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Pandemic labor force participation and net worth fluctuations*

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May 1, 2023

Abstract

The U.S. labor force participation rate (LFPR) experienced a record drop during the early pandemic. While it has since recovered to 62.2% as of December 2022, it was still 1.41 pp below its pre-pandemic peak. This gap is explained mostly by a permanent decline in the LFPR for workers older than 55. This paper argues that wealth effects driven by the historically high returns in major asset classes such as stocks and housing may have influenced these trends. Combining an estimated model of wealth effects on labor supply with micro data on balance sheet composition, we show that changes in net worth caused by realized returns explain half of the drop in LFPR in the 2020-21 period and over 80% of “excess retirements” during the same period.

1 Introduction

The COVID-19 pandemic threw the US economy into a short but deep recession, during which the labor force participation rate (LFPR) fell by 2.2 percentage points (pp) – its largest drop on record. While the LFPR quickly rebounded, it remained 1.41 pp below its pre-pandemic peak as of the end of 2022. Researchers, market practitioners, and policymakers alike have argued that the drop in LFPR may be contributing to a shortage of workers and excessive tightness of the labor market, which in turn may be contributing to inflation remaining high (Powell, 2022). However, a closer inspection of the data indicates that while the LFPR for prime-age workers (under age 54) has mostly recovered, the LFPR for older workers seems to have permanently fallen and failed to recover. Applying the pre-pandemic peak LFPR to the level of the civilian noninstitutional population aged 16 and over as of December 2022 suggests that there were about 3.73 million “missing workers” in the US economy.

Additionally, the share of the retired population has increased considerably, over and beyond what long-run demographic and shorter-run business cycle trends would predict. Comparing actual retirements to those predicted by a statistical model that allows for such trends (Montes et al., 2022) leads us to conclude that there were 3.27 million “excess retirees” in the US economy as of December 2022.

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At the same time as the US economy was recovering from the short pandemic recession, real returns boomed across various asset classes, namely stocks and housing. Driven partly by the reopening of the US economy after the 2020 lockdowns and partly by the robust monetary and fiscal policy responses to the macroeconomic effects of the pandemic, real returns for many assets were abnormally high during the years of 2020 and 2021, at least when compared to the historical record. The cumulative real return on a diversified index of stocks, the S&P 500, surpassed 35% between December 2019 and December 2021, versus a historical average of 17.5% for a 2-year period. The real return on housing was close to 20% over the same period, versus a historical average of 7.3%.

Neoclassical theory offers a natural connection between these two patterns: wealth effects on labor supply. Standard models of labor supply assume that leisure is a normal good, with its desired consumption rising in response to an increase in income or wealth. There is broad empirical evidence for this effect, especially when such increases in wealth are unexpected (Imbens et al., 2001). Moreover, these effects are likely to be more salient and relevant for older individuals, who are nearing retirement age, and for whom extensive-margin labor force participation decisions may be more elastic with respect to unexpected changes in wealth (Cheng and French, 2000; Zhao, 2018).

In this article, we try to quantify what share of the “missing workers” and “excess retirees” may be plausibly attributed to rising asset values during the pandemic. We proceed in three steps: first, we use the 2019 wave of the Survey of Consumer Finances as a representative sample of the balance sheet composition of US individuals at the beginning of the pandemic. In particular, we can estimate exposures to major asset classes such as stocks, housing, government bonds, and corporate bonds. Second, we impute realized returns on these asset classes to compute how the net worth for each individual changed during the pandemic, given their initial portfolio composition. Finally, we use an empirical model of wealth effects on labor supply (Benson and French, 2011) to estimate the impact of the estimated changes in net worth on labor force participation decisions at the individual level, and we aggregate these estimates using the appropriate weights. The final output is an estimate of the number of people who left the labor force due to changes in asset values. Since these estimates are generated at the individual level and then aggregated, we can produce them for different demographic groups.

In our baseline, most conservative exercise, we focus on people aged 55-70, whose retirement decision is plausibly more sensitive to wealth effects. We find that the predicted change in LFPR for this group accounts for almost 30% of the drop in aggregate LFPR between 2020 and 2021. If we expand the analysis to all those 55 and older, we can explain over 50% of the drop in aggregate LFPR over the same period. In terms of excess retirements, we can explain close to half of the observed excess retirements by considering only the 55-70 age group and more than 80% when focusing on all those 55 and older.

There are many reasons why people may have chosen to retire early or leave the labor force during the pandemic period other than unexpected changes in wealth. Older people were at greater risk of severe illness and death from COVID-19, which undoubtedly played an important role for those with occupations involving greater physical contact. Many news stories also reported on older

members of the household being responsible for taking care of loved ones as childcare facilities or other daycare institutions closed due to government-mandated lockdowns.¹ Wealth effects may not have been the only reason why people chose to retire, but may have rather compounded these other reasons, by allowing people to retire (as opposed to causing the retirement). We also report estimates for the 2020-22 period, which include 2022, a year of declining asset valuations. While asset values declined during this year, there were no significant changes in terms of LFPR, so our model explains a smaller share of the drop during this period. There are several other explanations for why the LFPR has failed to recover, such as reduced immigration flows starting in 2020 (Peri and Zaiour, 2022).

Literature Our work is related to several other studies that put forward rising (declining) asset values as a driver of early (late) retirement decisions and declines (increases) in LFPR. Coronado and Perzoek (2003) find that individuals who benefited from the bull stock market in the 1990s retired earlier than those who did not. Benson and French (2011) argue that sudden and unexpected declines in asset values, especially housing, during the Great Recession led to delayed retirements and higher than expected LFPR. Goda et al. (2011) find that individuals exposed to stock market declines during the Great Financial Crisis of 2007-08 delayed retirement but that this effect was partly attenuated by worsening labor market conditions. In more closely related work, Favilukis and Li (2023) argue that increases in housing wealth can fully explain the “Great Resignation” among older workers and that MSAs with more substantial price growth tend to have lower LFPR for homeowners around retirement age.

Our work is also related to the literature that dissects the post-pandemic drop in workers and hours worked. Lee et al. (2023) focus on the decline in aggregate hours worked post-pandemic and use micro data to decompose it into intensive and extensive margins. They find that more than half of the decline in total hours worked is due to a decline in the intensive margin, i.e., workers who remained in the labor force but reduced the number of hours they worked. Furthermore, they find that those whose hours declined tend to be prime age, educated men who tended to work long hours and had high earnings before the pandemic. They argue that this helps explain why the labor market remains tight even after the partial recovery in LFPR. We abstract from the intensive margin and focus on extensive margin decisions only. Hobijn and Şahin (2022) argue that the decline in LFPR may be overstated, as it does not account for either (i) the fact that the LFPR was probably above trend pre-pandemic due to business cycle factors, and (ii) there are natural long-term downward trends on LFPR due to demographics. Garcia and Cowan (2022) show that both women and men saw a reduction in work hours and the likelihood of working full-time in response to school closures. However, only women were less likely to work at all. These effects were concentrated among uneducated parents in occupations less likely to be compatible with telework.

The rest of the paper is organized as follows: section 2 presents and discusses trends in LFPR and in the retiree share, along with formal definitions of “missing workers” and “excess retirees”.

¹See, for example, this NPR story: <https://www.npr.org/2021/08/23/1028993124/these-older-workers-hadnt-planned-to-retire-so-soon-the-pandemic-sped-things-up>.

Section 3 presents data on asset valuations during the pandemic and the distribution of assets and net worth across ages before and during the pandemic. Section 4 presents our main exercise, where we impute realized net worth to compute predicted changes in LFPR across age groups, and section 5 concludes.

2 LFPR and the COVID Retirement Boom

In this section, we discuss recent trends in the US labor force participation rate (LFPR) and the retirement share.

2.1 Trends in LFPR

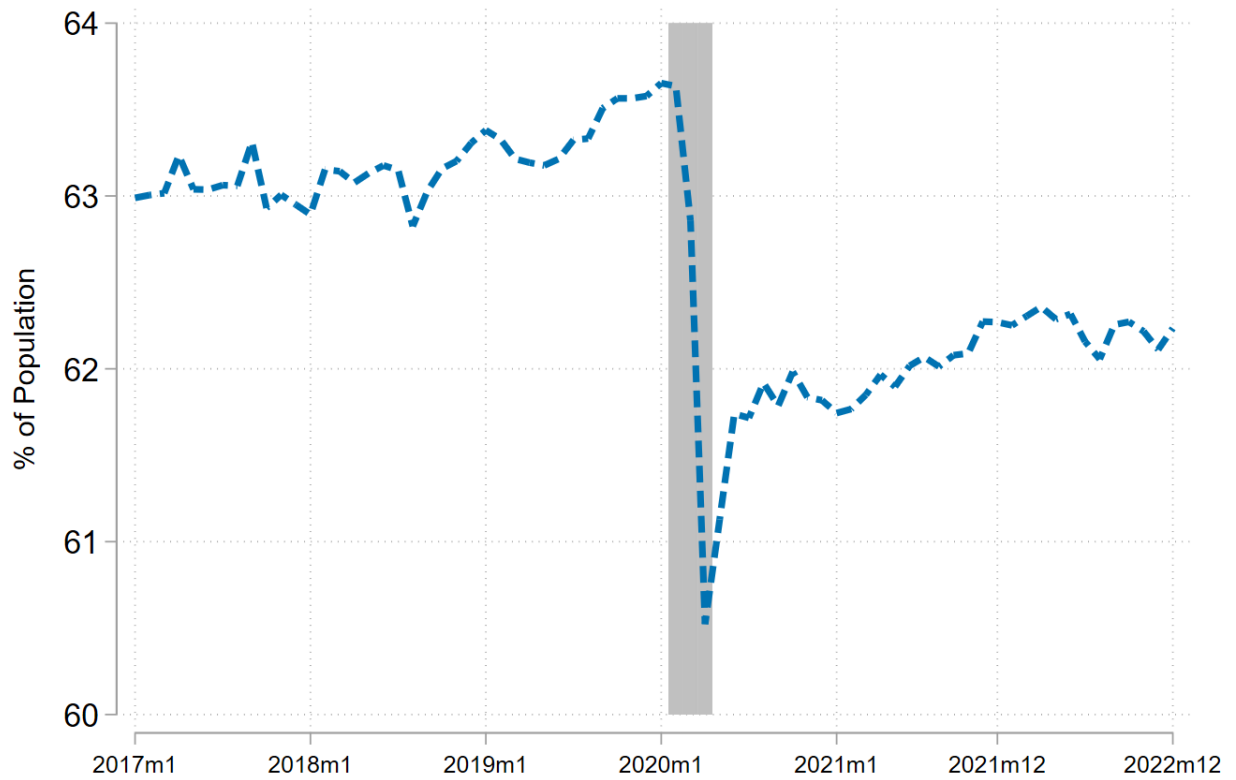
We start by analyzing the recent evolution of the US LFPR. Figure 1 plots the seasonally adjusted US LFPR between January 2017 and December 2022. It is important to point out that we compute the LFPR using microdata from the Current Population Survey (CPS) and apply a smoothing procedure over the CPS weights to account for breaks introduced by updated population controls as suggested by the BLS. This is important because the 2020 Census led to significant revisions of the CPS weights in January 2022, making the published LFPR series not comparable to previous dates. This issue is pointed out and discussed in detail by [Robertson and Willis \(2022\)](#) and [Montes et al. \(2022\)](#), who show the importance of using this smoothed procedure to generate LFPR estimates that are comparable throughout the period in analysis.² This weight smoothing procedure is described in detail in Appendix A. It is applied to all statistics reported in this paper based on the CPS, as this is particularly relevant for LFPR and the retirement share.

Figure 1 shows that the LFPR was stable and slightly increasing in the three years before the pandemic, rising from 62.98% in January 2017 to 63.64% in February 2020, the last full month before the effects of the COVID-19 pandemic and associated policy responses started percolating through the US economy. The first few months of the pandemic were characterized by the sharpest drop in LFPR on record: as of April 2020, the LFPR had fallen to 60.52%, a full 3.12 percentage points below its value two months prior. The following month was marked by what seemed to be a sharp recovery, to 61.74% in June 2020, but which then seemed to have stalled. The recovery has since been much slower: 61.81% at the end of 2020, 62.27% at the end of 2021, and 62.23% at the end of 2022. As of December 2022, the LFPR was 1.41 percentage points below its pre-pandemic peak. Accounting for the evolution of the civilian non-institutional population aged 16 and over between February 2020 and December 2022, this corresponds to about 3.73 million workers “missing” from the labor force.³

Throughout this article, we use this 3.73 million figure as the baseline number of missing workers in the US economy. As we show in the next section, this number is in the same order of magnitude as

²In particular, these adjustments showed that the US population was larger and younger than previously considered.

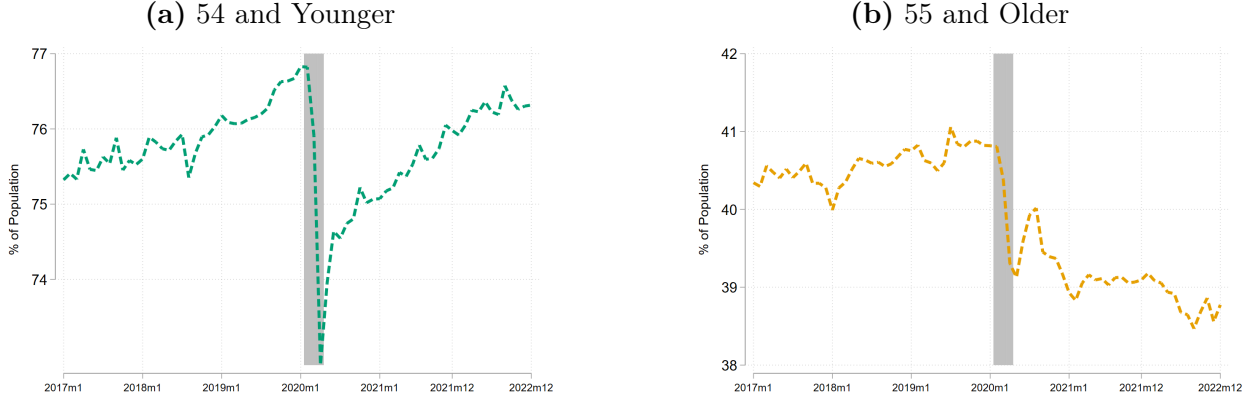
³This number corresponds to the difference between the size of the counterfactual labor force that we would observe given the population in December 2022 and the February 2020 LFPR of 63.64%, and the actual size of the LFPR in December 2022.



The LFPR is computed using CPS microdata with weights adjusted for changes in population controls as a result of the 2020 census. Data are seasonally adjusted using the X13-ARIMA-SEATS procedure from the Census Bureau.

Figure 1: Labor Force Participation Rate

the estimates for “excess retirements” in 2020-22 that are obtained once demographic and business cycle trends are taken into account. It is, however, worth pointing out that [Hobijn and Şahin \(2022\)](#) argue that this simple back-of-the-envelope calculation may overstate the real number of missing workers, as it does not account for pre-existing demographic trends that pushed the LFPR downwards. In other words, they argue that the LFPR in December 2022 should not be compared to its value in February 2020 but rather to a lower value that accounts for these downward trends.⁴



NOTE: The LFPR is computed using CPS microdata with weights adjusted for changes in population controls as a result of the 2020 census. Data are seasonally adjusted using the X13-ARIMA-SEATS procedure from the Census Bureau.

Figure 2: Labor Force Participation Rates by Age

Figure 2 decomposes the evolution of the LFPR across two age groups: those aged 54 and younger (left panel) and those aged 55 and older (right panel). The left panel shows that LFPR for those 54 and younger had been increasing before the pandemic, rising from 75.32% in January 2017 to 76.82% in February 2020. As with pretty much any demographic group, LFPR fell sharply in April 2020 to 72.86% but has recovered briskly since then. As of December 2022, it stood at 76.31%, 0.51 percentage points below its pre-pandemic peak. Given the size of the population in this age group, this corresponds to about 832 thousand missing workers, less than a quarter of the total number of missing workers in the US economy.

The right panel shows a very different picture for those aged 55 and older: their LFPR had been stable pre-pandemic, fell in the first few months of the pandemic, and despite a brief apparent recovery in late 2020, it has further declined since then. As of December 2022, LFPR for this age group was 38.77%, 2 pp below its pre-pandemic level. This corresponds to about 2.1 million missing workers in this age group. These aggregate patterns are consistent with the micro evidence documented by [Gregory \(2023\)](#), who finds that those who exit the labor force during large recessions tend to be older on average and were particularly older during the pandemic recession.

Our analysis in this section focuses on the extensive margin of labor supply only and abstracts

⁴This point is also emphasized by [Bullard \(2022\)](#), who argued that LFPR was on trend as of the beginning of January 2022, after an above-trend cycle in the pre-pandemic period.

from analyzing changes in the intensive margin of hours worked.⁵

2.2 The COVID Retirement Boom

Our analysis of LFPR trends around the pandemic displays different dynamics for younger and older workers. While the former seem to have mostly returned to the labor force, a significant fraction of the latter seem to have dropped out permanently. An important difference between younger and older workers is that the latter are much closer to their retirement. Older workers are much closer to an age where they can access retirement benefits from social security or private pension funds without penalties. Nie and Yang (2021) and Faria-e-Castro (2021) both documented a significant increase in retirements in mid to late 2021, more significant than what previous data trends would have suggested. In this section, we try to assess how much of the observed drop in LFPR can be ascribed to “excess retirements,” i.e., retirements above and beyond the level that would be predicted by long-run demographic and short/medium-run business cycle trends, as well as changes to the retirement benefits system.

We closely follow the methodology of Montes et al. (2022) and estimate a statistical model of retirement for different demographic groups that accounts for several long and short-run factors that could affect retirement decisions at the group level. We then compare observed retirement shares to those implied by the model and treat the difference as excess retirements. We divide the US population into 780 demographic subgroups j . Each subgroup is a tuple of age (16 to 80, with 80 corresponding to 80 or older), sex (men and women), education (less than bachelor’s degree and bachelor’s degree or more), and ethnicity (non-Hispanic white, non-Hispanic non-white, and Hispanic). For each subgroup, we compute retirement shares from the CPS microdata, where the retirement share is simply the fraction of people in that subgroup who are retired at any given point in time t

$$r_{j,t} = \frac{\sum_{i \in j} \omega_{i,t} \mathbb{I}[\text{retired}_{i,t}]}{\sum_{i \in j} \omega_{i,t}}$$

where $\omega_{i,t}$ is the (smoothed) CPS weight and $\mathbb{I}[\text{retired}_{i,t}]$ is an indicator variable equal to 1 if individual i identifies as being retired at time t .⁶

We compute retirement shares for each subgroup between January 1995 and December 2019. We then average them over each year and run regressions at the annual frequency between 1995 and 2019 for each subgroup j :

$$r_{j,t} = \beta_0^j + \beta_1^j \text{PIA}_{j,t} + \beta_2^j \hat{u}_t + \beta_3^j t + \varepsilon_{j,t}, \forall j$$

That is, we regress $r_{j,t}$ on three variables: the Social Security primary insurance amount (PIA) ratio for that subgroup in a given year $\text{PIA}_{j,t}$; the CBO’s estimate of the unemployment rate gap

⁵See Lee et al. (2023) for an analysis of the intensive margin.

⁶To define retirement, we use the EMPSTAT variable from CPS, available from IPUMS. We classify an individual as retired if EMPSTAT is equal to 36 (NILF, Retired).

\hat{u}_t ; and a linear time trend. $\varepsilon_{j,t}$ is the regression residual.

The PIA ratio is the fraction of a person’s full retirement benefit (called the PIA) that the person receives and depends on at what age the person decides to retire. People who retire at full retirement age receive their full PIA, so $PIA = 1$. People who retire before their full retirement age receive a fraction of their full retirement benefits, with that fraction depending on “how far” they are from their full retirement age when choosing to retire (Social Security benefits can only be collected after the age of 62), and so they have $PIA < 1$. Similarly, people who retire after their full retirement age receive a premium over their full retirement benefits up to the age of 70, after which the premium ceases growing if the person decides to delay retirement further. For these people, we have $PIA > 1$. For each subgroup, we compute the PIA of all the persons in that subgroup and then take an average for the subgroup to obtain $PIA_{j,t}$. More details on these calculations can be found in Appendix B. The PIA ratio is only included in the regressions for the subgroups aged 62 to 70.

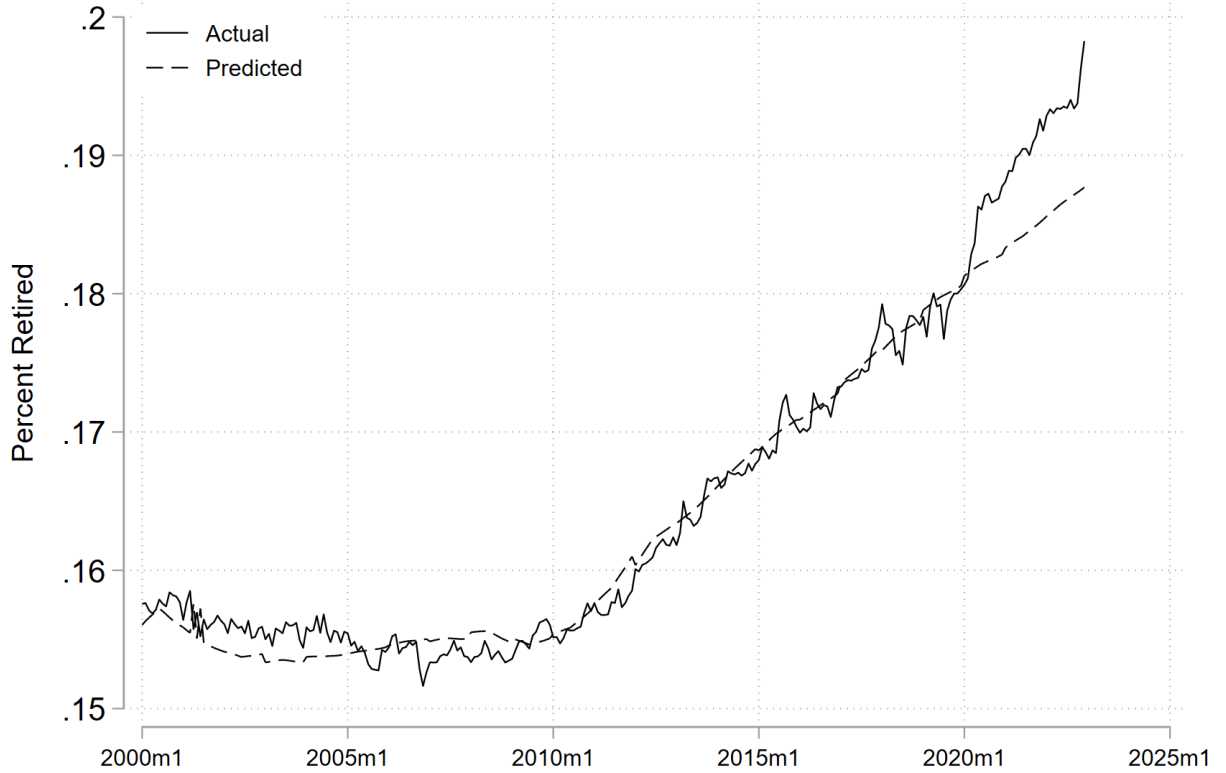
Besides the PIA ratio, the other two variables are the CBO unemployment rate gap and a linear time trend. The unemployment gap is a proxy for the business cycle and labor market slack. It is well documented by [Hobijn and Sahin \(2021\)](#), for example, that labor force participation decisions (on which we include the retirement decision) are sensitive to the state of the macroeconomy and the extent of slack in the labor market, with participation falling during recessions and rising during booms. Thus, the business cycle is an important determinant of retirement decisions. Finally, we include the time trend to account for other longer-term trends that may affect different demographic subgroups differently during the period under analysis.

We use the model estimates to arrive at predicted, counterfactual retirement shares for each subgroup for the 1995-2022 period, $\hat{r}_{j,t}$. For the estimation period 1995-2019, we use the predicted values from the regression. To extrapolate during the COVID years, 2020-22, we again closely follow the assumptions in [Montes et al. \(2022\)](#): (i) we assume that the PIA ratio would have evolved as legislated, (ii) we assume that the unemployment gap would have remained at its 2019 level, and (iii) we assume that the linear time trend would have evolved as predicted. We can then use these predictions to compute a counterfactual aggregate retirement share by aggregating the predicted shares for each subgroup using the subgroup weights:

$$\hat{r}_t = \frac{\sum_{j \in J} \omega_{j,t} \hat{r}_{j,t}}{\sum_{j \in J} \omega_{j,t}}$$

where $\omega_{j,t} \equiv \sum_{i \in j} \omega_{i,t}$ are the aggregate CPS weights for each of the subgroups. Figure 3 plots the retirement share observed in the data (solid line) versus the model prediction (dashed line). The figure shows that the model accurately tracks the retirement share over the estimation period. However, we observe a significant divergence starting in 2020, as the observed retirement share rises considerably over the predicted share. The difference between the two (the excess retirement share) increases from 0.1 pp in February 2020 to 0.6 pp in August 2020. The excess retirement share has kept increasing, surpassing one percentage point in late 2022. Given the civilian non-institutional population aged 16 and over as of December 2022, this corresponds to 3.27 million excess retirees.

These numbers align with those obtained using simpler statistical models, such as nonlinear time trends in [Faria-e-Castro \(2021\)](#).



NOTE: The retirement shares are computed using CPS microdata with weights adjusted for changes in population controls as a result of the 2020 census. The model predicting the retirement share follows [Montes et al. \(2022\)](#). Data are seasonally adjusted using the X13-ARIMA-SEATS procedure from the Census Bureau.

Figure 3: Actual vs. Expected Retirements

These estimates are in line with those in the literature. [Tuzemen \(2022\)](#), for example, finds that the number of “missing workers” as of March 2022 was 3.6 million, out of which about 2 million were estimated to be associated with a lower labor force participation rate for older workers. Our headline number of 3.27 million excess retirees corresponds to the estimate of our model as of December 2022 due to a large increase in excess retirements in late 2022. For March 2022, our model predicted 1.85 million excess retirees, a number that is very close to the one estimated by [Tuzemen \(2022\)](#).

2.3 Why did people choose to retire?

There are many potential reasons why people chose to retire in larger numbers during the pandemic. First and foremost, COVID-19 had much graver consequences for older people, and it had become known early on in the pandemic that older adults were much more likely to be hospitalized and

die from COVID-19. This significantly increased incentives to stop working, especially for those in contact-intensive occupations and those who could not easily transition to a remote working environment (Leibovici et al., 2020). Second, with daycare facilities closing under lockdowns, such as child care centers or nursing homes, caring for loved ones often fell on family members closer to retirement. Third, labor force participation tends to be procyclical, and people tend to join the labor force when labor market conditions are good and leave during recessions. These fluctuations are heterogeneous across demographic groups. The pandemic recession was associated with the largest documented increase in the unemployment rate in US history, and Hobijn and Şahin (2021) document a longer participation cycle for older workers, meaning that this group takes longer to return to the labor force after a recession.

A fourth reason why people may have chosen to retire in larger numbers is wealth effects on labor supply. Standard neoclassical economic theory postulates that labor supply decisions, both at the extensive and intensive margins, are driven by substitution effects from changes in wages and wealth effects from changes in income and wealth, among many other things. In particular, when leisure is assumed to be a normal good, increases in non-labor income or wealth should induce people to supply less labor at a given wage rate, everything else constant. Daly et al. (2009) and Benson and French (2011), for example, study how wealth and income losses may have kept the LFPR higher than what it would have been otherwise during the Great Recession. As we discuss in the next section, US households experienced historically large increases in net worth during the pandemic period. That is, they became wealthier thanks to booming returns in asset markets such as stocks and housing, and this may have negatively affected their willingness to work, contributing to a fall in the LFPR. While this may not have been the main driver behind labor force participation decisions, it may have compounded the other three, which were already particularly strong for older workers. It is also worth mentioning that while we focus our analysis on the extensive margin, wealth effects may also drive labor supply decisions at the intensive margin - increases in wealth during the pandemic would then be consistent with the intensive margin declines in hours documented by Lee et al. (2023) for that period.

3 Asset Prices and Net Worth around COVID

As discussed in the previous section, wealth effects can play an important role in people’s labor force participation decisions. Concurrent with the aforementioned dynamics of the LFPR and retirement share, there were large fluctuations in valuations for major asset classes during the pandemic. These changes in valuations had plausibly significant effects on households’ net worth. In this section, we first document these fluctuations in valuations for major asset classes and then analyze their impact on net worth at the individual level.

3.1 Asset Prices

We start by looking at the evolution of cumulative returns on major asset categories throughout the pandemic. Figure 4 plots cumulative real returns for four major asset classes from December 2019 to December 2022. The four major asset categories we consider are stocks, housing, government bonds, and corporate bonds. In addition, a fifth asset category, private businesses, is quantitatively significant for US households' portfolios, according to the Federal Reserve Board of Governors' Survey of Consumer Finances (SCF). There are, however, no good data sources for returns on private businesses besides other issues, namely the fact that the nature of private businesses is extremely heterogeneous, and so are their returns. This is likely to be less of an issue for financial assets such as stocks and bonds, which are traded frequently and have publicly observable returns, or even housing, whose geographically heterogeneous returns tend to be correlated with national trends.⁷

We choose proxies for the returns of each of the asset classes. For stocks, we use the cumulative return on the S&P500 index. For housing, we use the S&P/Case-Shiller US National Home Price Index. For government bonds, we use the yield on 10-year Treasurys; for corporate bonds, we use the ICE Bank of America US Corporate Index. The figure shows that despite negative returns in the first few months of the pandemic, thanks to the high degree of economic uncertainty and instability, stocks and housing performed exceptionally well during 2020 and 2021. Cumulative stock returns peaked at the end of 2021, at slightly over 35%, subsequently falling during 2022, possibly due to elevated inflation and a more restrictive monetary policy stance. Housing returns behaved more sluggishly, surpassing over 20% at their peak in the first half of 2022. As of the end of 2022, they were still above 15%. The returns on bonds, government or corporate, were relatively low at the early stages of the pandemic and quickly became negative, still in 2020.

This figure shows a wide variation in cumulative returns for major asset classes. Bonds, which posted the worst performances out of these four categories, tend to be a smaller fraction of individual portfolios, which are dominated by stocks and housing. These two asset categories performed extremely well by historical standards during 2020 and 2021 despite declines in cumulative returns during 2022. Since these assets are a significant part of household balance sheets, these high returns may have caused significant increases in household net worth during 2020 and 2021. Next, we investigate the effect of these return fluctuations on the net worth of individuals.

3.2 Impact on Individual Net Worth

3.2.1 Net worth across the age distribution

We are particularly interested in studying how the large fluctuations in returns observed during the pandemic affected the net worth of different households across the age distribution. To this end, we directly estimate changes in net worth caused by fluctuations in returns of different assets given the

⁷We do not explicitly consider bank deposits, as they make up a relatively small percentage of household assets, ranging from 4.9% for people aged 35-44 to 7.4% for those under the age of 35. Due to low interest rates, deposits earned very low returns during the period in analysis.



NOTE: We use the following series to compute returns for each asset class: the S&P 500 index for U.S. equities; the S&P/Case-Shiller U.S. National Home Price Index for housing; the constant maturity 10-year Treasury yield for government bonds; and the ICE BofA U.S. Corporate Index for corporate bonds. All returns are deflated by the core consumer price index. Shading represents a recession.

Figure 4: Cumulative Real Returns by Asset Class

portfolio composition of US households in different age groups. Our starting point is the 2019 Survey of Consumer Finances (SCF) published by the Board of Governors of the Federal Reserve System. The SCF is a triennial survey of US households' balance sheets and income. Of particular interest to us is the fact that it contains detailed information about the value and categories of different types of assets held by US households, as well as demographic characteristics such as age. While the SCF is conducted at the household level, we are interested in studying the impact of changes in net worth at the individual level, as we want to be able to express the results of our analysis in terms of number of people. For that reason, we transform the SCF to an individual-level dataset, and all SCF results and statistics we report refer to this individual-level transformed dataset unless otherwise noted.⁸ Figure 5 reports the portfolio composition for an average individual in each of six

⁸More specifically, we use the marital status indicator and assume that if the household is married, it is composed of two individuals, and if it is not married, it is composed of one individual only. This follows [Dettling and Hsu \(2014\)](#), who also argue that this is only an imperfect approximation for a minimal number of households, as most of the dependents in a household who are not captured by our approximation would be under the age of 16 and thus not part of the civilian noninstitutional population aged 16 and over.

age groups as of 2019: under the age of 35, 35-44, 45-54, 55-64, 64-74, and 75 and older. The figure decomposes the portfolio of individuals in each age category into three major asset classes (stocks, real estate, bonds), other assets, and debt owed by the individuals.

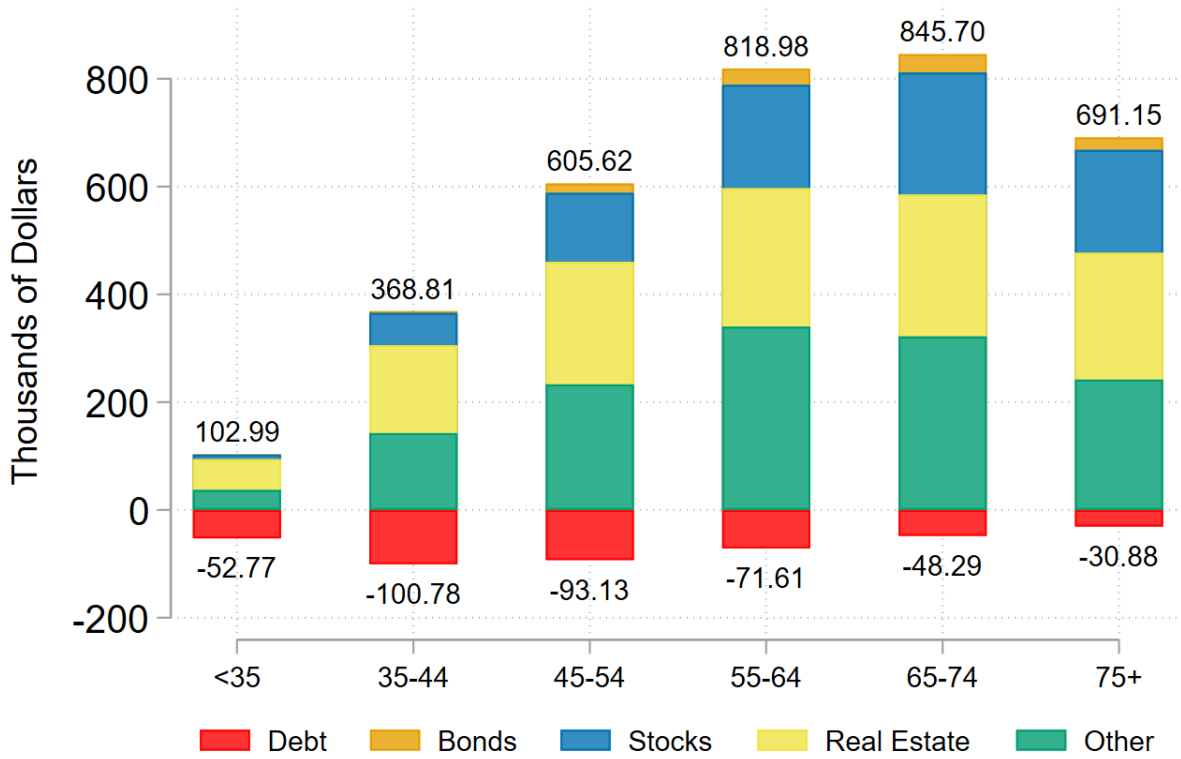


Figure 5: Portfolio Composition in 2019 SCF by Age

As expected, younger individuals tend to own fewer assets. Assets are increasing in age and peak for those aged 65-74. Younger individuals tend to hold primarily real estate (55.4% of their total assets), while the share of stocks increases with age, peaking at 27.6% for those aged 75 and older. Other assets is a residual category that is a significant and relatively constant share of total assets (between 35% for those 75 and older and 41.5% for those aged 55-64). A significant component of this residual category is private businesses. A predictable lifecycle pattern also emerges regarding debt: younger individuals tend to owe more debt. Debt is largest for those aged 35-44, likely due to mortgages associated with first-time home purchases. As age increases from this category onwards, the absolute value of debt falls even as the level of assets increases considerably. This suggests a very stark lifecycle profile in terms of net worth. We plot average net worth across the same age categories in Figure 6: net worth is lowest for the younger individuals, rising steeply as individuals become older and peaking at almost 800 thousand 2019 dollars for those aged 65-74.

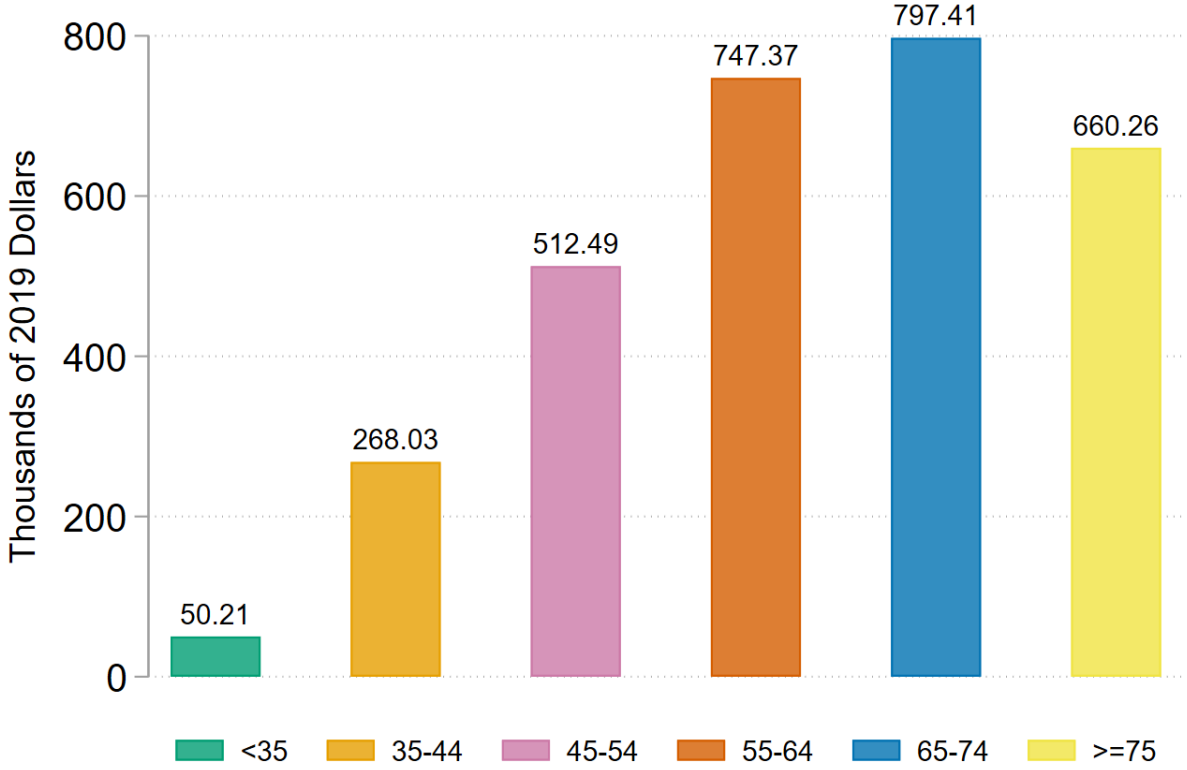


Figure 6: Net Worth in 2019 SCF by Age

3.2.2 Net worth in 2019-22

We now combine the 2019 SCF with data on realized returns for different asset classes in order to estimate the change in net worth experienced by different households during the pandemic period. Our approach relies on a series of assumptions: first, it assumes that 2019 portfolios, as observed in the SCF, are kept constant through 2022, including debt owed. Second, we assume that individuals are perfectly diversified within each asset category – this can either under or overstate changes in net worth due to a specific asset class. Third, we only consider changes in net worth arising from asset classes for which we can access data on realized returns. This means that we disregard potentially important asset categories such as private business, which may lead us to either under or overstate the actual change in net worth. Formally, we define net worth for individual i in 2019 as follows:

$$NW_{i,2019} = \sum_{j \in J} A_{i,2019}^j - B_{i,2019}$$

where $J = \{\text{stocks, real estate, corp. bonds, govt. bonds, other}\}$ are the asset classes we consider separately, and $B_{i,2019}$ is debt owed by the individual at the end of 2019. We then define net worth for individual i at some arbitrary period $t \geq 2019$ as follows

$$NW_{i,t} = \sum_{j \in J} R_{t,2019}^j A_{i,2019}^j - B_{i,2019}$$

where $R_{t,2019}^j$ is the cumulative gross real return between 2019 and t of asset category j . We measure $R_{t,2019}^j$ directly from the data for stocks, real estate, and both types of bonds, and we set $R_{t,2019}^{\text{other}} = 1$, i.e., zero real return for other assets. The change in net worth between 2019 and an arbitrary period $t \geq 2019$ is then given by the difference between the two.

$$\Delta NW_{i,t} = NW_{i,t} - NW_{i,2019}$$

While we perform this calculation at the individual level, Figure 7 summarizes the output across the age distribution, reporting the average change in net worth within each age category we consider. We conduct the exercise for two periods: the “return boom” period 2020-21, during which stock returns peaked (top panel), and the full 2020-22 sample (bottom panel), which also accounts for the drop in cumulative returns during 2022. During the boom period, while all age categories benefited from rising asset valuations in terms of their net worth, there was substantial heterogeneity. The youngest benefited the least in absolute terms, with their net worth rising by 15 thousand 2019 dollars, on average. Those aged 65-74 benefited the most in absolute terms, with an average increase of 135 thousand 2019 dollars. This large increase is due to their initially larger portfolios and their exposure to asset classes that performed well during this period, namely real estate and stocks.⁹

The bottom panel of Figure 7 considers the full sample period, including 2022, during which a fraction of the 2020-21 cumulative returns reversed. The figure shows that, while lower, net worth returns were still quite positive across age groups. The large exposure of older individuals to stocks means that their returns fell relatively more relative to the boom period. Still, individuals in the 65-74 age range generated a total average cumulative return of 62 thousand dollars during this period, more than the average in any other age category.

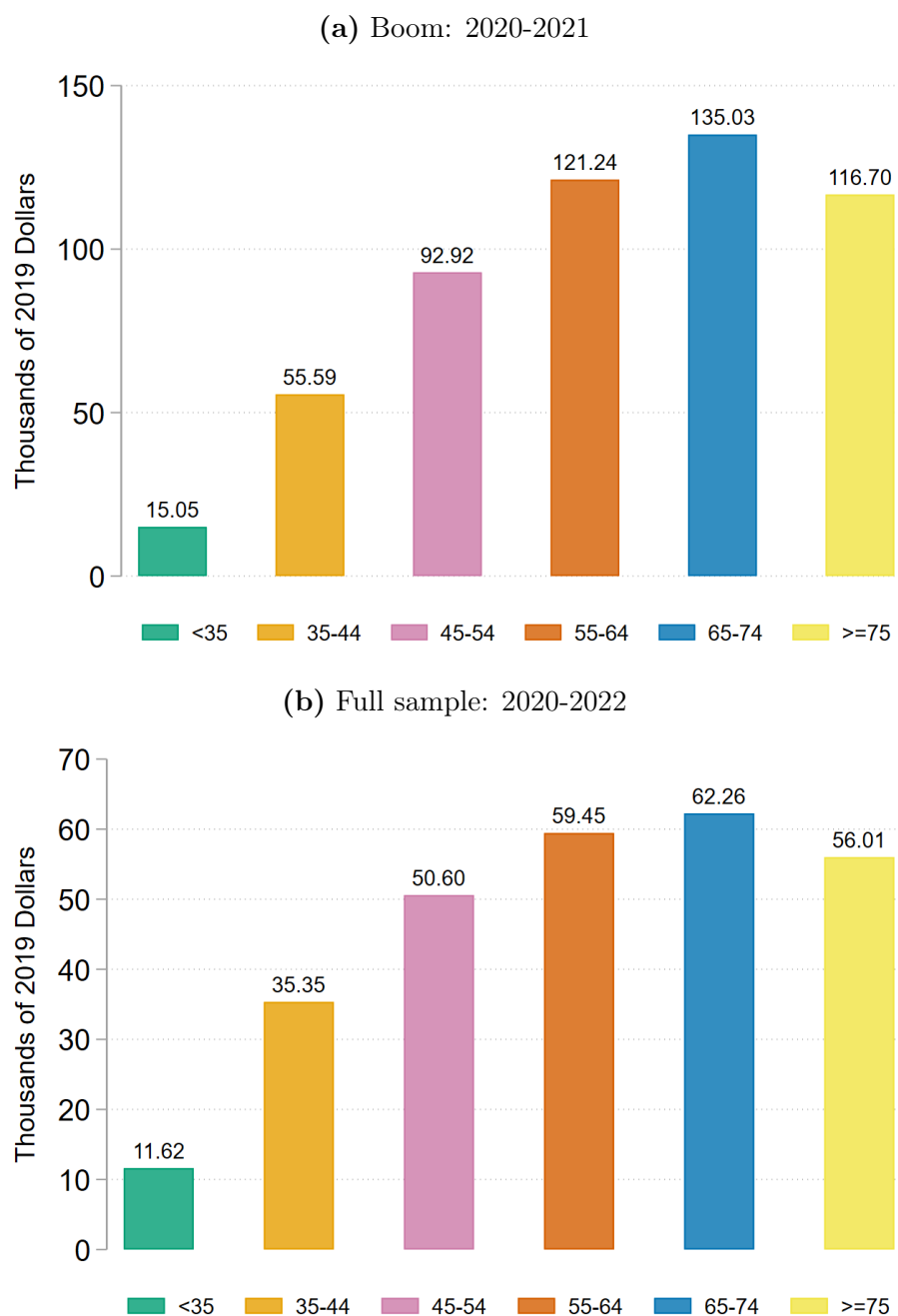
4 Impact of Net Worth changes on LFPR

Having documented the differential changes in LFPR trends across age groups and the heterogeneity in terms of exposures to asset gains and realized changes in net worth, we now try to quantify the relationship between the two.

4.1 A simple model of wealth effects

Our goal in this section is to determine how much of the decline in LFPR and increase in excess retirements since the beginning of the pandemic could be explained by changes in net worth for

⁹In terms of cumulative returns on net worth, the youngest age category performs the best, earning a cumulative return of 30% during the boom period, while those aged 55-64 perform the worst, earning an average return of 16.2%. This likely reflects the large weight of other assets in the portfolio of older individuals, for which we impute a zero return.



NOTE: We use the 2019 SCF for net worth and assume a constant portfolio over the period. We use the following series to compute returns for each asset class: the S&P 500 index for U.S. equities; the S&P/Case-Shiller U.S. National Home Price Index for housing; the constant maturity 10-year Treasury yield for government bonds; and the ICE BofA U.S. Corporate Index for corporate bonds. All returns are deflated by the core consumer price index. Shading represents a recession.

Figure 7: Average Returns on Net Worth

US individuals across the age distribution. To this end, we adapt the methodology in [Cheng and French \(2000\)](#), who estimate a statistical model that relates wealth shocks as a percentage of annual income to labor force participation decisions. [Benson and French \(2011\)](#) use this model to measure the impact of declines in wealth during the Great Recession on labor force participation. We closely follow these authors and apply their model estimates to the pandemic period.¹⁰ The model estimated by [Cheng and French \(2000\)](#) is the following:

$$-\Delta LFPR_i = \begin{cases} 0.010 \times \left(\frac{\Delta NW}{Y}\right)_i & , \text{ if } \left|\left(\frac{\Delta NW}{Y}\right)_i\right| < 8 \\ 0.032 + 0.006 \times \left(\frac{\Delta NW}{Y}\right)_i & , \text{ if } 8 \leq \left|\left(\frac{\Delta NW}{Y}\right)_i\right| < 30 \\ 0.152 + 0.002 \times \left(\frac{\Delta NW}{Y}\right)_i & , \text{ if } \left|\left(\frac{\Delta NW}{Y}\right)_i\right| \geq 30 \end{cases} \quad (1)$$

The model relates the labor force participation decision (on the left-hand side) to the change in net worth divided by annual earnings, allowing for nonlinearities in the response, depending on the specific ratio of change in net worth to earnings. This is a simple model of labor supply that abstracts from many other relevant factors that could be important for individual decisions on whether to participate or not in the labor force. Neoclassical models typically account for other factors that could influence this decision, such as age, health status, and the human capital – not just the financial capital – of the worker. It is also likely that these factors interact with changes in net worth: the participation decision of older workers, for example, is plausibly more sensitive to changes in net worth as the present discounted value of labor income and of their human capital is lower at that point. While the model does not explicitly account for these factors, we do control for age of the worker by separately applying this model to different age groups.

In the previous section, we computed the change in net worth for each individual in the SCF, from where we can also observe individual earnings. This allows us to compute the ratio $\left(\frac{\Delta NW}{Y}\right)_i$ for each individual. We then apply the model in 1 to each individual in the SCF and obtain an aggregate LFPR response by applying the appropriate SCF weights.

4.2 Explaining the decline in LFPR

Table 1 summarizes our main results. Results are reported for two time periods, December 2019 to December 2021 (the asset return boom period), as well as the full sample, December 2019 to December 2022. Within each period, each row corresponds to wealth effects in a single age group, and we think of these age groups as generating progressively less conservative results. The first row, for example, corresponds to a situation where we assume that the labor force participation decision is sensitive to wealth effects only for those aged 55-70. In the second row, we assume that all people older than 55 are sensitive to wealth effects, while the last row assumes that everyone aged 16 or older is sensitive. [Cheng and French \(2000\)](#) argue that those younger than 51 are unlikely to adjust their labor supply much in response to changes in asset values. [Daly et al. \(2009\)](#), however, argue that financial and credit market conditions could have been an important driver of labor force

¹⁰This procedure is the same used in [Faria-e-Castro \(2022\)](#).

participation decisions for young people during the Great Recession.¹¹

	Age	(1) LFPR impact (pp)	(2) People (million)	(3) % of LFPR drop
<i>2019 - 2021</i>	55-70	0.00376	0.99	28.73%
	55+	0.00669	1.76	51.13%
	16+	0.01002	2.64	76.62%
<i>2019 - 2022</i>	55-70	0.0024	0.65	18.13%
	55+	0.0044	1.17	32.77%
	16+	0.0069	1.84	51.62%

Table 1: Estimated impact of changes in net worth on LFPR

Column (1) of Table 1 reports the direct impact on aggregate LFPR from wealth effects for each age group. These numbers correspond to the weighted average of the predicted values obtained from applying 1 to each individual in the SCF. Columns (2) and (3) correspond to more interpretable versions of the same result. In column (2), we multiply the LFPR impact by the size of the civilian non-institutional population over the age of 16 as of the final period (December 2021 or 2022) to convert the estimated LFPR impact into a population estimate. Column (3) divides the LFPR impact by the total LFPR drop during the period in analysis, reporting the share of the total LFPR drop that can be plausibly explained by net worth effects.

The results show that during the asset boom period, almost a third of the total LFPR drop of 1.3 pp can be attributed to wealth effects for the population aged 55-70, likely to be the population segment whose retirement decision is most sensitive to wealth effects. If one expands the analysis to all those 55 and older, wealth effects can explain more than half of the drop in LFPR (51%). The population estimates imply that rising asset valuations during this period led to between 1 and 1.8 million people exiting the labor force out of about 3.4 million missing workers. If one considers the full period, 2019-2022, the results are smaller due to declining asset values during 2022. Still, wealth effects can explain between 18% and 33% of the total drop in LFPR during this period, depending on whether we consider only those aged 55-70 or 55 and older.

4.3 Explaining excess retirements

The same analysis can be applied to excess retirements, defined in section 2.2 as the difference between observed retirements and the number of retirements that would be predicted by a statistical model that takes into account demographic trends, the business cycle, and changes in retirement benefits legislation. Table 2 is similar to Table 1, but column (3) is replaced by the % of excess retirements that are explained by changes in net worth. The table shows that between 45% and 82% of the 2.2 million excess retirements can be explained by wealth effects for those aged 55-70 or 55 and older. For the entire 2019-2022 period, between 20% and 36% of the 3.3 million excess retirements can be explained by wealth effects.

¹¹More specifically, they argue that the credit crunch that followed the 2008-09 Financial Crisis may have hampered the ability of prospective college students to contract student loans, forcing them to look for jobs instead.

	Age	(1) LFPR impact (pp)	(2) People (million)	(3) % of Excess Retirements
<i>2019 - 2021</i>	55-70	0.00376	0.99	45.96%
	55+	0.00669	1.76	81.79%
<i>2019 - 2022</i>	55-70	0.0024	0.65	19.73%
	55+	0.0044	1.17	35.66%

Table 2: Estimated impact of changes in net worth on Excess Retirements

4.4 Robustness Checks

In this subsection, we perform a couple of robustness checks that involve recalculating by how much the increase in wealth can explain the LFPR drop and excess retirees under different assumptions. First, we relax our assumption on private business, namely that it provides zero returns, and instead assume that private business follows the return of the S&P 500. Second, we calculate the impact of excess returns on LFPR decisions, as opposed to total returns as in the baseline.

Returns on Private Businesses. In our baseline, we make a strong assumption regarding the returns on private businesses – that they earn zero return. We assume this because it is hard to compute the rates of return on this asset class, especially with the available public data. Therefore, we choose zero return because it provides a conservative lower bound for our estimations. We can assume instead that private businesses earned the same return as the S&P 500 during the period in analysis. This is a strong assumption in the opposite extreme, and we treat these numbers as an upper bound for the effects of changes in wealth on LFPR. As shown in Table 3, the percentage of LFPR drop than can be explained by the increase in wealth during 2019-2021 increases by 5 pp and 9 pp, for those 55-70 and 55 and older respectively. For the 2019-2022 period, when cumulative returns to the S&P 500 since 2019 were falling, our results are similar to the baseline. Additionally, we find that the increases in wealth during 2019-2021 account for 54% of excess retirees aged 55-70, and 96% of excess retirees 55 and older. These estimates are 10-15 pp higher than our baseline. For the 2019-2022 period, we find comparable estimates to our baseline.

	2019-2021		2019-2022	
	55-70	55+	55-70	55+
(1) LFPR impact (pp)	0.00443	0.00788	0.00255	0.00460
(2) People (M)	1.17	2.07	0.67	1.22
(3) % of LFPR drop	33.87%	60.24%	18.96%	34.26%
(4) % of Excess Ret.	54.19%	96.36%	20.64%	37.29%

Table 3: Robustness Exercise: Private businesses earning same returns as stocks

Excess Returns. In our baseline exercise, we apply the total return on each asset class to the LFPR model. Originally, [Cheng and French \(2000\)](#) apply the LFPR model to excess returns only, arguing that only returns in excess of what agents anticipated should have significant effects in

terms of LFPR decisions. In this robustness exercise, we adopt this more conservative approach and compute excess returns for each asset class, which are then imputed to the LFPR model.

To calculate excess returns, we measure the average real return of our four asset classes between December 2009 and November 2019. We treat these average real returns as the expectation of returns for each asset class for the following periods. We then compute excess returns by subtracting these average real returns from the realized ones. Since expected real returns are positive for all asset classes, this generates estimates for the change in LFPR that are smaller than our baseline estimates.

Our estimates for the impact of excess returns on LFPR are shown in Table 4. During the 2019-2021 period, asset returns were high and thus using excess returns we can still account for 19 and 35% of the drop in LFPR for the 55-70 and 55 and older age groups. However, when considering the period 2019-2022 we find excess returns to wealth can only account for 4% of the LFPR drop for those 55-70 and 7.5% for those 55 and older. In terms of excess retirees for the 2019-21 period, we can account for 31 and 56% of excess retirees for the 55-70 and 55 and older – compared to 46 and 82% in the baseline.

	2019-2021		2019-2022	
	55-70	55+	55-70	55+
(1) LFPR impact (pp)	0.00254	0.00456	0.00052	0.00103
(2) People (M)	0.67	1.20	0.14	0.27
(3) % of LFPR drop	19.44%	34.88%	3.87%	7.66%
(4) % of Excess Ret.	31.10%	55.79%	4.22%	8.34%

Table 4: Robustness Exercise: Excess returns

5 Conclusion

In this article, we have argued that wealth effects arising from the increase in net worth caused by booming asset returns in 2020-21 help explain a significant share of the drop in labor force participation rates during the same period, especially for older workers close to retirement.

We first documented that while the LFPR for prime-age workers has more or less recovered to its pre-pandemic levels, the LFPR for workers older than 55 seems to have declined permanently. Using a statistical model for the retired share that controls for several demographic characteristics as well as medium-term business cycle factors and longer-term trends, we also showed that the percentage of Americans who have retired is significantly higher than the predicted trend and that there were 3.3 million “excess retirees” as of December 2022.

We then argued that a significant share of these “missing workers” and “excess retirees” can be explained by combining a model of wealth effects on labor supply and estimated changes in net worth. More specifically, we imputed realized returns on major asset classes to micro data on individual balance sheets and portfolio composition as of 2019 from the SCF. We then applied a model that relates changes in net worth to labor force participation decisions to obtain predicted

changes in labor supply from those fluctuations in net worth. We showed that this exercise helps explain between 28.7% and 51.1% of the drop in LFPR in the 2020-21 period and between 46% and 82% of all “excess retirements”, depending on whether we consider the population aged 55-70 or everyone aged 55 and older.

There are many other reasons, besides wealth effects, why individuals may have chosen to retire during this period. However, these changes in net worth may have enabled retirements, even if primarily driven by these other reasons. An important question is whether these individuals may return to the labor force. On the one hand, recent developments in financial markets during 2022 have undone some of these abnormally high returns, especially in the stock market. On the other hand, long-run demographic trends related to decreased fertility and population aging create downward pressure on the LFPR, preventing it from returning to its pre-pandemic levels.

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A CPS Weight Smoothing

After every census, there is a period before the complete population counts are released where BLS publications use population estimates. In January 2022, the BLS released the 2020 census revisions to their population estimates. There was a significant revision to the number of people aged 65 and over. In fact, there were over 1.4 million fewer people 65 and older than were predicted in the BLS population estimates made before the final release of 2020 census data. These BLS revisions led to a 0.3 pp increase in labor force participation between December 2021 and January 2022. However, the 0.3 pp increase in LFPR is driven by a change in the population base being measured – not by an actual increase to the LFPR. To remove this jump in LFPR, we smooth the CPS weights between 2010 and 2022 to spread out the total effect of this jump. We obtain the population effects at the gender and age group sub-levels¹². We adjust for those employed, unemployed, and not in the labor force. Thus we have 48 total subgroups for which we adjust the weights based on the January 2022 population revisions. In order to smooth, we closely follow [Robertson and Willis \(2022\)](#) and [Montes et al. \(2022\)](#). We first calculate an adjustment factor:

$$AF_j = \frac{w_j + \alpha_j}{w_j} - 1$$

where the adjustment factor for group j , AF_j equals the original weight, w_j , plus the 2022 revision amount, α_j over the original weight, subtracted by one. We then linearly distribute the adjustment factor over the 2010-2022 time period, following [Montes et al. \(2022\)](#). This can be done in the following manner:

$$\hat{w}_j = w_j \times \left(1 + AF_j \times \frac{t}{T} \right)$$

where the smoothed weight for group j , \hat{w}_j , is equal to the original weight, w_j multiplied by one plus the adjustment factor multiplied by the current period t , over the total number of smoothing period T . In our application, the total number of smoothing periods is $T = 144$ because we smooth over 12 years at the monthly level.

B Retirement Model

One of the main components of the retirement model is the value of retirement Social Security, called PIA. Here we describe in depth the process of calculating the PIA. The way to calculate PIA is to find a person’s age in months in any given month and subtract that from their normal retirement age (NRA) in months. If they are past their NRA, multiply their months past NRA by the benefit for delaying retirement. If they are retiring early, multiply their months past NRA by the penalty for early retirement. The CPS, however, provides age in years but not the month of birth. This makes the calculation of PIA challenging, as the month of birth within a given year matters.

¹²We get this report in PDF format directly from the BLS. The age groups are 16-17, 18-19, 20-24, 25-34, 35-44, 45-54, 55-64, and older than 65.

Further, the year a person is born matters because the NRA and the premium paid on delaying retirement change over time. This means that if a person was 65 in January 2005, they might have been born in 1940 and have a normal retirement age of 65 years and six months, or they might have been born in 1939 and have a normal retirement age of 65 years and four months. Because of this issue, we calculate the PIA ratio at the subgroup level. We assume a uniform distribution of birth months for each subgroup, with the current observation month being a potential birth month. Take, for example, a subgroup of uneducated, white females aged 65 in January 2005. For this subgroup, individuals could have been born in January 1940 or February 1939 through December 1939. For each possible birth year, we calculate the average PIA ratio. Then, we weight the two PIA ratios uniformly based on the number of months one could have been born in that year:

$$\text{PIA} = \frac{11}{12} \times \text{PIA}_{1939} + \frac{1}{12} \times \text{PIA}_{1940}$$

The PIA ratio of each year will depend firstly on the normal retirement age of that year.¹³

Birth Year	Age of Normal Retirement
≤ 1937	65
1938	65 and 2 months
1939	65 and 4 months
1940	65 and 6 months
1941	65 and 8 months
1942	65 and 10 months
1943-1954	66
1955	66 and 2 months
1956	66 and 4 months
1957	66 and 6 months
1958	66 and 8 months
1959	66 and 10 months
≥ 1960	67

For the case where the person is younger – in our example their birth year is 1940 – we calculate the time from normal retirement as:

$$\text{time from NRA} = \text{NRA} - \text{age} - \frac{\text{month} - 1}{2}$$

Here, the NRA and age are both expressed in months. The last term accounts for the average months of a person's age for the more recent birth year. In our example, the person born in 1940 would have turned 65 in January 2005, so the calculation would be $786 - 780 - \frac{1-1}{2}$. Thus, the time from retirement would be six months.

For the case where the person is older – 1939 in our example – we calculate the time from normal retirement as:

$$\text{time from NRA} = \text{NRA} - \text{age} - \frac{12 + \text{month} - 1}{2}$$

¹³We obtain normal retirement ages from <https://www.ssa.gov/oact/progdata/nra.html>.

For our example, this would be 784 months - 780 - $\frac{12+1-1}{2}$. In this example, the time from normal retirement would be -2 months, indicating that the person is past their NRA. This calculation is based on our assumption of a uniform distribution of birth months. Thus, on average, for the people in our subgroup born in 1939, their birth month would be July, making them 65 years and six months old in January 2005 – two months past their NRA of 65 and four months.

Once we have the months from NRA for both possible birth years, we can calculate the PIA ratio. For early retirement, the penalty follows a standard calculation¹⁴:

$$\text{penalty} = \begin{cases} -\frac{5}{9} \times .01 \times t & \text{if } t \leq 36 \\ -\left[\frac{5}{9} \times .01 \times 36 + \frac{5}{12} \times .01 \times (t - 36)\right] & \text{if } t > 36 \end{cases}$$

The penalty for early retirement is 5/9ths of 1 percent for the first 36 months. Then, on top of the 36 months, there is a 5/12ths of 1 percent penalty for each additional month. The premium for delayed retirement depends on the birth year and is capped once the person reaches 70. The maximum number of months for which a person can increase the premium for delayed retirement is the difference between 70 and their NRA.

Birth Year	Gains for Delayed Retirement
1917-1924	3%
1925-1926	3.5%
1927-1928	4%
1929-1930	4.5%
1931-1932	5%
1933-1934	5.5%
1935-1936	6%
1937-1938	6.5%
1939-1940	7%
1941-1942	7.5%
≥1943	8%

The final calculation for the PIA ratio for the subgroup of uneducated, white females aged 65 in January 2005 is then given by:

$$\text{PIA} = 1 + \frac{11}{12} \times (.07 \times 2) + \frac{1}{12} \left(-\frac{5}{9} \times .01 \times 6 \right)$$

¹⁴For information on penalties for early retirement and gains for delayed retirement see https://www.ssa.gov/OACT/quickcalc/early_late.html