulus payments, and unprecedented forbearance on debt payments having a buffering effect on credit score for labor force exits during COVID-19.

Table 4: Key OLS Regression Coefficients Predicting Change in Credit Score (Aim 2)

	Δ Credit Score from Q1				
	Q2	Q3	Q4	Q5	Q6
	Beta (S.E.)	Beta (S.E.)	Beta (S.E.)	Beta (S.E.)	Beta (S.E.)
Panel A: Explanatory Variable = Left Labor Force					
Covid=1	2.568***	3.477***	3.864***	4.412***	5.331***
	(0.035)	(0.044)	(0.050)	(0.055)	(0.059)
Left LF=1	-2.163***	-2.294***	-3.474***	-4.758***	-5.011***
	(0.268)	(0.241)	(0.262)	(0.259)	(0.253)
Covid=1 x Left LF=1	2.569***	2.557***	2.705***	3.227***	2.704***
	(0.286)	(0.295)	(0.319)	(0.314)	(0.311)
In LF Q1=1	1.409***	2.088***	2.621***	3.709***	4.620***
	(0.090)	(0.089)	(0.131)	(0.193)	(0.157)
Panel B: Explanatory Variable = Active UI Claim					
Covid=1	2.543***	3.440***	3.876***	4.446***	5.339***
	(0.035)	(0.044)	(0.050)	(0.054)	(0.058)
Active UI claim=1	-2.955***	-4.708***	-3.955***	-4.392***	-5.192***
	(0.372)	(0.534)	(0.560)	(0.538)	(0.618)
Covid=1 x Active UI claim=1	4.026***	7.293***	5.150***	5.087***	6.825***
	(0.390)	(0.571)	(0.620)	(0.609)	(0.706)
In LF Q1=1	1.344***	1.951***	2.386***	3.300***	4.068***
	(0.090)	(0.088)	(0.130)	(0.193)	(0.158)
Panel C: Explanatory Variable = Change in Wages					
Covid=1	2.673***	3.540***	3.887***	4.528***	5.389***
	(0.035)	(0.043)	(0.050)	(0.054)	(0.058)
Δ Wage	0.858***	1.308***	1.595***	2.044***	2.272***
	(0.042)	(0.046)	(0.053)	(0.055)	(0.067)
Covid=1 x Δ Wage	-0.068	0.028	0.081*	0.026	0.089
	(0.041)	(0.019)	(0.036)	(0.020)	(0.054)
In LF Q1=1	0.739***	0.786***	0.818***	1.474***	2.013***
	(0.059)	(0.074)	(0.082)	(0.087)	(0.091)
Observations	1,725,489	1,730,355	1,734,018	1,740,116	1,736,185
Mean	1.578	1.464	1.141	2.516	3.178
SD	23.034	29.588	33.869	37.206	39.875
Unique Individuals	935,484	940,777	946,448	952,724	948,384

***p<.001; **p<.01; *p<.05; Standard errors in parentheses

Notes: Models estimated using OLS. All models include the vector of covariates summarized in Equation 2. Sample is full sample, not limited to those in the labor force as of Q1.

4.2.2 Change in payment status.

Tables 5.1 to 5.3 summarize the results predicting payment status as of the current quarter, controlling for payment status at baseline. Here, we see evidence of generous payment forbearance being a key mechanism contributing to the buffering effect. Panel A of Tables 5.1 to 5.3 show that labor force exits among older adults were typically associated with a significant increase in debt nonpayment (Table 5.1) and severe payment delinquency (Table 5.2). During COVID-19, the interaction term indicates that older adults exiting the labor force were significantly more likely to miss debt payments (Table 5.1). However, those exiting the labor force during COVID-19 were significantly less likely to be severely delinquent (Table 5.2)—the interaction coefficient nearly fully offsetting the typical increase in severe delinquency associated with labor force exits. Instead, forbearance plays a key role. Older adults exiting the labor force during COVID-19 were 0.6 to 0.9 percentage points more likely to be in forbearance on any debt in 2020 or 2021 (Table 5.3).

Similar results are observed for older adults with an active UI claim—an event that is typically associated with an increase in non-payment as well as severe delinquency for older adults (Panel B). However, during COVID-19, the increased probability of severe delinquency associated with a UI claim (Table 5.2) was almost completely offset in most quarters—with the probability of being in forbearance (Table 5.3) much higher for those with an active UI claim. An increase (decrease) in quarterly earned income (Panel C) was associated with a significant decrease (increase) in being in non-payment status (Table 5.1)—an effect that is even larger during the first three quarters of the COVID-19 pandemic. However, while increases in earned income were also associated with decreased probability of severe delinquency (Table 5.2), there was no added effect of changes in earned income on being in severe delinquency during COVID-19. On the other hand, older adults with larger increases in earned income were less likely to have any debt in forbearance during COVID-19. Similarly, older adults with decreases in earned income were more likely to have debt in forbearance (Table 5.3).

Table 5.1: Key OLS Regression Coefficients Predicting Any Nonpayment of Debt

	Q2 Beta (S.E.)	Q3 Beta (S.E.)	Q4 Beta (S.E.)	Q5 Beta (S.E.)	Q6 Beta (S.E.)
Panel A: Explanatory Variable = Left Labor Force					
Covid=1	0.051***	0.033***	0.036***	0.023***	0.021***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Left LF=1	0.000	0.004**	0.004**	0.006***	0.006***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Covid=1 x Left LF=1	0.014***	0.011***	0.010***	0.007***	0.006***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
In LF Q1=1	0.004***	0.005***	0.007***	0.004***	0.004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Panel B: Explanatory Variable = Active UI Claim					
Covid=1	0.050***	0.033***	0.036***	0.023***	0.022***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Active UI=1	0.002	0.013***	0.006*	0.012***	0.011***
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Covid=1 x Active UI=1	0.041***	0.018***	0.022***	0.008*	0.004
	(0.003)	(0.004)	(0.004)	(0.003)	(0.004)
In LF Q1=1	0.002***	0.005***	0.008***	0.005***	0.005***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Panel C: Explanatory Variable = Change in Wages					
Covid=1	0.052***	0.033***	0.037***	0.024***	0.022***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Δ Wage	-0.005***	-0.003***	-0.002***	-0.003***	-0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Covid=1 x Δ Wage	-0.001*	-0.000**	-0.000**	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
In LF Q1=1	0.010***	0.010***	0.011***	0.009***	0.008***
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Observations	1,725,489	1,730,355	1,734,018	1,740,116	1,736,185
Mean	0.052	0.042	0.045	0.038	0.035
SD	0.222	0.202	0.208	0.19	0.183
Unique Individuals	935,484	940,777	946,448	952,724	948,384

***p<.001; **p<.01; *p<.05; Standard errors in parentheses

Notes: Models estimated as linear probability models using OLS. All models include the vector of covariates summarized in Equation 2. Sample is full sample, not limited to those in the labor force as of Q1.

Table 5.2: Key OLS Regression Coefficients Predicting Any 60+ Day Payment Delinquency

	Q2 Beta (S.E.)	Q3 Beta (S.E.)	Q4 Beta (S.E.)	Q5 Beta (S.E.)	Q6 Beta (S.E.)
Panel A: Explanatory Variable = Left Labor Force					
Covid=1	-0.003***	-0.007***	-0.007***	-0.007***	-0.008***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Left LF=1	0.007***	0.011***	0.011***	0.010***	0.009***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Covid=1 x Left LF=1	-0.008***	-0.010***	-0.007***	-0.005***	-0.004***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
In LF Q1=1	0.000	0.001**	0.002***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Panel B: Explanatory Variable = Active UI Claim					
Covid=1	-0.003***	-0.007***	-0.007***	-0.007***	-0.008***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Active UI claim=1	0.009***	0.021***	0.014***	0.016***	0.014***
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Covid=1 x Active UI claim=1	-0.013***	-0.026***	-0.014***	-0.014***	-0.013***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
In LF Q1=1	0.000	0.001***	0.003***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Panel C: Explanatory Variable = Change in Wages					
Covid=1	-0.004***	-0.007***	-0.007***	-0.007***	-0.008***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Δ Wage	0.000	-0.001***	-0.002***	-0.003***	-0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Covid=1 x Δ Wage	0.000	-0.000	0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
In LF Q1=1	0.000	0.003***	0.005***	0.005***	0.005***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	1,725,489	1,730,355	1,734,018	1,740,116	1,736,185
Mean	0.022	0.021	0.023	0.022	0.019
SD	23.034	29.588	33.869	37.206	39.875
Unique Individuals	935,484	940,777	946,448	952,724	948,384

***p<.001; **p<.01; *p<.05; Standard errors in parentheses

Notes: Models estimated as linear probability models using OLS. All models include the vector of covariates summarized in Equation 2. Sample is full sample, not limited to those in the labor force as of Q1.

Table 5.3: Key OLS Regression Coefficients Predicting Any Debt in Forbearance During COVID-19

	Q2 Beta (S.E.)	Q3 Beta (S.E.)	Q4 Beta (S.E.)	Q5 Beta (S.E.)	Q6 Beta (S.E.)
Panel A: Explanatory Variable = Left Labor Force					
Left LF=1	0.006***	0.009***	0.006***	0.006***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
In LF Q1=1	0.009***	0.009***	0.011***	0.006***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Panel B: Explanatory Variable = Active UI Claim					
Active UI claim=1	0.040***	0.030***	0.026***	0.016***	0.013***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
In LF Q1=1	0.006***	0.008***	0.011***	0.006***	0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Panel C: Explanatory Variable = Change in Wages					
Δ Wage	-0.007***	-0.005***	-0.002***	-0.002***	-0.001
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
In LF Q1=1	0.016***	0.015***	0.014***	0.009***	0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	881,576	881,322	879,776	878,550	878,406
Mean	0.062	0.045	0.048	0.034	0.033
SD	0.241	0.207	0.214	0.181	0.178
Unique Individuals	881,576	881,322	879,776	878,550	878,406

***p<.001; **p<.01; *p<.05; Standard errors in parentheses

Notes: Models estimated as linear probability models using OLS. All models include the vector of covariates summarized in Equation 2. Sample is full sample, not limited to those in the labor force as of Q1.

4.2.3 Change in debt levels.

Tables 6.1-6.3 summarize the results predicting changes in debt levels from Q1 to the current quarter. In general, leaving the labor force (Panel A) was negatively associated with the change in total debt (Table 6.1), mortgage debt (Table 6.2), and credit card debt (Table 6.3), which could indicate reduced consumption through debt after older adults exit the labor force. Along these lines, an increase in total quarterly earnings since Q1 (Panel C) was associated with an increase in total debt (Table 6.1), an increase in mortgage debt (Table 6.2), and an increase in credit card debt (Table 6.3). This is in line with consumption through debt increasing as quarterly earnings increase. Having an active UI claim was sometimes negatively associated with the change in total debt in some of the quarters (Table 6.1), with no consistent significant relationship to mortgage debt or credit card debt. We observe no significant interaction between COVID-19 and labor force exits, earnings, or UI claims for total debt or mortgage debt. However, we do observe some significant differences with credit card debt during COVID-19 (Table 6.3), where older adults leaving the labor force or having a UI claim during COVID-19 experience an even greater reduction in credit card debt. We cannot determine how much of this reduction is due to reduced consumption and thus spending on credit cards during COVID-19 or acceleration in repayment of credit card debt.

Table 6.1: Key OLS Regression Coefficients Predicting Change in Total Household Debt Since Q1

	Q2 Beta (S.E.)	Q3 Beta (S.E.)	Q4 Beta (S.E.)	Q5 Beta (S.E.)	Q6 Beta (S.E.)
Panel A: Explanatory Variable = Left Labor Force					
Covid=1	-0.0050***	-0.0060***	-0.0015*	0.0006	0.0007
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Left LF=1	-0.0157**	-0.0231***	-0.0317***	-0.0436***	-0.0509***
	(0.005)	(0.004)	(0.004)	(0.004)	(0.003)
Covid=1 x Left LF=1	0.0104	-0.0010	-0.0056	-0.0007	0.0001
	(0.005)	(0.004)	(0.005)	(0.004)	(0.004)
In LF Q1=1	0.0092***	0.0203***	0.0290***	0.0357***	0.0410***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)
Panel B: Explanatory Variable = Active UI Claim					
Covid=1	-0.0047***	-0.0060***	-0.0018*	0.0003	0.0004
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Active UI=1	-0.0029	-0.0154*	-0.0166*	-0.0084	-0.0217**
	(0.004)	(0.006)	(0.007)	(0.006)	(0.007)
Covid=1 x Active UI=1	-0.0052	0.0020	-0.0060	-0.0111	-0.0073
	(0.005)	(0.007)	(0.008)	(0.008)	(0.008)
In LF Q1=1	0.0088***	0.0182***	0.0252***	0.0297***	0.0336***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Panel C: Explanatory Variable = Change in Wages					
Covid=1	-0.0043***	-0.0064***	-0.0029***	0.0004	-0.0004
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Delta Wage	0.0115***	0.0214***	0.0285***	0.0332***	0.0438***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Covid=1 x Delta Wage	0.0003	0.0003	0.0008	0.0004	0.0000
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
In LF Q1=1	-0.0014	-0.0023*	-0.0030*	-0.0004	-0.0058***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	1,725,489	1,730,355	1,734,018	1,740,116	1,736,185
Mean	-0.008	-0.011	-0.01	-0.018	-0.02
SD	0.326	0.435	0.507	0.549	0.588
Unique Individuals	935,484	940,777	946,448	952,724	948,384

***p<.001; **p<.01; *p<.05; Standard errors in parentheses

Notes: Models estimated using OLS. All models include the vector of covariates summarized in Equation 2. Sample is full sample, not limited to those in the labor force as of Q1.

Table 6.2: Key OLS Regression Coefficients Predicting Change in Mortgage Debt Since Q1

	Q2 Beta (S.E.)	Q3 Beta (S.E.)	Q4 Beta (S.E.)	Q5 Beta (S.E.)	Q6 Beta (S.E.)
Panel A: Explanatory Variable = Left Labor Force					
Covid=1	0.0006	-0.0052***	0.0001	0.0018**	0.0016*
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Left LF=1	-0.0098*	-0.0136***	-0.0179***	-0.0242***	-0.0267***
	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
Covid=1 x Left LF=1	0.0054	-0.0025	-0.0029	-0.0002	-0.0039
	(0.005)	(0.004)	(0.004)	(0.003)	(0.003)
In LF Q1=1	0.0057***	0.0120***	0.0160***	0.0193***	0.0224***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Panel B: Explanatory Variable = Active UI Claim					
Covid=1	0.0007*	-0.0053***	0.0000	0.0017**	0.0013*
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Active UI=1	0.0004	-0.0073	-0.0064	-0.0002	-0.0086
	(0.003)	(0.005)	(0.005)	(0.005)	(0.005)
Covid=1 x Active UI=1	-0.0068*	-0.0010	-0.0092	-0.0127*	-0.0141*
	(0.003)	(0.005)	(0.006)	(0.006)	(0.006)
In LF Q1=1	0.0055***	0.0106***	0.0140***	0.0160***	0.0183***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Panel C: Explanatory Variable = Change in Wages					
Covid=1	0.0011**	-0.0055***	-0.0009	0.0017**	0.0007
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Delta Wage	0.0093***	0.0160***	0.0202***	0.0235***	0.0301***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Covid=1 x Delta Wage	0.0001	0.0002	0.0003	0.0005	0.0002
	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)
In LF Q1=1	-0.0027***	-0.0047***	-0.0058***	-0.0054***	-0.0089***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	1,725,489	1,730,355	1,734,018	1,740,116	1,736,185
Mean	-0.006	-0.012	-0.015	-0.017	-0.021
SD	0.256	0.344	0.399	0.43	0.463
Unique Individuals	935,484	940,777	946,448	952,724	948,384

***p<.001; **p<.01; *p<.05; Standard errors in parentheses

Notes: Models estimated using OLS. All models include the vector of covariates summarized in Equation 2. Sample is full sample, not limited to those in the labor force as of Q1.

Table 6.3: Key OLS Regression Coefficients Predicting Change in Credit Card Debt Since Q1

	Q2 Beta (S.E.)	Q3 Beta (S.E.)	Q4 Beta (S.E.)	Q5 Beta (S.E.)	Q6 Beta (S.E.)
Panel A: Explanatory Variable = Left Labor Force					
Covid=1	-0.0061***	-0.0074***	-0.0084***	-0.0099***	-0.0101***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Left LF=1	-0.0012*	-0.0012**	-0.0022***	-0.0024***	-0.0030***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Covid=1 x Left LF=1	0.0001	-0.0016**	-0.0014**	-0.0018***	-0.0007
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
In LF Q1=1	0.0001	0.0005***	0.0005*	0.0009***	0.0006*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Panel B: Explanatory Variable = Active UI Claim					
Covid=1	-0.0061***	-0.0074***	-0.0084***	-0.0100***	-0.0101***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Active UI=1	-0.0010	-0.0010	-0.0025**	-0.0007	-0.0000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Covid=1 x Active UI=1	-0.0004	-0.0025**	-0.0013	-0.0026**	-0.0047***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
In LF Q1=1	0.0000	0.0004**	0.0003	0.0004**	0.0002
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Panel C: Explanatory Variable = Change in Wages					
Covid=1	-0.0061***	-0.0074***	-0.0085***	-0.0100***	-0.0102***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Delta Wage	0.0002	0.0006***	0.0011***	0.0012***	0.0024***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Covid=1 x Delta Wage	0.0006	0.0005***	0.0008***	0.0003*	0.0001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
In LF Q1=1	-0.0006***	-0.0007***	-0.0015***	-0.0009***	-0.0021***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	1,725,489	1,730,355	1,734,018	1,740,116	1,736,185
Mean	-0.002	-0.003	-0.001	-0.005	-0.004
SD	0.04	0.053	0.061	0.067	0.073
Unique Individuals	935,484	940,777	946,448	952,724	948,384

***p<.001; **p<.01; *p<.05; Standard errors in parentheses

Notes: Models estimated using OLS. All models include the vector of covariates summarized in Equation 2. Sample is full sample, not limited to those in the labor force as of Q1.

4.2.4 Heterogenous demographic and financial characteristics.

We next explore heterogeneous effects of baseline demographic and financial characteristics on changes in credit outcomes during COVID-19 for older adults who left the labor force—a vector of triple-interaction coefficients, where each baseline covariate is multiplied by the COVID-19 period indicator and the indicator for leaving the labor force as of a given quarter. The full results of the triple interaction models are available from the authors upon request, but we summarize key findings here. We find some evidence of significant heterogeneity by age, credit score, any available credit at baseline, and wage earnings at baseline. The oldest adults leaving the labor force were more likely to have an increase in nonpayment of debt, but no significant difference in rates of delinquency or in credit score. In line with the buffering effects of COVID-19-era benefits and accommodations for more vulnerable people, we find that older adults exiting the labor force with lower credit scores and lower wage income at baseline experienced more of a COVID-19-era boost to credit score and reductions in severe payment delinquency than those with higher baseline credit scores or wages. We find no statistically different effects of older adults leaving the labor force during COVID-19 by gender, majority race of the ZIP code, or household size.

4.3 Labor Force Exits, Credit, and County-Level Social Security Claims

Our final set of analyses move to the county level to examine COVID-19-era differences in factors that predict early claiming of Social Security retirement benefits. Table 7 reports the results for key coefficients, with complete regression results reported in Appendix G. The first column reports the results with the interaction for the COVID-19 period and the share of working adults ages 62-66 leaving the labor force in the same year as specified in equation (3), while the second column adds interaction terms for the COVID-19 period and baseline indicators of financial vulnerability. In pre-COVID-19 periods, there was a positive relationship between the share of older adults leaving the labor force in a county and the share claiming social security retirement benefits, where a one percent increase in the share leaving the labor force in a year was associated with about a 0.5 percent increase in the share claiming social security retirement benefits in a county and year.

In the COVID-19 period, however, the relationship between labor exits and claiming was nearly offset after controlling for heterogeneous COVID-19-era differences in baseline indicators of financial vulnerability on claiming behaviors (column 2). While county-level indicators of financial vulnerability tend to not significantly predict early retirement claiming in pre-COVID-19 periods, we find significant interactions during COVID-19. Specifically, during COVID-19, social security retirement claiming was higher in counties where adults ages 62 to 66 had lower average credit scores, higher average levels of non-housing debt, and a lower share with collections debt as of the baseline quarter. In all periods, higher average available credit in a county is associated with increased early retirement claiming. In pre-COVID-19 periods, higher levels of non-housing debt associated with reduced claiming—which aligns with prior studies that find that older adults with higher debt levels and who experience debt stress work longer and are less likely to claim early (Butrica and Karamcheva 2018, 2020; Haurin, Moulton, and Loibl 2022). However, this relationship is more than offset during COVID-19 periods where counties with older adults holding higher levels of non-housing debt were more likely to claim social-security-retirement benefits early. This may indicate the differential availability and perceived risk associated with working during COVID—leading those with higher debt burdens to claim social security benefits early rather than continue working.

Table 7: Key OLS Regression Coefficients Predicting Social Security Retirement Claims (Aim 3)

	Baseline Beta (S.E.)	Interactions Beta (S.E.)
Covid=1	-0.001	0.594*
	(0.011)	(0.249)
% Left LF During Year	0.462**	0.523***
	(0.158)	(0.150)
Covid x Left LF	-0.195	-0.492*
	(0.145)	(0.198)
% in LF in Q1	-0.052	-0.074
	(0.076)	(0.067)
Q1 Avg Wage Earnings (10K)	-0.019	-0.005
	(0.017)	(0.017)
Covid x Wage Earnings		-0.056*
		(0.027)
Q1 Avg Credit Score (100)	-0.025	0.005
	(0.050)	(0.043)
Covid x Credit Score		-0.074*
		(0.037)
Q1 % with Available Credit	0.355*	0.316*
	(0.144)	(0.141)
Covid x % Available Credit		0.014
		(0.094)
Q1 Avg. Non-Housing Debt (100K)	-0.116	-0.205**
	(0.068)	(0.068)
Covid x Non-Housing Debt		0.322**
		(0.111)
Q1 % with Collections	0.048	0.104
	(0.054)	(0.058)
Covid x % with Collections		-0.151*
		(0.067)
Q1 % Urban	0.002	0.005
	(0.006)	(0.006)
Observations	264	264
Mean	0.172	0.172
Standard Deviation	0.025	0.025
N	88	88
F-statistic	14	10

***p<.001; **p<.01; *p<.05; Standard errors in parentheses

Notes: Models estimated using OLS. All models include the vector of covariates summarized in Equation 3.

5. Discussion

The COVID-19 pandemic is associated with an increase in labor force exits among older adults (Powell 2022; Montes, Smith, and Dajon 2022). Generous COVID-19-era unemployment benefits combined with reductions in consumption helped to offset reductions in income from labor force exits—perhaps reducing demand for Social Security claiming typically associated with exits from the labor force for the average older adult. However, questions arise about heterogeneous effects, particularly for financially vulnerable older adults. Were financially vulnerable older adults more (or less) likely to exit the labor force during COVID? Did older adults' labor force exits during COVID-19 result in more (or less) economic insecurity as measured in credit data than exits in pre-COVID-19 periods? Did counties with a larger share of financially vulnerable older adults experience an increase (or decrease) in early Social-Security-retirement claims during COVID? This paper sought to inform these questions using rich individual-level credit data linked to wage earnings and unemployment claims data for a random sample of older adults in Ohio.

Our first set of findings indicates that COVID-19-era exits from the labor force were greater for the oldest older adults (ages 67+) than younger older adults (ages 50-66) in the first 15 months of the COVID-19 pandemic—a finding that is persistent through the second quarter of 2021 when our study period ends. However, despite being more likely to exit the labor force, the oldest adults were not more likely to file unemployment claims during the COVID-19 pandemic relative to their younger counterparts. Female older adults, those living in majority Black ZIP codes, and separately those from urban ZIP codes, were significantly more likely to exit the labor force during the COVID-19 quarters than during pre-COVID-19 quarters in Ohio.

Unique to our study, we find that older adults who exited the labor force during the COVID-19 pandemic in Ohio were more financially vulnerable on a variety of credit and wage characteristics compared to older adults who exited the labor force in pre-COVID-19 periods. While we find older adults with lower credit scores in all periods are more likely to exit the labor force, this effect was nearly ten times larger after the initial onset of the pandemic in Q2 of 2020. Older adults with lower credit scores were also much more likely to claim unemployment insurance benefits during the pandemic. We find that working older adults without access to revolving credit were more likely to exit the labor force during COVID-19 and more likely to have an Unemployment Insurance (UI) claim relative to pre-pandemic periods. We also find that higher baseline wages prior to the pandemic associate with reduced likelihood of COVID-19-era unemployment benefit claims among older adults in Ohio.

Despite more financially vulnerable older adults exiting the labor force during COVID-19, our second set of findings indicates that COVID-19-era protections may have buffered negative spillovers to economic insecurity—at least in the short term. In our analysis of labor force exits on credit outcomes, we find that exits from the labor force among older adults during COVID-19 were more likely to result in nonpayment of debts than exits pre-COVID-19. However, older adults exiting the labor force were *not* more likely to experience severe delinquency, and labor force exits during COVID-19 were associated with relatively smaller decreases in credit scores than labor force exits pre-COVID-19. At the same time, older adults exiting the labor force during COVID-19 were more likely to have mortgage, auto, or personal loan debt in forbearance than those not exiting the labor force. This suggests that creditor forbearances may have helped to offset the negative effects of COVID-19-era labor force exits on older adults' economic security—at least in the short term. Our study period ends in the second quarter of 2021, near the period when mortgage forbearance extensions began to expire. It is important to continue to monitor the financial health of these older adults after COVID-19-era forbearances end.

Our third set of findings shed light on how indicators of older adults' financial vulnerabilities associate with early social-security-retirement-claiming behaviors during COVID-19. While we do not have access to individual-level Social Security claims, we obtain quarterly claims data aggregated to the county level for Ohio—allowing more granularity than prior studies that aggregate data by state or study national trends and allowing us to incorporate indicators of older adults' financial vulnerability that vary between counties and over time. We find evidence of heterogeneous effects during COVID-19, where counties with older adults holding higher levels of non-housing debt and lower credit scores had a higher share claiming early retirement benefits during COVID-19 relative to pre-COVID-19 periods. At the same time, the association between labor force exits and early retirement benefit claiming is muted during COVID-19—leading to the finding in prior research that increased labor force exits during COVID-19 did not result in an increase in early social security retirement claiming. Early claiming during COVID-19 appears to be more associated with indicators of financial vulnerability than labor exits. It will be important to continue to monitor the economic security of those claiming Social-Security-retirement benefits early during the COVID-19 pandemic, as they may be more financially vulnerable than prior cohorts.

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Appendix

Appendix A: Summary Statistics for Covariates, Aim 1

	Q1 2018		Q1 2020	
	Mean	SD	Mean	SD
Age	58.783	6.539	59.064	6.644
Age: 50-61 years old (0,1)	0.705	0.456	0.680	0.466
Age: 62-66 years old (0,1)	0.178	0.383	0.191	0.393
Age: 67-71 years old (0,1)	0.075	0.264	0.080	0.272
Age: 72+ years old (0,1)	0.042	0.200	0.048	0.214
% Female	0.506	0.500	0.504	0.500
HH Size	2.338	1.058	2.365	1.065
% Majority Black Zip	0.058	0.234	0.059	0.235
Urban (0,1)	0.792	0.406	0.795	0.404
Credit Score (100s)	7.320	0.988	7.318	0.993
Has Available Credit (0,1)	0.859	0.348	0.865	0.342
HH Mort Debt (100K)	0.570	0.749	0.583	0.773
HH CC Debt (100K)	0.080	0.125	0.083	0.129
HH Student Loan Debt (100K)	0.129	0.326	0.136	0.353
HH Auto Debt (100K)	0.131	0.178	0.145	0.194
Quarterly Wage Earnings (10K)	1.298	1.552	1.376	2.284
% With Other HH Income	0.526	0.499	0.548	0.498
N	293,564		302,728	

Notes: Sample is individuals who were in the labor force as of baseline quarter (Q1) and are included in the Q2 regressions.

Appendix B: Summary Statistics for Covariates, Aim 2

	Q1 2018		Q1 2020	
	Mean	SD	Mean	SD
Age	66.861	11.945	67.414	12.079
Age: 50-61 years old (0,1)	0.396	0.489	0.372	0.483
Age: 62-66 years old (0,1)	0.158	0.364	0.161	0.368
Age: 67-71 years old (0,1)	0.142	0.349	0.139	0.346
Age: 72+ years old (0,1)	0.305	0.460	0.328	0.469
% Female	0.529	0.499	0.525	0.499
HH Size	2.287	1.072	2.308	1.075
% Majority Black Zip	0.062	0.240	0.061	0.238
Urban (0,1)	0.780	0.414	0.781	0.414
Credit Score (100)	7.285	0.973	7.272	0.979
Has Available Credit (0,1)	0.771	0.420	0.768	0.422
HH Mort Debt (100K)	0.418	0.684	0.425	0.706
HH CC Debt (100K)	0.062	0.111	0.065	0.115
HH Student Loan Debt (100K)	0.083	0.262	0.087	0.285
HH Auto Debt (100K)	0.095	0.157	0.103	0.17
Quarterly Wage Earnings (10K)	0.457	1.247	0.478	1.818
% With Other HH Income	0.389	0.487	0.408	0.491
% in Labor Force in Q1	0.771	0.420	0.343	0.475
% With Active UI	0.007	0.085	0.053	0.223
Labor Exit Q2 Q1	0.012	0.110	0.065	0.246
Labor Exit Q3 Q1	0.024	0.154	0.038	0.191
Labor Exit Q4 Q1	0.028	0.164	0.042	0.201
Labor Exit Q5 Q1	0.034	0.181	0.050	0.218
Labor Exit Q6 Q1	0.039	0.193	0.054	0.225
Wages Q2-Q1 (10K)	-0.034	0.939	-0.127	1.647
Wages Q3-Q1 (10K)	-0.044	1.029	-0.066	2.233
Wages Q4-Q1 (10K)	-0.029	0.955	-0.025	1.984
Wages Q5-Q1 (10K)	-0.029	1.263	-0.066	1.944
Wages Q6-Q1 (10K)	-0.054	1.530	-0.070	2.009
N	843913		881576	

Notes: Sample is all individuals observed in the baseline quarter (Q1) who are included in the Q2 regressions.

Appendix C: Summary Statistics for Aim 3

	2018		2019		2020	
	Mean	SD	Mean	SD	Mean	SD
OASI Claims Per Population (Age 62-66)	0.174	0.021	0.177	0.029	0.164	0.023
% Left LF During Year	0.060	0.018	0.061	0.019	0.077	0.024
Q1 % in LF	0.348	0.070	0.353	0.068	0.359	0.071
Q1 % Female	0.510	0.036	0.510	0.034	0.509	0.024
Q1 Avg HH Size	2.181	0.095	2.202	0.146	2.191	0.109
Q1 % Urban	0.403	0.420	0.406	0.421	0.403	0.420
Q1 Avg Credit Score (100)	7.403	0.143	7.372	0.160	7.374	0.153
Q1 Avg Wage Earnings (10K)	0.418	0.145	0.445	0.178	0.440	0.154
Q1 % with Other HH Income	0.363	0.070	0.378	0.081	0.381	0.074
Q1 Avg HH Mort Debt (100K)	0.354	0.142	0.355	0.141	0.359	0.138
Q1 Avg HH Non-House Debt (100K)	0.208	0.037	0.217	0.043	0.227	0.042
Q1 % with Collections	0.283	0.063	0.282	0.069	0.285	0.069
Q1 % with Available Credit	0.826	0.051	0.815	0.050	0.819	0.049
% with Accommodations in 2020					0.040	0.016
Q1 Median House Value (100K)	1.346	0.362	1.402	0.381	1.476	0.407
N	88		88		88	

Note: Sample is 88 Ohio counties measured in three periods (2018, 2019, and 2020).

Appendix D: OLS Regression Results for Left Labor Force Since Q1 (Aim 1), Full Specification

	Q2	Q3	Q4	Q5	Q6
Covid=1	0.309***	0.073***	0.052***	0.063***	0.059***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
62-66	0.027***	0.054***	0.067***	0.078***	0.093***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
67-71	0.039***	0.080***	0.093***	0.118***	0.143***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
72+	0.037***	0.075***	0.088***	0.119***	0.144***
	(0.002)	(0.003)	(0.003)	(0.004)	(0.003)
Covid x 62-66	0.011***	0.018***	0.019***	0.021***	0.018***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Covid x 67-71	0.060***	0.059***	0.064***	0.067***	0.057***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Covid x 72+	0.098***	0.106***	0.102***	0.098***	0.081***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Female=1	-0.006***	0.004**	-0.001	-0.007***	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Covid x Female	0.009***	0.005*	0.006***	0.012***	0.009***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Maj Black Zip=1	0.002	-0.002	-0.002	0.000	0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Covid x Black Zip	-0.006	0.015***	0.017***	0.010**	0.011**
	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)
Q1 HH Size	0.001*	0.003***	0.003***	0.004***	0.005***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Covid x HH Size	0.005***	0.003***	0.003***	0.003**	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Q1 Wage Earnings (10K)	-0.004***	-0.004**	-0.003**	-0.008***	-0.002**
	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)
Covid x Wages	-0.000	-0.002	-0.003	0.000	-0.002
	(0.001)	(0.003)	(0.002)	(0.003)	(0.002)
Other HH Wages in Q1=1	-0.005***	-0.010***	-0.012***	-0.016***	-0.016***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Covid x Other Wages	-0.008***	-0.001	-0.001	0.001	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Any Available Credit Q1	-0.009***	-0.013***	-0.017***	-0.022***	-0.025***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Covid x Available Credit	-0.013***	-0.007*	-0.008**	-0.011***	-0.011***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Q1 Credit Score	-0.003***	-0.003***	-0.005***	-0.006***	-0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Covid x Credit Score	-0.023***	-0.007***	-0.004***	-0.005***	-0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Q1 HH Mort Debt (100K)	-0.000	-0.000	-0.002**	-0.002*	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Covid x Mort	-0.001	-0.002	-0.001	-0.003*	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Q1 HH CC Debt (100K)	-0.017***	-0.032***	-0.042***	-0.046***	-0.047***

	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
Covid x CC	-0.017**	-0.007	0.003	-0.002	-0.010
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Q1 HH Student Debt (100K)	-0.002*	-0.004**	-0.006***	-0.010***	-0.011***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Covid x Student	-0.020***	-0.003	-0.002	0.001	0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Q1 HH Auto Debt (100K)	-0.011***	-0.019***	-0.023***	-0.020***	-0.031***
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Covid x Auto	-0.009*	-0.021***	-0.022***	-0.029***	-0.015***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Urban	-0.002	0.003	-0.003	0.006**	0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Covid x Urban	0.010***	0.007***	0.010***	0.002	0.006**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Constant	0.081***	0.110***	0.141***	0.170***	0.154***
	(0.017)	(0.017)	(0.018)	(0.019)	(0.019)
N	596292	604322	612107	620261	627653
Mean	0.113	0.090	0.099	0.118	0.128
SD	0.317	0.285	0.299	0.323	0.334
Unique Individuals	358725	363276	368449	373513	377543
F-statistic	406	132	157	200	222

***p<.001; **p<.01; *p<.05; Standard errors in parentheses

Notes: OLS regression coefficients; Sample is limited to individuals in the labor force (LF) as of Q1 of a given year.

Appendix E: OLS Regression Results for Active UI Claim (Aim 1)

	Q2	Q3	Q4	Q5	Q6
Covid=1	0.305***	0.166***	0.129***	0.118***	0.098***
	(0.006)	(0.005)	(0.005)	(0.005)	(0.004)
62-66	-0.004***	-0.003***	-0.004***	-0.005***	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
67-71	-0.006***	-0.004***	-0.006***	-0.010***	-0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
72+	-0.009***	-0.008***	-0.010***	-0.014***	-0.009***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Covid x 62-66	-0.008***	0.002	0.004**	0.001	0.005***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Covid x 67-71	-0.030***	0.003	0.010***	0.007***	0.009***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
Covid x 72+	-0.046***	0.004	0.012***	0.008***	0.011***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Female=1	-0.003***	-0.001	-0.006***	-0.011***	-0.005***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
Covid x Female	-0.008***	-0.005***	-0.003**	-0.003***	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Maj Black Zip=1	0.001	-0.002	-0.000	-0.002	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Covid x Black Zip	-0.015***	0.009***	0.006**	0.007**	0.005*
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
Q1 HH Size	-0.000	-0.000	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Covid x HH Size	-0.002*	-0.000	-0.000	-0.001*	-0.001*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Q1 Wage Earnings (10K)	-0.001***	-0.000	-0.000***	-0.001***	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Covid x Wages	-0.005***	-0.003***	-0.002***	0.000	-0.001**
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Other HH Wages in Q1=1	-0.001	-0.000	-0.001**	-0.002***	-0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Covid x Other Wages	0.006***	0.002	0.002	0.002*	0.002
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Any Available Credit Q1	-0.000	0.002*	0.001	0.000	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Covid x Available Credit	0.007*	-0.005*	-0.006**	-0.006**	-0.006**
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Q1 Credit Score	-0.005***	-0.006***	-0.005***	-0.006***	-0.006***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Covid x Credit Score	-0.019***	-0.014***	-0.012***	-0.011***	-0.009***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Q1 HH Mort Debt (100K)	0.001	-0.000	0.000	-0.001	-0.001*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Covid x Mort	-0.007***	-0.002**	-0.001	0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Q1 HH CC Debt (100K)	-0.009***	-0.012***	-0.009***	-0.007***	-0.008***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)

Covid x CC	-0.023***	-0.003	-0.007	-0.002	-0.004
	(0.005)	(0.004)	(0.004)	(0.004)	(0.003)
Q1 HH Student Debt (100K)	0.001	0.001	-0.002**	-0.002**	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Covid x Student	-0.016***	-0.006***	-0.001	-0.001	-0.002
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Q1 HH Auto Debt (100K)	-0.000	-0.001	-0.001	0.002	0.003*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Covid x Auto	0.009*	-0.007*	-0.005*	-0.008**	-0.006**
	(0.004)	(0.003)	(0.002)	(0.003)	(0.002)
Urban	0.009***	-0.002	-0.002*	0.001	0.001
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Covid x Urban	-0.022***	0.011***	0.013***	0.012***	0.006***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	0.029*	0.053***	0.060***	0.085***	0.075***
	(0.014)	(0.011)	(0.009)	(0.012)	(0.012)
N	596292	604322	612107	620261	627653
Mean	0.079	0.046	0.036	0.039	0.031
SD	0.270	0.209	0.187	0.194	0.173
Unique Individuals	358725	363276	368449	373513	377543
F-statistic	345	133	91	95	66

***p<.001; **p<.01; *p<.05

Notes: Sample is limited to individuals in the labor force (LF) as of Q1 of a given year.

Appendix F: OLS Regression Results for Changes in Wages ($10,000) Since Q1 (Aim 1)

	Q2	Q3	Q4	Q5	Q6
Covid=1	-0.403***	-0.176***	-0.102*	-0.181***	-0.115***
	(0.034)	(0.043)	(0.045)	(0.044)	(0.035)
62-66	-0.174***	-0.217***	-0.244***	-0.242***	-0.277***
	(0.014)	(0.011)	(0.010)	(0.012)	(0.007)
67-71	-0.382***	-0.448***	-0.490***	-0.460***	-0.529***
	(0.032)	(0.032)	(0.027)	(0.033)	(0.020)
72+	-0.520***	-0.574***	-0.619***	-0.559***	-0.658***
	(0.045)	(0.043)	(0.038)	(0.052)	(0.028)
Covid x 62-66	-0.013	-0.031*	-0.058***	-0.048**	-0.038***
	(0.014)	(0.015)	(0.014)	(0.016)	(0.010)
Covid x 67-71	-0.056	-0.079*	-0.117**	-0.112**	-0.092***
	(0.030)	(0.040)	(0.037)	(0.043)	(0.027)
Covid x 72+	-0.081	-0.126*	-0.163**	-0.160*	-0.104**
	(0.043)	(0.054)	(0.053)	(0.066)	(0.040)
Female=1	-0.238***	-0.265***	-0.283***	-0.216***	-0.250***
	(0.024)	(0.023)	(0.020)	(0.028)	(0.016)
Covid x Female	0.028	-0.009	-0.010	-0.033	-0.005
	(0.023)	(0.028)	(0.028)	(0.035)	(0.021)
Maj Black Zip=1	-0.059***	-0.063***	-0.063***	-0.060***	-0.058***
	(0.006)	(0.007)	(0.007)	(0.007)	(0.006)
Covid x Black Zip	0.009	-0.020**	-0.035***	-0.023**	-0.022**
	(0.006)	(0.007)	(0.007)	(0.008)	(0.007)
Q1 HH Size	-0.014***	-0.016***	-0.017***	-0.017***	-0.020***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Covid x HH Size	-0.007***	-0.004*	-0.005*	-0.002	-0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Q1 Wage Earnings (10K)	-0.715***	-0.765***	-0.779***	-0.652***	-0.811***
	(0.054)	(0.051)	(0.043)	(0.065)	(0.034)
Covid x Wages	-0.177***	-0.087	-0.044	-0.168*	-0.046
	(0.051)	(0.063)	(0.059)	(0.080)	(0.046)
Other HH Wages in Q1=1	-0.025***	-0.021***	-0.018***	-0.010	-0.014**
	(0.005)	(0.005)	(0.005)	(0.006)	(0.004)
Covid x Other Wages	0.010	-0.010	-0.007	-0.015	-0.003
	(0.005)	(0.006)	(0.007)	(0.008)	(0.006)
Any Available Credit Q1	0.036***	0.035***	0.039***	0.044***	0.052***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Covid x Available Credit	-0.013*	-0.005	0.007	-0.001	0.005
	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)
Q1 Credit Score	0.060***	0.043*	0.037*	0.052*	0.030*
	(0.014)	(0.018)	(0.017)	(0.021)	(0.013)
Covid x Credit Score	0.090***	0.098***	0.110***	0.095***	0.107***
	(0.012)	(0.011)	(0.010)	(0.010)	(0.008)
Q1 HH Mort Debt (100K)	0.010	0.021	0.010	0.022	0.002
	(0.011)	(0.014)	(0.015)	(0.016)	(0.012)
Covid x Mort	0.255***	0.280***	0.303***	0.304***	0.312***
	(0.021)	(0.022)	(0.020)	(0.034)	(0.020)
Q1 HH CC Debt (100K)	0.091***	0.085**	0.062*	0.080	0.082**
	(0.027)	(0.030)	(0.030)	(0.043)	(0.026)

Covid x CC	0.089***	0.091***	0.095***	0.089***	0.103***
	(0.007)	(0.007)	(0.006)	(0.009)	(0.006)
Q1 HH Student Debt (100K)	0.030***	0.005	0.004	0.001	-0.005
	(0.008)	(0.009)	(0.009)	(0.011)	(0.008)
Covid x Student	0.173***	0.191***	0.204***	0.166***	0.199***
	(0.014)	(0.015)	(0.013)	(0.019)	(0.012)
Q1 HH Auto Debt (100K)	-0.033*	0.001	0.010	0.004	-0.008
	(0.015)	(0.018)	(0.017)	(0.022)	(0.015)
Covid x Auto	0.013	0.022*	0.014	0.010	0.014
	(0.008)	(0.009)	(0.009)	(0.010)	(0.007)
Urban	0.011	0.004	0.005	0.023	0.012
	(0.011)	(0.013)	(0.014)	(0.015)	(0.011)
Covid x Urban	0.120***	0.127***	0.140***	0.121***	0.130***
	(0.014)	(0.014)	(0.012)	(0.016)	(0.009)
Constant	-0.019	-0.041	-0.082	-0.167***	-0.020
	(0.051)	(0.050)	(0.051)	(0.049)	(0.046)
N	596292	604322	612107	620261	627653
Mean	-2392.484	-1690.026	-977.053	-1494.042	-1950.000
SD	17679.140	17083.654	17251.051	15100.684	17796.168
Unique Individuals	358725	363276	368449	373513	377543
F-statistic	396	105	86	97	156

***p<.001; **p<.01; *p<.05

Notes: Sample is limited to individuals in the labor force (LF) as of Q1 of a given year.

Appendix G: OLS Regression Results for County OASI Claims Ages 62-66 (Aim 3)

	(1)	(2)	(3)	(4)
Covid=1	-0.001	0.594*	0.600*	0.376
	(0.011)	(0.249)	(0.253)	(0.314)
% Left LF During Year	0.462**	0.523***	0.523***	
	(0.158)	(0.150)	(0.150)	
Covid x Left LF	-0.195	-0.492*	-0.478*	
	(0.145)	(0.198)	(0.195)	
% in LF in Q1	-0.052	-0.074	-0.074	-0.010
	(0.076)	(0.067)	(0.067)	(0.074)
Q1 % with Available Credit	0.355*	0.316*	0.316*	0.290*
	(0.144)	(0.141)	(0.141)	(0.138)
Q1 % Female	-0.061	-0.011	-0.012	-0.058
	(0.081)	(0.091)	(0.091)	(0.125)
Q1 Avg HH Size	-0.019	-0.017	-0.017	-0.034
	(0.032)	(0.038)	(0.038)	(0.041)
Q1 % Urban	0.002	0.005	0.005	0.006
	(0.006)	(0.006)	(0.006)	(0.006)
Q1 Avg Credit Score (100)	-0.025	0.005	0.005	-0.008
	(0.050)	(0.043)	(0.043)	(0.044)
Q1 Avg Wage Earnings (10K)	-0.019	-0.005	-0.005	-0.007
	(0.017)	(0.017)	(0.017)	(0.016)
Q1 % with Other HH Income	-0.019	-0.044	-0.044	-0.033
	(0.068)	(0.069)	(0.069)	(0.070)
Q1 Avg HH Mort Debt (100K)	-0.008	-0.007	-0.007	0.001
	(0.024)	(0.026)	(0.026)	(0.032)
Q1 Avg HH Non-Housing Debt (100K)	-0.116	-0.205**	-0.205**	-0.173*
	(0.068)	(0.068)	(0.068)	(0.082)
Q1 % with Collections	0.048	0.104	0.103	0.060
	(0.054)	(0.058)	(0.059)	(0.058)
Median House Value (100K)	-0.010	-0.010	-0.010	-0.013
	(0.007)	(0.006)	(0.007)	(0.008)
Covid x % in LF		0.127	0.122	0.047
		(0.067)	(0.069)	(0.087)
Covid x Mort Debt		-0.006	-0.005	-0.005
		(0.023)	(0.023)	(0.025)
Covid x Non-Housing Debt		0.322**	0.326**	0.286*
		(0.111)	(0.116)	(0.118)
Covid x % with Collections		-0.151*	-0.148*	-0.108
		(0.067)	(0.066)	(0.067)
Covid x % with Available Credit		0.014	0.023	0.008
		(0.094)	(0.095)	(0.108)
Covid x % Female		-0.199	-0.194	-0.140
		(0.109)	(0.110)	(0.133)
Covid x HH Size		-0.007	-0.007	0.009
		(0.038)	(0.039)	(0.044)
Covid x % Urban		-0.013*	-0.014*	-0.014*
		(0.006)	(0.006)	(0.006)
Covid x Credit Score		-0.074*	-0.076*	-0.054

		(0.037)	(0.038)	(0.045)
Covid x Wage Earnings		-0.056*	-0.053	-0.050
		(0.027)	(0.029)	(0.025)
Covid x % Other HH Income		0.099	0.098	0.103
		(0.074)	(0.075)	(0.082)
% with Accommodations during Covid			-0.064	
			(0.195)	
% With Active UI in Q1				0.001
				(0.212)
Covid x Active UI in Q1				0.084
				(0.260)
Obs	264	264	264	264
Mean	0.172	0.172	0.172	0.172
StDv	0.025	0.025	0.025	0.025
N	88	88	88	88
F-statistic	14	10	10	14

***p<.001; **p<.01; *p<.05; Standard errors in parentheses

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