Great Layoff, Great Retirement and Post-pandemic Inflation*

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Abstract

The Covid-19 shock caused a dramatic spike in retirees. We show that retirement is countercyclical and that the peculiarity of the pandemic lay in the magnitude of the "Great Layoff" in March-April 2020, which triggered the "Great Retirement." Counties more exposed to the Great Layoff experienced larger wage increases that drew younger individuals from outside the labor force to compensate for the loss of workers. An estimated model with endogenous labor market participation quantifies the Great Retirement's contribution to overall inflation from 2020:Q1 to 2024:Q4 at about 3%, rising to roughly 6% when heterogeneous worker productivities are incorporated.

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JEL classification: E30, E24, J21.

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1 Introduction

Inflation has been unexpectedly high in the aftermath of the Covid-19 pandemic. Understanding the causes of such unexpected inflation is of key importance for both scholars and policy makers, and it sparked a prolific debate. Focusing on the US economy, recent contributions identified as main drivers of inflation the sudden increase in the demand for goods relative to services coupled with domestic and international supply chain disruptions, large fiscal measures alongside accomodative monetary policy stimulating demand in a limited-supply environment, the increase in energy prices as well as labor market tightness (see Section 2).

This paper adds to the literature on causes and effects of labor market tightness on inflation outcomes, investigating a particular channel: retirement decisions. Specifically, we focus on the supply side of the labor market by analyzing the large and persistent impact that the temporary layoffs at the onset of the pandemic had on retirement behavior and on the age-composition of the labor force. The contribution of the paper is twofold. First, we provide empirical support to the following chain of events. The pandemic-induced layoffs triggered a surge in early retirements, a phenomenon labeled as "Great Retirement" (see e.g., Montes et al., 2022). This, in turn, reduced labor supply by older cohort and increased labor market tightness, which led to higher nominal wages and induced the substitution of retired workers with younger workers previously not participating to the labor market. Ultimately, pandemic-induced layoffs caused inflationary pressures in the form of higher wages. Second, we develop a New Keynesian model with endogenous labor market participation and retirement to account for these facts and to quantify the impact that the Great Retirement had on recent inflation.

Motivating evidence. Figures 1 and 2 display some key facts about layoffs, labor force participation and retirement behavior that motivate our analysis. Data refer to the US and are based on the Job Openings and Labor Turnover Survey (JOLTS) of the Bureau of Labor Statistics (BLS), and on the Current Population Survey (CPS) conducted by the US Census Bureau for the BLS (see Appendix A for a detailed data description). In March and April 2020 lockdowns and anti-pandemic measures triggered the "Great Layoff", i.e., an unprecedented surge in layoffs and discharges with about 22 millions workers separated from their jobs in only two months (Figure 1, left panel). Moreover, an unprecedented high share of layoffs involved older workers. At the same time, in April 2020, the overall labor force dropped dramatically, with about 8 millions individuals flowing out of the labor force (Figure 1, middle panel). Importantly, this drop is very persistent and the labor force only reached

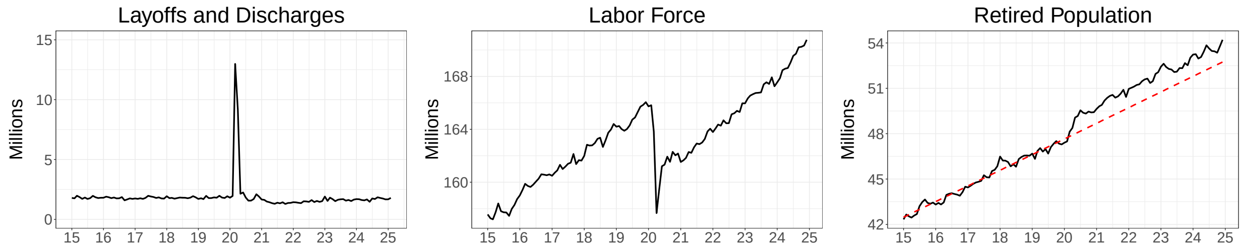

Figure 1. **Unprecedented surge in layoffs, persistent drop in the labor force and increase in retirement. Left**: Layoffs and discharges in millions (data: FRB San Francisco, based on JOLTS, BLS). **Middle:** Labor force (age 16+) in millions (data: CPS-IPUMS, BLS). **Right**: The solid black line denotes retirees in millions (age 16+), while the dashed red line is a linear trend estimated from 2015:M1 to 2020:M2 (data: CPS-IPUMS, BLS).

its pre-pandemic level after about 3 years. Moreover, the number of retirees increased by 2 millions in a few months – from February to July 2020 – opening a persistent gap in levels with respect to the pre-pandemic trend – roughly 1.2 millions people – that has not been reabsorbed yet (Figure 1, right panel).[1] Figure 2 depicts labor force participation (LFP) by age group.[2] Following the sudden drop in the first months of the Covid-19 pandemic, LFP

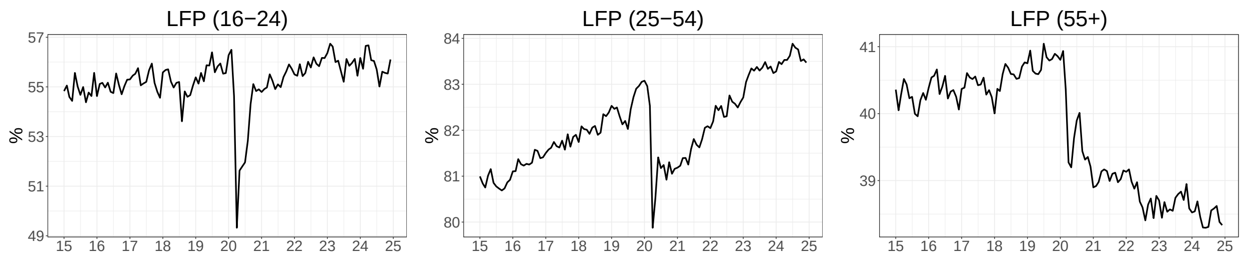

Figure 2. **Labor force participation by age group. Left**: Age group 16 – 24. **Middle:** Age group 25 – 55. **Right:** Age group 55+ (data: CPS-IPUMS, BLS).

recovered for individuals in both 16–24 and 25–54 age groups. The former quickly recovered

[1]Note that also the share of retired population persistently remained above the pre-pandemic trend by about 0.5 percentage points (see Figure 6). As suggested by Montes et al. (2022), we adjust weights of respondents to the CPS to reflect updated population controls introduced by the Census Bureau and the Bureau of Labor Statistics (see Appendix A for details).

[2]See Hobijn and Şahin (2022) for a thorough analysis of the effects of the pandemic on labor force participation, distinguishing between the participation cycle and its trend (see also Elsby et al., 2019; Hobijn and Şahin, 2021). They attribute the pre-pandemic positive movements in labor force participation, observed from 2015 onward, to cyclical upward pressures, given the long-run declining trend mainly driven by demographic factors, i.e., aging.

after a few months, while the latter displayed a much more persistent effect of the initial shock. On the other hand, LFP for individuals aged 55 or older showed an overall downward trend.

From pandemic-induced layoffs to inflationary pressures. Motivated by the evidence above, we proceed in two steps. First, we empirically evaluate the relationship between layoffs and retirement behavior. Using the Atlanta Fed's Harmonized Variable and Longitudinally Matched (HVLM-CPS) dataset, we establish that, in general, workers who are unemployed due to a layoff are significantly more likely to retire than employed workers. The impact of a layoff on retirement decisions is, as expected, much stronger for older workers. Importantly, the mechanism highlighted in the paper is not specific to the Covid-19 pandemic, but it operates following any negative shock that leads to a decrease in employment. Our empirical analysis suggests that there is nothing special about the Covid-19 shock regarding the relationship between layoffs and retirement decisions. Simply put, the peculiarity of the Covid-19 shock lies in its unprecedented size that led to a "Great Layoff", which is at the origin of the "Great Retirement". Second, we assess whether this mechanism, from the Great Layoff to the Great Retirement, had any inflationary effect via higher wage growth. In particular, we exploit the unanticipated variation in layoffs during the Covid-19 pandemic to study its dynamic effect on retirement and wages using a county-level exposure research design. Using data from the Quarterly Census of Employment and Wages (QCEW) by the BLS, we show that counties most affected by the Great Layoff display a significantly larger increase in retirement and nominal wages, and that this effect is persistent over time. Moreover, these counties display a larger reduction of individuals not in labor force and not retired, i.e., younger workers flowing into the labor force.

The results above therefore provide empirical support to the following chain of events: (i) the Great Layoff due to the pandemic shock triggered the Great Retirement; (ii) the latter contributed to post-pandemic inflation by increasing labor market tightness and putting upward pressure on wages; (iii) the increase in wages stimulates younger workers not in the labor force to enter the labor force to make up for the gap, as suggested by Figures 1 and 2. Taken together, these results indicate that the temporary labor-demand shock underlying the Great Layoff also precipitated the Great Retirement, and that the resulting contraction in labor supply generated sufficient upward pressure on nominal wages to draw younger non-participants into employment, thereby offsetting the loss of retiring workers.

Quantifying the impact of the Great Retirement on inflation. In order to interpret the empirical evidence presented above, we develop a two-agent New Keynesian (TANK) model with matching frictions and endogenous labor force participation. Our framework extends the model in Campolmi and Gnocchi (2016) by introducing two types of households, *young* and *old*, facing a labor force participation decision. Both types can be employed (participating in market production), unemployed (home producing and looking for jobs) or non-participant (solely home producing). Heterogeneity across types is related to productivity at home, utility derived from home-produced goods, and non-participation benefits, i.e., pension. To quantify the role that the Great Retirement has played in the post-pandemic inflation dynamics, we estimate the model on US data and perform a counterfactual exercise.[3,4] Our findings suggest that the Great retirement had: (*i*) a positive impact on inflation equal to roughly 3 percentage (cumulative) points of inflation from 2020:Q1 up to 2024:Q4, divided roughly in 0.56 p.p. in 2020, 0.74 p.p. in 2021, 0.70 p.p. in 2022, 0.60 p.p. in 2023 and 0.38 p.p. in 2024; (*ii*) a negative impact on output, peaking at a cumulative reduction of 0.64 percentage points in 2023:Q2, divided roughly in 0.30 p.p. in 2020, 0.28 p.p. in 2021, 0.02 p.p. in 2022, with the effect beginning to fade in the second half of 2023. Given that observed cumulative inflation between 2020:Q1 and 2024:Q4 has been about 22.1%, the Great Retirement explains almost 1/7 of the overall increase in prices. On the other hand, the cumulative GDP growth in the same period has been about 13%, hence the effect of the Great Retirement on economic activity has been negligible.

Layout. The paper is organized as follows. Section 2 relates our work to the existing literature. Section 3 presents empirical evidence on the impact that the Great Layoff had on labor force participation, retirement behavior and wage dynamics. Section 4 develops and estimates a general equilibrium model with heterogeneous agents - young and old - and endogenous participation in the labor market to quantitatively assess the role played by the Great Retirement in the post-pandemic inflation surge. Section 5 introduces an additional dimension of heterogeniity allowing for different workers prioductivities - skileld and unskilled. Finally, Section 6 concludes.

2 Related Literature

Our paper contributes to two main strands of literature. The first examines the determinants of post-pandemic inflation, while the second explores how retirement behavior interacts with

[3]Our investigation aims at assessing the role of early retirement as a driver of labor market tightness and ultimately the *marginal* effect of this particular channel on inflation. Needless to say, the literature analyzes many other forces that contributed – some much more forcefully – to the post-pandemic inflation surge, see Section 2.

[4]Cairo et al. (2025) also estimate a model with endogenous participation and show the role of labor market frictions in successfully forecasting slow recoveries in unemployment and missing disinflations in the aftermath of recessions, such as the Great Recession.

business cycle dynamics. In this section we discuss how our work connects to these two strands.

Determinants of post-pandemic inflation. The United States experienced a sharp and largely unexpected surge in inflation following the Covid-19 pandemic, which has prompted an intense debate on the underlying causes of this rise. This is not the place to review the full range of mechanisms proposed in the literature; we therefore focus on the contributions that examine the role of the labor market and are most closely related to our paper.[5] Ball et al. (2022) decompose headline inflation into core inflation and deviations of headline from core, with the two components being driven by different factors. In particular, they find that much of the rise in core inflation, especially during 2022, is explained by labor market tightness, with the rest being explained by a pass-through of headline shocks into core inflation. This empirical evidence motivates our focus on labor market factors as drivers of post-pandemic inflation. Benigno and Eggertsson (2023) explain the inflation surge via nonlinearities in a Phillips curve where the measure of economic slack is given by the vacancy-to-unemployed ratio. Specifically, the Phillips curve is steeper when there is labor shortage, so that the increase in the labor market tightness after the pandemic explains the rise in inflation. Although our paper does not incorporate nonlinearities in the Phillips curve, it shares a similar perspective by emphasizing the role of labor market factors in driving inflation. However, it focuses specifically on the retirement channel and quantifies its impact on inflation in the post–Covid-19 period. Crump et al. (2022) argue that the unemployment gap is a better measure of labor market tightness (see also Furman and Powell, 2021; Şahin, 2022; Barlevy et al., 2024) once the evolution of natural rate of unemployment is properly measured (see Crump et al., 2019). They show that the inflation behavior was driven by a strong and persistent rise in the natural rate of unemployment in the aftermath of the pandemic, and that the final convergence to long-run price stability depends critically on expectations on the reduction in the unemployment gap. In our theoretical framework, labor market tightness is defined as the ratio of the number of job vacancies to the number of job seekers at the beginning of the period. Braun and Ikeda (2022) explores the role of aging in explaining Japanese inflation. Cacciatore et al. (2024) show that reallocating time from market work to household tasks reduces aggregate demand when uncertainty increases, and this leads to higher inflation, especially when such uncertainty is accompanied by policies that shift time use toward household activities, such as lockdown restrictions during the COVID-19 pandemic. While both studies consider Walrasian labor markets, our analysis is based on a

[5] Without any claim of comprehensiveness, examples of papers studying various channels contributing to the recent inflation surge include Amiti et al. (2023); Bianchi et al. (2023); Comin et al. (2023); di Giovanni et al. (2023); Gagliardone and Gertler (2023); Koch and Noureldin (2024); Bernanke and Blanchard (2025).

frictional labor market framework.

Labor force participation, retirement and the business cycle. Our study also relates to the literature on the relationship between labor force participation and business cycle factors. Shimer (2013) analyzes the flow of workers between employment, unemployment, and inactive and shows that the share of inactive workers rises during recessions due to unemployed workers dropping out of the labor force. The determinants of the pro-cyclical behavior of labor force participation have been analyzed in Elsby et al. (2019) and Hobijn and Şahin (2021). They find that, since unemployed workers are more likely to leave the labor force, a recession rises unemployment and leads to a reduction in labor force participation. Hobijn and Şahin (2022) applies a similar analysis to the recent post-pandemic period. The findings are coherent with the ones of the literature investigating the response of retirement to business cycle fluctuations. Gorodnichenko et al. (2013) estimate the response of retirement on the unemployment rate and show that retirement increases when the unemployment rate rises. Coile and Levine (2009, 2011) show that retirement decisions are responsive to aggregate economic conditions, such as the unemployment rate and long-run fluctuations of stock market returns. These results indicate that older workers may decide to retire under unfavorable macroeconomic conditions. However, as shown in Chan and Stevens (2004), it is in particular older displaced workers that show higher rates of retirement. Maestas et al. (2013) study the relationship between local labor demand shifts and the outcomes of older working individuals. Using data from the Census and the Health and Retirement Study, they find evidence that local labor demand conditions affect labor and retirement behavior, and that older individuals are especially responsive to local labor demand shifts in the service industry. Birinci et al. (2024) decompose the factors behind the Great Retirement using a partial-equilibrium framework. Their analysis shows that the surge in job separations was the primary driver of the increase in retirements, while fiscal policy measures and high stock-market returns contributed to its persistence. Meanwhile, Gertler et al. (2022) emphasize the destabilizing countercyclical impact of temporary layoffs, driven by "loss-of-recall", a phenomenon in which workers initially on temporary layoff ultimately lose their jobs permanently.

Our paper confirms that laid-off workers, especially older ones, are more likely to retire and adds three results. First, this layoff–retirement link remained unchanged during the Covid-19 pandemic, implying that the Great Retirement was simply the consequence of the Great Layoff. Second, exploiting cross-county variation, we show that counties more exposed to layoffs in March–April 2020 experienced larger increases in retirement thereafter. Third, these same counties also recorded stronger nominal wage growth, to induce individuals from outside the labor force into employment to offset the labor-supply loss caused by the larger number of retirees.

3 The impact of the Great Layoff: empirical evidence

The aim of this section is twofold. First, we empirically investigate the relationship between layoffs and retirement. Second, we leverage on the Great Layoff natural experiment to estimate the dynamic responses of retirement and wages to exogenous shifts of labor demand.

3.1 Layoff and retirement decision

In this section we use the Atlanta Fed's Harmonized Variable and Longitudinally Matched Current Population Survey (HVLM-CPS) to study retirement decisions of individuals. The survey collects detailed data on the labor force status of respondents and a variety of demographic information.[6] In the HVLM-CPS individuals are longitudinally matched and the dataset includes information about past values of some variables (in particular 1 month, 2 months, and 12 months before the survey). We exploit the longitudinal dimension to determine the impact of a layoff-induced change in employment status on retirement decisions. To this end, we restrict our sample to consider only individuals who, in the month before the survey, were either employed, or unemployed because of a layoff. We then estimate a linear probability model where the outcome variable indicates whether the respondent is retired at the time of the survey as a function of the employment status in the previous month (1 if unemployed because of layoff and 0 if employed). Our sample consists of monthly data ranging from January 1994 to December 2024, and the results of pooled OLS estimations are reported in Table 1 separately for individuals aged over 55 (columns 1 – 3) and all individuals above 16 (columns 4 – 6).[7]

Columns 1 and 4 show that individuals who are laid off are significantly more likely to retire each month. Moreover, the impact of a layoff on the decision to retire is much stronger for older workers. In columns 2 and 5 we consider only respondents who were employed 12 months before the survey. This allows us to focus on respondents who participated in the labor market and have worked in the recent past. In addition, we can control for industry

[6] The survey is constructed as a rotating panel. Individuals are interviewed for a total of 8 times divided into two equal periods of four months. See https://www.bls.gov/opub/hom/cps/design.htm#rotation-of-the-sample for further information.

[7] Our sample starts in 1994 because, starting in that year, the survey also include data on the respondents' activity if out of the labor force, including retirement.

	Dependent variable: Retired					
	Age over 55			Full sample		
	(1)	(2)	(3)	(4)	(5)	(6)
Layoff	0.056***	0.030***	0.033***	0.014***	0.009***	0.009***
Covid-19	–	–	0.000	–	–	0.000
Covid-19 × Layoff	–	–	−0.011	–	–	−0.000
Controls	no	yes	yes	no	yes	yes
n.obs	3,231,459	328,938	328,938	15,796,438	1,501,790	1,501,790

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 1. **Laid off workers are more likely to retire, and Covid-19 was not special in this respect.** OLS estimation with state, month and year fixed effects and standard errors clustered at the state level. Columns (1)-(3) are estimated on the sample of population aged over 55. Columns (4)-(6) are estimated for all ages. Moreover, columns (2)-(3) and (5)-(6) consider only individuals who were employed 12 months before and include industry fixed effects.

of employment (12 months before the survey) and assign each respondent to a wage decile (using wages reported 12 months before the survey). We also control for other individual characteristics that may affect retirement decisions, such as age, gender, ethnicity, level of education, and we include state, month, year and industry fixed effects. Columns 2 and 5 show that results on the impact of layoffs holds after controlling for demographic, social and economic characteristics of respondents.[8] Finally, in columns 3 and 6 we include two additional regressors: a Covid-19 dummy, taking value 1 if the survey is conducted between March 2020 and May 2023 and the interaction between this Covid-19 dummy with the employment status of respondents.[9] These two additional regressors are not statistically significant, suggesting that retirement behavior did not change during the Covid-19 period. Therefore, the Great Retirement was not a "special" feature of the pandemic itself but was quantitatively relevant due to the unusually large magnitude of the pandemic-induced layoff shock.

Why do layoffs cause older individuals to retire? Chan and Stevens (2004) show that a job loss after age 50 doubles the probability of retirement since it is harder for older displaced workers to find new jobs due to the loss of firm-specific skills, the employers' unwillingness to invest in workers near the end of their careers, high search costs, or other barriers to reemployment such as age discrimination. Moreover, they point out that a job loss alters the earnings, pensions and wealth available to workers, and this may lead to voluntary retirement

[8] Estimates of coefficients associated to individual controls are reported in Appendix B.1.

[9] In March 2020 the World Health Organization (WHO) declared Covid-19 a pandemic, while in May 2023 the WHO recommended that Covid-19 no longer fitted the definition of a Public Health Emergency of International Concern (PHEIC).

due to changed retirement incentives. Coile and Levine (2011) argue that the relatively short horizon in the labor force may reduce older workers or prospective employer's willingness to invest in additional human capital. Hirsch et al. (2000) argue that job opportunities for older workers are restricted (e.g., jobs requiring substantial computer use or where return to tenure is high). Therefore, the wage that a new employer might offer could be well below the worker's previous wage, reducing the likelihood of an offer being accepted. These mechanisms are not peculiar to the pandemic crisis but are more general, helping to explain the positive relationship between retirement and unemployment observed in studies such as Gorodnichenko et al. (2013) and Coile and Levine (2009, 2011). However, the unprecedented wave of layoffs in March and April 2020, amounting to about 22 million workers, i.e., over 13% of the labor force, made this phenomenon particularly evident.

Flow analysis. To further substantiate our argument concerning the role of the Great Layoff in driving the Great Retirement, we analyze labor market flows into retirement.

The three panels in the first row of Figure 3 display gross flows from employment (E) to unemployment due to layoffs (UL), from unemployment due to layoffs to retirement (R), and from employment to retirement, respectively. The flow from UL to R (first row, middle panel) closely mirrors the flow from E to UL (first row, first panel). Notably, the transition from layoff-related unemployment to retirement lags behind layoffs by a few months and demonstrates a more gradual decrease. We interpret this delay as reflecting the time individuals require to finalize retirement decisions, particularly amid the uncertainty of the early Covid-19 period. This observed pattern aligns with the regression results in Table 1, indicating a stable proportional relationship between layoffs and retirements, unchanged during the pandemic.

However, the figures in the first row show the gross flows in terms of millions of individuals, which is the result of the product between the stock size of the outgoing state (i.e., number of people employed or unemployed) and the proportion of people transitioning between states. To isolate the transition behavior itself, the second row of Figure 3 presents monthly transition probabilities between these labor market states.[10] As expected, the estimated series of transition probabilities reveals a sharp increase in the transition from employment into unemployment due to layoffs (second row, first panel) between 2020 and

[10] Gross labor market flows are computed using monthly CPS data from 1998 to 2024, which we link longitudinally by leveraging the CPS's rotating-panel design (see, e.g., Elsby et al., 2015; Gertler et al., 2022). We seasonally adjust the transition probability series using a 12-month moving average of the raw data. Finally, we correct for time aggregation bias following the approaches proposed by Shimer (2012) and Elsby et al. (2015).

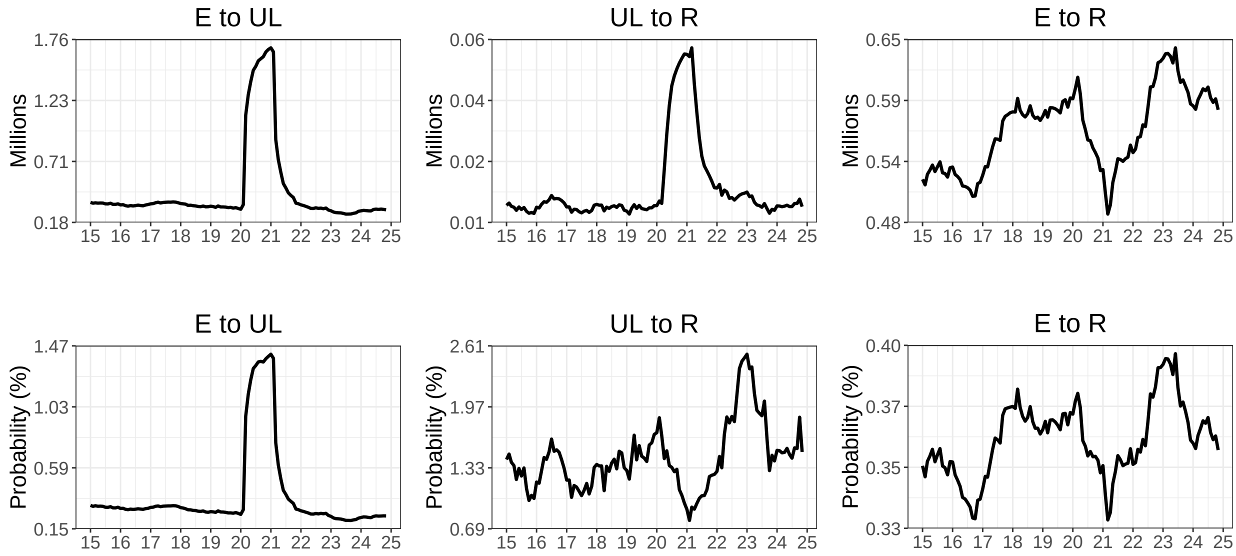

Figure 3. **Flows also suggest that retirement was mainly induced by the dynamics of layoffs.** First row: Monthly flows. Second row: Monthly transition probabilities. Labor market statuses are labeled as follows: employment (E), unemployment due to layoffs (UL), retirement (R).

2021 due to the Covid-19 shock. However, the transition probability from layoff-related unemployment to retirement (second row, second panel) remains relatively stable. The noticeable fluctuations between 2020 and 2023 are mechanically induced by the lag between layoffs and retirement decisions.[11] By late 2023, the transition probability was back to about its pre-pandemic level. Indeed, the motivation evidence in Figure 1 shows that while the layoff surge was concentrated in March and April 2020, the number of retirees rose with a slight lag, creating a persistent gap throughout 2020. Thus, there is no indication that the initial rise in retirements stemmed from an increased inclination to retire, rather than from the Great Layoff. Given the initial decrease in the probability of moving from UL to R, the immediate effect of the Great Layoff was, if anything, a temporary *reduction* in retirement propensity out of layoffs, not an increase.

[11] This probability drops during 2020 as layoffs increase before retirement does, reaching a value around 0.7% at the peak of layoffs, subsequently rising to approximately 2.6% in 2023, as layoffs rapidly decrease while retirement decisions pick up as being more sluggish. This finding aligns with the analysis of Nie and Yang (2021), who argue that the sharp rise in retirements during the pandemic was primarily driven by a significant drop in the flow from retirement back to employment, while the flow from unemployment to retirement actually declined during the pandemic years. Indeed, Nie and Yang (2021) also emphasize that the sharp increase in unemployment between February and April 2020 largely accounts for the fall in the unemployment-to-retirement transition rate.

Similar considerations emerge when analyzing the transitions from employment into retirement (E to R), although the variations here are smaller. This is because the employed population is substantially larger and exhibited less fluctuation compared to the group experiencing layoffs (UL) during this period. Specifically, the flow from employment to retirement initially declines, reflecting the shrinking number of employed individuals, and subsequently recovers gradually alongside the employment recovery, eventually returning to pre-pandemic levels by late 2023. After its initial drop, the probability of transitioning from employment into retirement increases modestly, from about 0.3% to a peak near 0.4%, only slightly above pre-pandemic values. Once again, we interpret these fluctuations, both in gross flows and in transition probabilities, as indicative of the lag involved in retirement decisions, particularly under the heightened uncertainty characteristic of the early Covid-19 period.

In the following section, we present evidence demonstrating that the temporary labor demand shock responsible for the Great Layoff caused the Great Retirement, exerting upward pressure on nominal wages in order to induce entry from the pool of younger non-participants to compensate for retirement-driven decline in labor supply.

3.2 Responses of retirement and wages to the Great Layoff

In this section we study whether the mechanism linking layoffs to retirement decisions contributed to inflationary pressures during the Covid-19 pandemic. To this end, we estimate dynamic responses of retirement and wages to the Great Layoff (see Appendix A for a detailed data description).

Before outlining our empirical strategy, the following remarks are important. First, the drop in employment registered in the March and April 2020 is almost entirely due to layoffs. This is shown in the left panel of Figure 4 that plots the change in the employment level (in absolute value) against the number of layoffs occurred in March and April 2020 by BLS supersector.[12] The rationale for presenting this evidence is that, in what follows, we use the employment drop to capture the Great Layoff since employment data are available at a finer industry aggregation level. Second, the impact of the Covid-19 shock varied across sectors depending on their "social nature", or contact-intensiveness, rather than being determined by other economic factors. As shown in the right panel of Figure 4, Leisure, and Hospitality

[12]Supersectors are derived from the BLS aggregation of NAICS sectors. We excluded from the analysis supersectors labeled Public Administration and Unclassified. Small discrepancies between the drop in employment and the sum of layoffs in March and April 2020 are potentially due to differences in the reference period for each count. In fact, the reference period for employment count is the pay period that includes the 12th of the month, while for layoffs it is the entire calendar month (see https://www.bls.gov/jlt/jltprovq.htm for details).

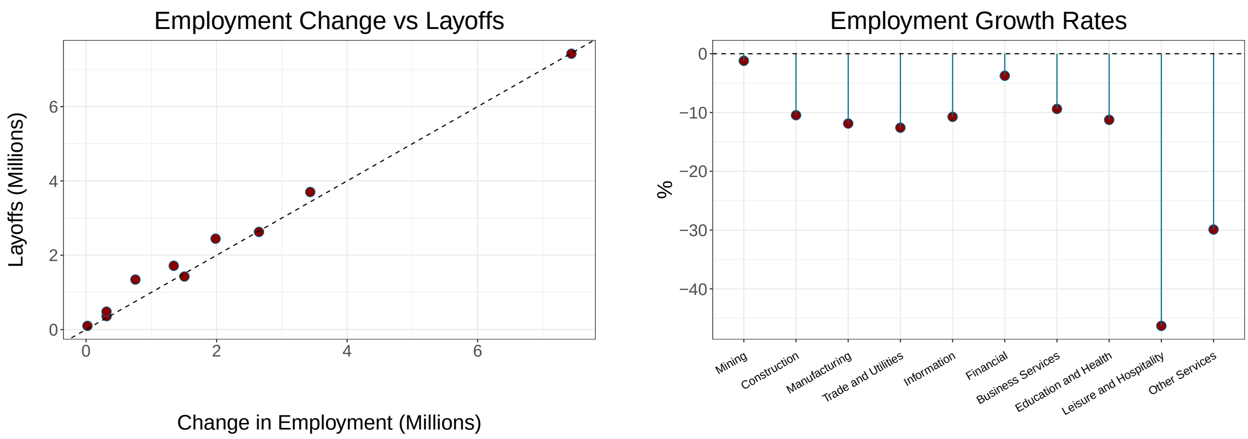

Figure 4. **Employment changes are mostly layoffs and they are asymmetric across sectors. Left**: Change in national employment level between February 2020 and April 2020 (in absolute value) and sum of layoffs occurred in March and April 2020 by BLS supersector (data: JOLTS, BLS and QCEW, BLS). **Right**: National employment growth rate between February 2020 and April 2020 by BLS supersector (data: QCEW, BLS).

and Other Services are the two most affected sectors by the Covid-19 shock, respectively featuring a 46% and 30% drop in employment in April 2020 compared to February 2020. We exploit differential exposure to contact-intensive industry at the county level, and use cross-sectional variation to estimate the dynamic multipliers of interest.

More specifically, our empirical strategy is an exposure research design, which leverages on the unanticipated variation in layoffs naturally occurred in March and April 2020. Our measure of county exposure to the common labor demand shock caused by Covid-19 is the average change in employment across industries, weighted by industry shares in each county's employment. In particular, we project pandemic-induced drops in employment occurred in March and April 2020 using a shift-share variable (Bartik, 1991):

$$z_\ell = -\sum_n \left(\frac{E_{\ell,n,t_0}}{\sum_n E_{\ell,n,t_0}} \right) \times \left(\log E^{-\ell}_{n,t_2} - \log E^{-\ell}_{n,t_1} \right) , \tag{1}$$

where E_{ℓ,n,t_0} denotes county ℓ employment in industry n at time t_0, so that the first term in Eq. (1) denotes the county-level share of each industry at time t_0. The shift term in Eq. (1) is the growth rate in national employment between time t_2 and t_1 for each industry n, outside of the state in which county ℓ is located.[13] In our empirical exercise we set $t_0 = 2019$, so

[13] As pointed out in Adão et al. (2019), the leave-one-out strategy in the construction of the national growth rates avoids the finite sample bias coming from using own-observation information. However, given the high number of locations, using national growth rates over all states has no practical implications for

that industry shares are fixed to an initial time period prior to the Covid-19 shock,[14] while the shift term considers employment growth between February 2020 (t_1) and April 2020 (t_2), capturing therefore the Great Layoff. Notice that, to better interpret the results, we multiply the shock in Eq. (1) by (-1), so that a higher value indicates a larger negative change in employment. Moreover, our analysis includes 302 sectors (NAICS 4 level) and 280 counties.[15]

To quantify the dynamic effects of the Great Layoff on labor market outcomes, we compute quarterly cumulative changes in the outcome of interest from 2020:Q1, and estimate the following equation for each quarter in the interval 2019:Q1 to 2024:Q4

$$\Delta y_{\ell,q} = \alpha_q + \beta_q z_\ell + \mathbf{X}'_{\ell,t_0}\gamma_q + \varepsilon_{\ell,q} \ . \tag{2}$$

The labor market outcomes (y) of interest are the retired-to-population ratio, (log) nominal wages, labor force as well as individuals not in labor force and not retired over total population. We thus estimate separate regressions for each outcome and for each quarter between 2019:Q1 and 2024:Q4, so that $\Delta y_{\ell,q}$ is the change in an outcome for county ℓ between 2020:Q1 and quarter q.[16] Eq. (2) is akin to standard projection equations in the VAR literature. However, instead of exploiting time series variation, we estimate average dynamic effects β_q of the exogenous labor demand shift by exploiting cross-sectional variation at each quarter q. Estimation of Eq. (2) for quarters prior to 2020:Q1 allows to evaluate the presence of pre-trends in outcomes. Finally, as standard in the literature (see, e.g., Goldsmith-Pinkham et al., 2020), the vector of controls $\mathbf{X}'_{\ell,t_0}$ includes county-level covariates measured in 2019, i.e., in the same time period as the industry shares, as well as state fixed effects.[17] Results of the estimation of Eq. (2) are reported in Figure 5. All regressions are weighted by counties' population above 16 years of age in 2019 and standard errors are clustered at the state level.

Overall, results in Figure 5 show that there are no significant pre-trends and that the temporary negative labor demand shock of March and April 2020 had a significant and persistent effect on labor market outcomes, continuing well into 2023 and only dampening in 2024. The estimated response of retirement (Figure 5, top-left panel) confirms our previous findings: the Great Layoff triggered early retirement of the older segment of displaced workers. We

our results.

[14]Industry shares are computed as average shares over the year 2019.

[15]We include in the analysis only counties for which we have CPS-IPUMS data on retirement.

[16]By construction, $\Delta y_{\ell,q} = 0$ in $q =$ 2020:Q1.

[17]County-level controls include American Community Survey (ACS) data by the US Census on the share of population by age group (20–34, 35–54 and 55+), male to female ratio, old-age and child dependency ratio, population share with college or higher education, and share of foreign born population in 2019.

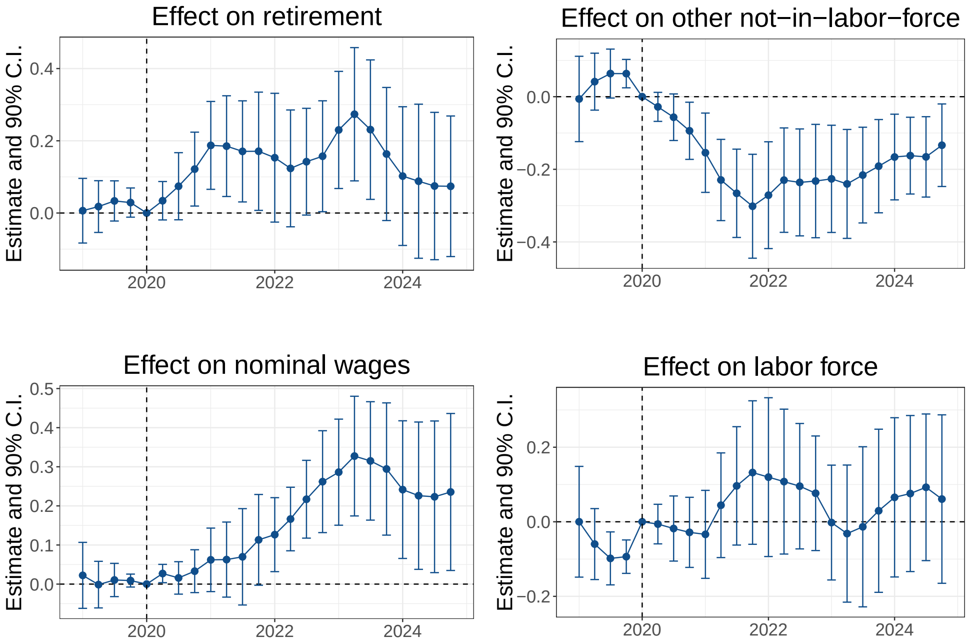

Figure 5. **Counties more exposed to the Great Layoff display higher retirement and higher wages. Top left**: Dynamic response of retirement to the Great Layoff (data: CPS-IPUMS, BLS and QCEW, BLS). **Top right**: Dynamic response of individuals not in labor force and not retired to the Great Layoff (data: CPS-IPUMS, BLS and QCEW, BLS). **Bottom left**: Dynamic response of nominal wages to the Great Layoff (data: QCEW, BLS). **Bottom right**: Dynamic response of labor force to the Great Layoff (data: CPS-IPUMS, BLS and QCEW, BLS).

thus observe a stronger increase in retirement in counties most exposed to contact-intensive industries. The response of the share of individuals who are not in the labor force but not retired (Figure 5, top-right panel) is consistent with the evidence presented in Figure 2: counties more exposed to the Great Layoff because of their industrial composition display a stronger reduction of individuals not in labor force and not retired, i.e., younger workers flowing into the labor force. The response of nominal wages (Figure 5, bottom-left panel) documents the inflationary effect of the Great Layoff: counties more exposed to the temporary negative labor demand shock experience a larger *increase* in nominal wages. The positive response of wages to a negative labor demand shock is consistent with the fact that the latter was, on the one hand, quickly reabsorbed, but, on the other hand, it caused a shortfall in the labor supply due to the Great Retirement. The increase in wages was then necessary to induce the entry of new workers that were outside the labor force to make up for the gap. The resulting net effect on the labor force is thus not significant (Figure 5, bottom-right panel).

We are aware that the county-level average wage may change over time due to potential composition effects. The first is a between-industries composition effect. In fact, as shown in Figure 4, layoffs were concentrated in Leisure and Hospitality and Other Services supersectors, which are characterized by relatively lower wages (see Figure B.2.1, left panel, in Appendix B.2 displaying average wage in 2019 against employment change by BLS supersector). However, we control for this between-industry composition effect by weighting county-level sectoral wages for their relative size (in terms of employment) in each county in 2019. The second is a within-industry composition effect, potentially due to the fact that only low-wage workers have been laid off in each industry. However, as shown in Figure B.2.1 (right panel) in Appendix B.2, supersectors with more layoffs are not systematically associated to larger changes in the average wage between 2019 and 2020.

The evidence above suggests that the Great Layoff led to a substitution of older workers exiting into retirement with younger individuals previously outside the labor force, and that this reallocation required a substantial increase in nominal wages. What is the effect of this reallocation of labor supply on post-pandemic inflation? Since inflation data at the county level are unavailable, we cannot replicate the same analysis we conducted for wages. Instead, we rely on a model to estimate the quantitative impact of the Great Retirement on overall inflation.

4 The impact of Great Retirement on post-pandemic inflation

This section presents a model to rationalize the empirical findings presented so far and to quantify the impact that the Great Retirement had on inflation in the aftermath of the Covid-19 crisis. The aim of this section is twofold. First, we develop a two-agents New Keynesian (TANK) model with endogenous retirement decisions building on the work of Campolmi and Gnocchi (2016). Second, we estimate the model and use it to quantify the impact of the Great Retirement on post-pandemic inflation via a counterfactual exercise.

4.1 A TANK model with endogenous retirement decisions

The model economy comprises households deriving utility from both market-produced and home-produced goods, firms producing an homogeneous intermediate good in perfect competition, and producers of a differentiated final good operating under monopolistic competition and subject to nominal rigidities as in Calvo (1983). The labor market is characterized by search frictions as in Diamond (1982) and Mortensen and Pissarides (1999). Households' members can be categorized as employed (devoting their time to market production), unemployed (allocating time between job search and home production) or non-participant (dedicating time solely to home production). There are two household types: young individuals deciding whether to join the labor market or remain out of it, and older individuals deciding between labor market participation and retirement. The difference between young non-participant and old retired agents is that the latter receive a retirement benefit. Firms in the intermediate-good sector require a household member to produce and incur vacancy posting costs during their search for matches. Additionally, jobs are terminated at an exogenous rate. In this section we describe the model and characterize equilibrium conditions, while the Online Appendix contains more details and the derivations.

Households. The economy is populated by two households types, young (y) and old (o), both with unit mass and indexed by $a \in \{y, o\}$. The share of young households in the economy is ζ, which is an exogenous parameter reflecting the demographic structure of the economy. Agents can choose their labor market status among the following options: participant (L) or non-participant (N). In turn, labor market participants can be either employed (E) or unemployed (U), so that, in each period t, $L_{a,t} = E_{a,t} + U_{a,t}$ denotes the participation rate of type a. Overall employed, unemployed and non-participant masses are respectively given by $E_t = \zeta E_{y,t} + (1-\zeta)E_{o,t}$, $U_t = \zeta U_{y,t} + (1-\zeta)U_{o,t}$ and $N_t = \zeta N_{y,t} + (1-\zeta)N_{o,t}$. Moreover, we have that $E_t + U_t + N_t = 1$. In what follows, we will refer to old non-participant agents as *retired*. The difference between young non-participant and old retired agents is that the latter receive a *pension*.

Before the beginning of each period t, i.e., after all decisions have been taken in period $t-1$, employed agents are separated from their jobs at an exogenous rate ρ_t following an exogenous AR(1) process $\rho_t = (1-\rho_\rho)\bar{\rho} + \rho_\rho \rho_{t-1} + \epsilon_t^\rho$.[18] Unemployed, non-participants and separated workers at the end of period $t-1$, i.e., $U_{t-1} + N_{t-1} + \rho_t E_{t-1}$ constitute the group of non-employed agents in period t. A part S_t of this group will search for a job in period t, while the remaining part will enter non-participation. Therefore we have that

$$S_t + N_t = U_{t-1} + N_{t-1} + \rho_t E_{t-1} \; ,$$

with $S_t \geq 0$. As in Campolmi and Gnocchi (2016), we assume instantaneous hiring, so that

[18] All innovations in the AR(1) processes discussed throughout the model are assumed to be independent and identically distributed normal variables with zero mean. For a generic innovation term ϵ_t^x we denote its variance by σ_x^2.

the group of job searchers S_t does not coincide with unemployed agents U_t. In particular, denoting by f_t the job finding rate common across agent types, we can write unemployment as a function of job searchers as $U_t = (1 - f_t)S_t$. Moreover, since separation can only occur exogenously, we can write employment as a function of job searchers as $E_t = (1 - \rho_t)E_{t-1} + f_t S_t$.[19] This means that, by choosing participation L_t conditional on the finding rate f_t and the stock of employed in the previous period, E_{t-1}, households can indirectly decide on E_t and U_t. Employed agents earn a nominal salary W_t, unemployed agents receive a real unemployment benefit b^u, while non-participants are entitled to a real pension b_t^n only if old. Therefore, the benefit from being out of the labor force is equal 0 for young agents, $b_{y,t}^n = 0$, and equal to b_t^n for old agents, $b_{o,t}^n = b_t^n$. Birinci et al. (2024) shows that the stock market boom contributed to the persistence of the increase in retirement. To allow the model to possibly catch this fact, we assume that b_t^n evolves over time in response to fluctuations in productivity. Specifically, we set $b_t^n = b^n \Phi_t$, where Φ_t wants to capture the stock market dynamics and thus it is correlated with the exogenous productivity process A_t defined below. Formally, we define $\Phi_t = A_t^{\varsigma}$, where ς is a scaling parameter.

Young and old households can borrow and lend each other in a credit market. Following the literature on incomplete markets with zero net asset holdings, we introduce portfolio costs for holding or issuing debt to ensure unique and bounded dynamics (Bodenstein, 2011). Income is pooled within each household and decisions are taken collectively, so that all members are insured against consumption risks due to variations in the labor market status (see e.g., Campolmi and Gnocchi, 2016; Andolfatto, 1996; Merz, 1995) within each household type (young or old). Hence, the real budget constraint of the old-type is given by

$$C_{o,t} = D_{o,t} - \frac{R_{t-1}}{\Pi_t} D_{o,t-1} + E_{o,t}\frac{W_t}{P_t} + b^u U_{o,t} + b_t^n N_{o,t} - T_t + \frac{tr + \tau_t}{1-\zeta} + d_t - \frac{\lambda}{2}(D_{o,t})^2 \ , \tag{3}$$

where $C_{o,t} \equiv \left[\int_0^1 C_{o,i,t}^{\frac{\epsilon-1}{\epsilon}} di\right]^{\frac{\epsilon}{\epsilon-1}}$ is a bundle of market-produced goods, $P_t \equiv \left(\int_0^1 P_{i,t}^{1-\epsilon} di\right)^{\frac{1}{1-\epsilon}}$ is the corresponding aggregate price index, $\Pi_t \equiv P_t/P_{t-1}$ is gross inflation, $D_{o,t}$ is real debt (negative if the household type is a saver), R_t is the gross nominal interest rate, T_t are lump-sum taxes, tr and τ_t which are transfers from young to old households if positive (see below the description of fiscal policy), d_t are real dividends from firms, and $\frac{\lambda}{2}(D_{o,t})^2$ are portfolio costs (which are then rebated to households via lump-sum transfers). Similarly, the real

[19] Also note that, since separation is exogenous, the employed getting out of the labor force cannot exceed separated workers in the previous period, i.e., $\rho_t E_{t-1}$. On the other hand, flows from unemployment to out of labor force can be as large as the unemployed in the previous period, i.e., U_{t-1}. Hence, the labor force will always be at least as large as the number of agents who did not lose their job exogenously and are still at work, i.e., $L_t \geq (1 - \rho_t)E_{t-1}$.

budget constraint of young agents is given by

$$C_{y,t} = D_{y,t} - \frac{R_{t-1}}{\Pi_t} D_{y,t-1} + E_{y,t} \frac{W_t}{P_t} + b^u U_{y,t} - T_t - \frac{tr + \tau_t}{\zeta} + d_t - \frac{\lambda}{2} (D_{y,t})^2 \ , \tag{4}$$

and credit market clearing implies that $(1-\zeta)D_{o,t} = -\zeta D_{y,t}$.

Following Campolmi and Gnocchi (2016), both types of household derive utility from the consumption of market-produced and home-produced goods. Home-produced goods are the result of housework time, which can be heterogeneous across household types, and are defined as $h_{a,t}$. For each household type, the housework time foregone by the employed relative to agents out of the labor force is normalized to one. Moreover, unemployed agents still bear a job search cost $\Gamma \in (0,1)$, so that the housework time foregone by the unemployed is a fraction of the housework time foregone by the employed. The home-production function takes the form

$$h_{a,t} = \left[A^h_{a,t} (1 - E_{a,t} - \Gamma U_{a,t}) \right]^{1-\alpha_h} \ , \tag{5}$$

where $\alpha_h \in [0,1)$, and $A^h_{a,t}$ is a stochastic productivity process which differs across household types and follows an AR(1) of the form $\log(A^h_{a,t}) = \rho^h_a \log(A^h_{a,t-1}) + \epsilon^h_{a,t}$.

The flow utility function is defined as

$$\mathcal{U}_{a,t} \equiv Z_t \log(C_{a,t} - \xi C_{a,t-1}) + \phi \frac{(h_{a,t})^{1-\nu_a}}{1-\nu_a} \ , \tag{6}$$

where Z_t is a preference shock following $\log(Z_t) = \rho_Z \log(Z_{t-1}) + \epsilon^Z_t$, parameter ξ describes habit formation, ϕ is a scaling parameter and we allow for type-specific inverse intertemporal elasticities of substitution of home consumption $\nu_a \geq 0$.

Optimality of households' behavior is characterized by the conventional Euler equation and the participation condition. The Euler equation is given by

$$R_t \mathbb{E}_t \left(Q^a_{t,t+1} \Pi^{-1}_{t+1} \right) + \lambda D_{a,t} = 1 \ , \tag{7}$$

where $Q^a_{t,t+1} \equiv \beta \left(\frac{C_{a,t} - \xi C_{a,t-1}}{C_{a,t+1} - \xi C_{a,t}} \frac{Z_{t+1}}{Z_t} \right)$ is the stochastic discount factor. The participation condition may also differ across types due to different elasticities ν_a, home productivities $A^h_{a,t}$ and outside options $b^n_{a,t}$ and it is given by

$$\begin{aligned} b^n_{a,t} + MRS_{a,t} = {} & f_t \frac{W_t}{P_t} + (1-f_t)\left(b^u + (1-\Gamma) MRS_{a,t}\right) + \\ & \mathbb{E}_t \left[Q^a_{t,t+1} f_t (1-\rho_{t+1}) \frac{1-f_{t+1}}{f_{t+1}} (b^n_{a,t+1} + \Gamma MRS_{a,t+1} - b^u) \right] \ , \end{aligned} \tag{8}$$

where $MRS_{a,t} \equiv \frac{C_{a,t}-\xi C_{a,t-1}}{Z_t}\phi A^h_{a,t}(1-\alpha_h)(h_{a,t})^{-\frac{\alpha_h}{1-\alpha_h}-\nu_a}$ denotes the value of home-produced goods generated by the marginal non-participant in terms of market consumption goods. The participation condition in Eq. (8) requires equating the benefits of allocating the marginal non-employed agent (at the beginning of period t) between S_t and N_t.

Eq. (8) is one of the central equations in our endogenous participation choice model, so it is important to provide intuition to interpret it. To start, note that at the optimum, the value of participating in the labor market as a searcher, denoted by $V^S_{a,t}$, must equal the value of remaining out of the labor force, denoted by $V^N_{a,t}$. Formally, optimality requires that

$$V^N_{a,t} = V^S_{a,t}\,. \tag{9}$$

Since being a searcher is a temporary state, because individuals either find a job or remain unemployed within the period, the value of being a searcher can be expressed as $V^S_{a,t} = f_t V^E_{a,t} + (1-f_t)V^U_{a,t}$, where $V^E_{a,t}$ and $V^U_{a,t}$ denote, respectively, the value of being employed and unemployed. We can thus rewrite condition (9) as

$$\begin{aligned} b^n_{a,t} + MRS_{a,t} + \mathbb{E}_t Q^a_{t,t+1} V^N_{a,t+1} &= f_t \frac{W_t}{P_t} + (1-f_t)\left(b^u + (1-\Gamma)MRS_{a,t}\right) \\ &+ \mathbb{E}_t \left[Q^a_{t,t+1}\left(f_t(1-\rho_{t+1})V^E_{a,t+1} + (1-f_t+f_t\rho_{t+1})\,V^S_{a,t+1}\right)\right]. \end{aligned}$$

The left-hand side of this equation captures the direct benefit of non-participation in period t, which includes the pension benefit $b^n_{a,t}$ and the value of home-produced goods generated by the marginal non-participant $MRS_{a,t}$ (who devotes the full unit of time to home production), and its continuation value.

The first term on the right-hand side represents the direct benefit of participating as a searcher: the labor income from becoming employed (with probability f_t) plus the unemployment compensation and the value of home production for those not hired (with probability $1-f_t$), where the unemployed can allocate a fraction $(1-\Gamma)$ of their time to home production, yielding $(1-\Gamma)MRS_{a,t}$.

The second term on the right-hand side reflects the continuation value of the searcher. The probability that a searcher finds a job in t and remains employed in $t+1$ (i.e., is not separated) is $f_t(1-\rho_{t+1})$, in which case the individual attains value $V^E_{a,t+1}$. Conversely, the probability that the individual remains a searcher at the beginning of $t+1$ (either because no job was found in t or because separation occurred) is $1-f_t+f_t\rho_{t+1}$.

Since optimality implies that in every period $V^S_{a,t} = V^N_{a,t}$, the condition above can be written as

$$b^n_{a,t} + MRS_{a,t} = f_t \frac{W_t}{P_t} + (1-f_t)\left(b^u + (1-\Gamma)MRS_{a,t}\right) \\ + \mathbb{E}_t\left[Q^a_{t,t+1} f_t (1-\rho_{t+1})\left(V^E_{a,t+1} - V^S_{a,t+1}\right)\right] ,$$

which shows that the direct benefit of non-participation in the labor market must equal the direct benefit of participating as a searcher, plus the expected continuation value associated with transitioning into and remaining in employment. The latter term captures the probability of becoming employed in period t and retaining the job in period $t+1$, multiplied by the net gain from being employed rather than remaining out of the labor force.

Finally, using both $V^E_{a,t+1} = (V^S_{a,t+1} - (1-f_{t+1})V^U_{a,t+1})/f_{t+1}$ and $V^S_{a,t+1} = V^N_{a,t+1}$, the Online Appendix shows that the condition above can be rewritten as

$$b^n_{a,t} + MRS_{a,t} = f_t \frac{W_t}{P_t} + (1-f_t)(b^u + (1-\Gamma)MRS_{a,t}) \\ + \mathbb{E}_t\left[Q^a_{t,t+1} f_t (1-\rho_{t+1}) \frac{1-f_{t+1}}{f_{t+1}} (V^N_{a,t+1} - V^U_{a,t+1})\right] ,$$

and that, since the difference between $V^N_{a,t+1}$ and $V^U_{a,t+1}$ corresponds to the direct benefit of non-participation, $b^n_{a,t+1} + MRS_{a,t+1}$, net of the direct benefit of unemployment, $b^u + (1 - \Gamma)MRS_{a,t+1}$, the expression above simplifies to Eq. (8).

Intermediate-good producers. There is a continuum of firms $j \in [0,1]$ producing an homogeneous intermediate good using labor as the only production input. Given the search frictions *à la* Diamond (1982) and Mortensen and Pissarides (1999), if a firm j is not matched with a worker in period t, it may post a vacancy at cost k in terms of final good C. If the vacancy is filled, firm j immediately produces $X_{j,t} = A_t$, where A_t is productivity following an AR(1) process $\log(A_t) = \rho_A \log(A_{t-1}) + \epsilon^A_t$. The price of the intermediate good, sold in a competitive market, is denoted by P^X_t.

The firm keeps producing until the job is exogenously discontinued, so that the value of a filled vacancy is given by

$$V^J_t = \frac{P^X_t}{P_t} A_t - \frac{W_t}{P_t} + \mathbb{E}_t[(1-\rho_{t+1})Q^y_{t,t+1} V^J_{t+1}] , \tag{10}$$

where we assumed that the future value of a filled vacancy is discounted according to the stochastic discount factor of young agents. This is consistent with literature on TANK models, where firms are typically managed by one of the agents' type (see e.g., Bilbiie et al., 2024, among others).

The free entry condition ensures that the cost of opening a vacancy equals its expected benefit, that is

$$k = q_t V_t^J \ , \tag{11}$$

where q_t denotes the probability of filling the vacancy. Substituting Eq. (11) into (10) we obtain the job creation condition

$$\frac{k}{q_t} = \frac{P_t^X}{P_t} A_t - \frac{W_t}{P_t} + \mathbb{E}_t \left[(1 - \rho_{t+1}) Q_{t,t+1}^y \frac{k}{q_{t+1}} \right] \ . \tag{12}$$

Final-good producers. Final-good producers, indexed by $i \in [0,1]$, face a probability $(1-\delta)$ of resetting prices in each period as in Calvo (1983) and produce differentiated goods using the following linear technology

$$Y_{i,t} = X_{i,t} \tag{13}$$

in a monopolistically competitive market. Denoting by $P_{i,t}^*$ the optimal price set by the firms adjusting in period t, the downward-sloping demand function faced by firms is

$$Y_{i,t} = \left(\frac{P_{i,t}^*}{P_t} \right)^{-\epsilon} Y_t \ , \tag{14}$$

where ϵ is the elasticity of substitution and Y_t is aggregate income. In equilibrium, all price-resetting firms choose the same price $P_{i,t}^* = P_t^*$ given by a weighted average of current and future real marginal costs $RMC_t \equiv P_t^X / P_t$, with weights depending on expected future demand and the discount factor. In each period t, the average price level is given by the aggregator

$$P_t^{1-\epsilon} = (1-\delta)(P_t^*)^{1-\epsilon} + \delta P_{t-1}^{1-\epsilon} \ , \tag{15}$$

so that inflation is linked to the optimal relative price according to

$$\Pi_t = \left[\frac{1 - (1-\delta) \left(\frac{P_t^*}{P_t} \right)^{1-\epsilon}}{\delta} \right]^{\frac{1}{\epsilon - 1}} \ , \tag{16}$$

where P_t^*/P_t includes a cost-push shock similar to Adjemian et al. (2008) and Abbate and Thaler (2019), which follows $\log(\mu_t) = \rho_\mu \log(\mu_{t-1}) + \epsilon_t^\mu$.[20]

Search frictions and equilibrium wages. Let V_t represent the total number of job vacancies, the matching between job seekers and vacancies follows $M_t = \omega V_t^{1-\gamma} S_t^\gamma$, where ω measures matching efficiency. Labor market tightness is defined as $\theta_t \equiv V_t/S_t$. Participation and job posting decisions influence the job finding rate, given by $f_t = \omega\theta_t^{1-\gamma}$, and the vacancy filling rate, denoted as $q_t = \omega\theta_t^{-\gamma}$. When a non-employed individual, after incurring the search cost Γ, meets a firm, wages are collectively negotiated by a union. The surplus from reaching an employment agreement for a household corresponds to the net gain of having one additional member employed rather than unemployed, given the chosen level of labor force participation $L_t = \bar{L}$. Formally, this surplus is defined as $V_{a,t}^w = V_{a,t}^E - V_{a,t}^U$ and can be expressed as

$$V_{a,t}^w = \frac{W_t}{P_t} - b^u - (1-\Gamma)MRS_{a,t} + \mathbb{E}_t\left[Q_{t,t+1}^a(1-\rho_{t+1})(1-f_{t+1})V_{a,t+1}^w\right] . \tag{17}$$

According to Eq. (17), the value of an employment match, i.e., the employment surplus, corresponds to the current-period advantage of being employed relative to being unemployed, plus the discounted expected continuation of that advantage into the future. The contemporaneous gain from moving from unemployment to employment reflects the difference between the direct marginal benefit of employment, given by the real wage W_t/P_t, and the direct marginal benefit of unemployment, represented by the unemployment benefit and the value of home production, $b^u + (1-\Gamma)MRS_{a,t}$. The persistence of the surplus over time depends on the joint probability that the worker maintains the current employment relationship and that unemployment remains costly or, putting it differently, that the match survives (with probability $1-\rho_{t+1}$) and that unemployed workers do not find a job (with probability $1-f_{t+1}$). Hence, the term $(1-\rho_{t+1})(1-f_{t+1})$ captures the extent to which the current employment surplus is expected to persist into the next period (see the Online Appendix for a detailed derivation).

When bargaining wages, the union considers the average surplus for workers, given by $V_t^w \equiv \zeta V_{y,t}^w + (1-\zeta)V_{o,t}^w$. The optimal wage $(W_t/P_t)^*$ that maximizes the Nash product $(V_t^w)^{1-\eta}(V_t^J)^\eta$ satisfies the first-order condition for the Nash bargaining problem given by

[20] Both papers use a revenue tax mechanism which captures a cost-push shock and allows a recursive formulation of the nonlinear problem (see Online Appendix for details).

the sharing rule

$$\eta V_t^w = (1-\eta) V_t^J \ , \tag{18}$$

where η denotes the relative bargaining power of the firms. Moreover, we introduce a simple form of nominal wage rigidity, where the nominal wage evolves as a weighted average between the newly optimal wage and the wage of last period, so the dynamics of the real wage is

$$\frac{W_t}{P_t} = (1-\theta_w)\left(\frac{W_t}{P_t}\right)^* + \theta_w \frac{W_{t-1}}{P_{t-1}}\Pi_t^{-1}, \tag{19}$$

and θ_w represents the degree of inertia in nominal wage dynamics. While admittedly ad hoc, the introduction of Eq. (19) follows a line of literature that models frictions in wage determination in a parsimonious manner, albeit without grounding them in first principles (see, e.g., Blanchard and Gali, 2007; Gagliardone and Gertler, 2023).

Market clearing. The aggregate production of the intermediate-good sector is given by

$$X_t = \int_0^1 X_{j,t} dj = A_t E_t \ , \tag{20}$$

while the standard aggregate resource constraint can be written as

$$Y_t = C_t + kV_t \ , \tag{21}$$

where aggregate output is defined by the standard aggregator

$$Y_t = \left(\int_0^1 Y_{i,t}^{\frac{\epsilon-1}{\epsilon}} di\right)^{\frac{\epsilon}{\epsilon-1}} \ . \tag{22}$$

Using Eqs. (13) and (14), we can write the aggregate production function as

$$Y_t = \frac{X_t}{\Delta_t} \ , \tag{23}$$

where Δ_t is a measure of price dispersion defined as

$$\Delta_t = \int_0^1 \left(\frac{P_{i,t}}{P_t}\right)^{-\epsilon} di \ . \tag{24}$$

Monetary policy. To close the model we specify the following monetary policy rule

$$R_t = R_{t-1}^{\rho_R} \left(\frac{\Pi_t^{\phi_\pi} \tilde{Y}_t^{\phi_y}}{\beta} \right)^{1-\rho_R} mp_t, \tag{25}$$

where R_t is gross nominal interest rate, ρ_R measures the degree of monetary policy inertia, Π_t is gross inflation rate, $\tilde{Y}_t$ is a measure of the output gap computed as the ratio between output and flexible price output, and mp_t is an i.i.d. monetary policy shock.

Fiscal policy. We keep fiscal policy as simple as possible, assuming no government spending, only lump-sum taxes or transfers, and a balanced budget. Moreover, to capture a possible role for fiscal transfers during the Covid-19 period, we include a stochastic transfer across generations. Hence fiscal policy entails: (i) a lump-sum tax, equally paid by the two agents, which is used to finance the unemployment benefits and the pensions, so that, $T_t = U_t b^u + (1-\zeta) b^n N_{o,t}$; (ii) a fixed transfer tr that ensures consumption equality between the two household types in steady state;[21] (iii) a stochastic transfer τ_t, subject to an exogenous shock $\tau_t = \rho_\tau \tau_{t-1} + \epsilon_t^\tau$.

4.2 Calibration and estimation

A subset of parameters is calibrated to match steady-state values commonly used in the literature and consistent with U.S. data, while the remaining parameters are estimated using Bayesian techniques. The full list of calibrated parameters is shown in Table 2. Specifically, the values of unemployment benefit, pension and scale parameter in the utility function are calibrated to match the employment rate, the participation rate of workers over 55 years of age, and the overall participation rate. The share of young population is set to reflect demographic data in the US. To estimate the model, we use US quarterly data from 1998:Q1 to 2019:Q4 on real GDP growth, CPI inflation, shadow policy rate from Wu and Xia (2016), change in labor force participation, change in retirement rate, real wage growth, real consumption growth and unemployment of people over 55 years of age (see Appendix A for a detailed data description).

[21] We ensure symmetric consumption levels in steady state as in Bilbiie et al. (2022).

	Param	Value	Target/Source
Discount factor	β	0.99	4% Average real return
Elasticity of substitution between consumption goods	ϵ	6	20% Price mark-up
Home production function	α_h	1/3	Campolmi and Gnocchi (2016)
Firms' bargaining power	η	0.4	Campolmi and Gnocchi (2016)
Elasticity of matches to searchers	γ	0.6	Campolmi and Gnocchi (2016)
Households' search cost	Γ	0.368	ATUS
Firms' search cost	κ	0.054	10% Vacancy cost per filled job over real wage
Unemployment benefit	b^u	0.31	95.5% Employment rate
Relative preference for home over market goods	ϕ	1.34	63% Participation rate
Matching efficiency	ω	0.76	2/3 Job filling rate
Pension	b^n	0.49	40% participation rate of workers over 55
Share of young population	ζ	0.63	Share of population over 16 and under 55
Portfolio costs	λ	0.01	Montoro and Ortiz (2023)

Table 2. Calibrated parameters

		Prior			Posterior			
	Param	Dist	Mean	SD	Mode	Median	10%	90%
Inverse of intertemporal elasticity young	ν_y	IG	2	2	1.5233	1.4186	1.2078	2.9077
Inverse of intertemporal elasticity old	ν_o	IG	2	2	2.1512	2.3216	1.6171	3.6915
Consumption habits	ξ	B	0.5	0.1	0.7712	0.7818	0.7245	0.8309
Calvo Parameter	δ	B	0.5	0.1	0.6699	0.6775	0.6415	0.7163
Wage Stickiness Parameter	θ_w	B	0.5	0.1	0.4344	0.4397	0.3837	0.4985
Job-separation rate	ρ	B	0.12	0.1	0.2460	0.2752	0.2251	0.3400
Pension scaling parameter	ς	N	0.5	0.1	0.3924	0.3773	0.2468	0.5085
Monetary policy parameter	ϕ_π	N	1.5	0.1	1.5231	1.5296	1.4010	1.6585
Monetary policy parameter	ϕ_y	G	0.125	0.05	0.0962	0.1157	0.0644	0.1923
Persistence of policy rate	ρ_R	B	0.75	0.1	0.5759	0.6019	0.5240	0.6715
Persistence of technology shock	ρ_A	B	0.5	0.1	0.7266	0.7012	0.6017	0.7830
Persistence of HP technology shock (young)	ρ_y^h	B	0.5	0.1	0.5215	0.5269	0.3960	0.6557
Persistence of HP technology shock (old)	ρ_o^h	B	0.5	0.1	0.5144	0.5081	0.3770	0.6433
Persistence of preference shock	ρ_Z	B	0.5	0.1	0.8335	0.8416	0.7961	0.8788
Persistence of cost-push shock	ρ_μ	B	0.5	0.1	0.3380	0.3444	0.2488	0.4516
Persistence of tax redistribution shock	ρ_τ	B	0.5	0.1	0.4397	0.4516	0.3318	0.5747
Persistence of separation shock	ρ_ρ	B	0.5	0.1	0.6915	0.6428	0.4978	0.7589
Std. technology shock	σ_A	IG	0.1	1	0.0117	0.0118	0.0105	0.0132
Std. HP technology shock (young)	$\sigma_{y,h}$	IG	0.1	1	0.0290	0.0273	0.0205	0.0443
Std. HP technology shock (old)	$\sigma_{o,h}$	IG	0.1	1	0.0235	0.0252	0.0193	0.0358
Std. preference shock	σ_Z	IG	0.1	1	0.0357	0.0380	0.0322	0.0453
Std. monetary shock	σ_{mp}	IG	0.1	1	0.0138	0.0136	0.0119	0.0156
Std. cost-push shock	σ_μ	IG	0.1	1	0.0218	0.0238	0.0185	0.0323
Std. tax redistribution shock	σ_τ	IG	0.1	1	0.0304	0.0358	0.0261	0.0547
Std. separation shock	σ_ρ	IG	0.1	1	0.0264	0.0271	0.0219	0.0333
Std. Measurement Error LFP	σ_{lfp}	IG	0.05	1	0.0056	0.0057	0.0051	0.0064
Std. Measurement Error Retirement	σ_{ret}	IG	0.05	1	0.0058	0.0058	0.0052	0.0064
Std. Measurement Error Real wage	σ_{rw}	IG	0.05	1	0.0063	0.0061	0.0057	0.0070
Std. Measurement Error Consumption	σ_c	IG	0.05	1	0.0057	0.0059	0.0052	0.0064
Std. Measurement Error U old	$\sigma_{o,u}$	IG	0.05	1	0.0055	0.0056	0.0049	0.0062

Table 3. Estimated parameters. Codes B, IG, N, and G under prior distribution stand for Beta, Inverse Gamma, Normal, and Gamma respectively.

4.3 Features of the estimated model

Table 3 reports the list of estimated parameters, information on priors and the estimated posterior mode. The posterior mode of the estimated structural parameters shows that the data calls for a high value of the habit persistence parameter, a lower wage stickiness than price stickiness and standard values for the monetary policy parameters. The intertemporal elasticity parameters are comparable across types, with the estimated posterior mode being slightly higher for young agents. The technology, separation, and preference shocks are the most persistent, whereas the tax redistribution and cost-push shocks display lower persistence.

Figure C.1.1 in Appendix C.1 reports the historical decomposition (HD) for the period 2020 and 2021 for GDP, inflation, retirement and labor force participation. The model interprets the Covid-19 shock primarily as a large negative demand shock, leading to a sharp decline in output, inflation, and labor force participation, along with a marked increase in retirements at the onset of the pandemic. The model also points to a significant role of monetary policy in gradually supporting output, at the cost of higher inflation. The separation shock affects the dynamics of both retirement and labor force participation, while the remaining shocks play only a minor role. Appendix C.1 also report the variance decomposition for GDP, inflation, retirement and labor force participation.

Appendix C.2 examines the business-cycle properties of retirement and labor-force participation. In the full sample, retirement is countercyclical whereas participation is procyclical. However, once the Covid years are excluded, this pattern disappears, and both retirement and participation become essentially acyclical (see Table C.2.1). This finding is consistent with our historical decomposition. To illustrate this, Figure C.2.1 reports impulse-response functions to an aggregate demand shock and an aggregate supply (TFP) shock. An aggregate demand shock generates a countercyclical response of retirement and a procyclical response of participation, whereas an aggregate supply shock yields the opposite pattern. Hence, the cyclical behavior of these variables depends on the nature of the shocks hitting the economy, with the exceptionally large demand shock during the Covid period dominating their observed dynamics in the last years of our sample.

Motivated by recent findings from Graves et al. (2023), which highlight the influence of monetary policy on household labor market participation decisions, Appendix C.3 explores the impact of monetary policy shocks. First, Figure C.3.1 compares the model-implied impulse response functions with empirical ones obtained from local projections at a monthly frequency, using monetary policy shocks from Jarociński and Karadi (2020). The empirical responses are broadly consistent with those predicted by the model, providing external validation and empirical support for our main mechanism. Both retirement and labor force participation increase on impact, as predicted by the model, with the response of retirement being persistent. Inflation decreases on impact, while the empirical response of output falls only with a delay. Second, the left panel of Figure C.3.2 reports impulse responses to a monetary policy shock under different relative shares of old and young agents, showing that the effects of monetary policy in our framework depend on the population's age structure. Results are consistent with our main narrative: the larger the share of old individuals, the stronger the response of retirement, inflation, and participation, while the effect on output remains negligible. More generally, in our model the effects of all shocks are contingent on the age structure of the population (see for example the right panel of Figure C.3.2 that shows how impulse responses for a demand shock changes with the population structure).

4.4 The impact of the Great Retirement on inflation

We now want to use the model to assess the impact of the Great Retirement on macroeconomic variables, and, above all, inflation. In our model the path of retirement affects inflation, because an increase in retirement leads to a decline in labor force participation, which in turn increases labor market tightness. In a tighter labor market the vacancy filling rate drops, leading to an increase in the value of a filled vacancy. The latter effect, coupled with the increase in households' outside option when deciding whether to participate in the labor market, puts upward pressure on wages. By construction, hence, our model reproduces the same mechanisms suggested by the empirical analysis in Section 3.2, where we showed that counties more exposed to the pandemic shock exhibit a relatively larger increase in retirement and in nominal wages. The increase in nominal wages draws individuals, who were previously outside, into the labor force to compensate for the shortfall created by the surge in retirements. In the model, this mechanism induces higher inflation, because intermediate-good producers, operating in perfect competition, increase their price causing higher marginal costs for final goods producers. Thus, we can use our estimated model to evaluate the effect of the Great Retirement on inflation, for which we have no data at the county level.

In order to do that, we need to determine the behavior of the model economy in a counterfactual scenario in which the Great Retirement never happened. To engineer the counterfactual dynamic path of retirement in our TANK model, we use shocks to home-productivity of old agents $A^h_{o,t}$, because these shocks directly affect retirement decisions of old agents. In fact, a change in productivity at home has a direct effect on the value of home-produced goods generated by the marginal non-participant, and thus on the benefit of being

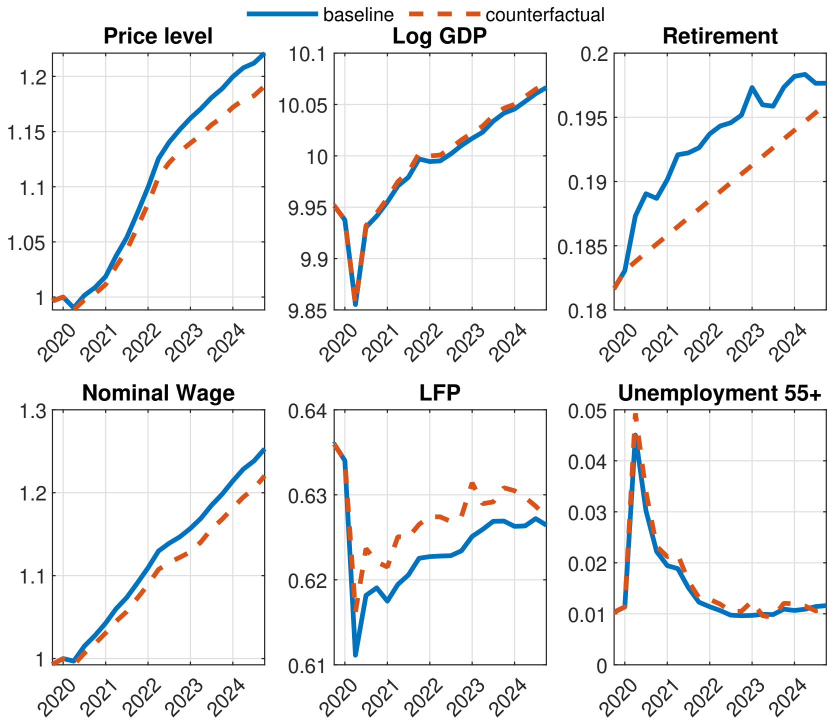

Figure 6. **A counterfactual economy where the Great Retirement never happened.** The figure compares simulations from the baseline model (solid blue line) with those from a counterfactual scenario (dashed orange line) where the Great Retirement is absent. The baseline reflects smoothed values generated by the estimated model and aligns with actual data. In the counterfactual simulation, the home-productivity of old agents is engineered to ensure that retirements follow the linear trend observed between 2011:Q1 and 2019:Q4.

out of the labor force.[22] We then perform the following counterfactual exercise. First, we compute the smoothed values of endogenous variables and exogenous shocks from 1998:Q1 to 2024:Q4 using the Kalman smoother with estimated parameters set at their posterior mode. We then simulate the model with the obtained smoothed shocks, but changing the path of home-productivity of old agents to control for the behavior of retirement. That is, we set the values of shocks to $A^h_{o,t}$ so that retirement follows the pre-Covid-19 linear trend estimated from 2011:Q1 to 2019:Q4. Figure 6 shows the simulation from the baseline model (blue solid line) and from the counterfactual model (orange dashed line), obtained using the parameter estimated posterior modes. By construction, the baseline model reproduces the actual data of the observed variables. The difference between baseline and counterfactual

[22]Figure C.3.3 in Appendix C.3 reports the dynamic responses to a shock to home-productivity of old agents.

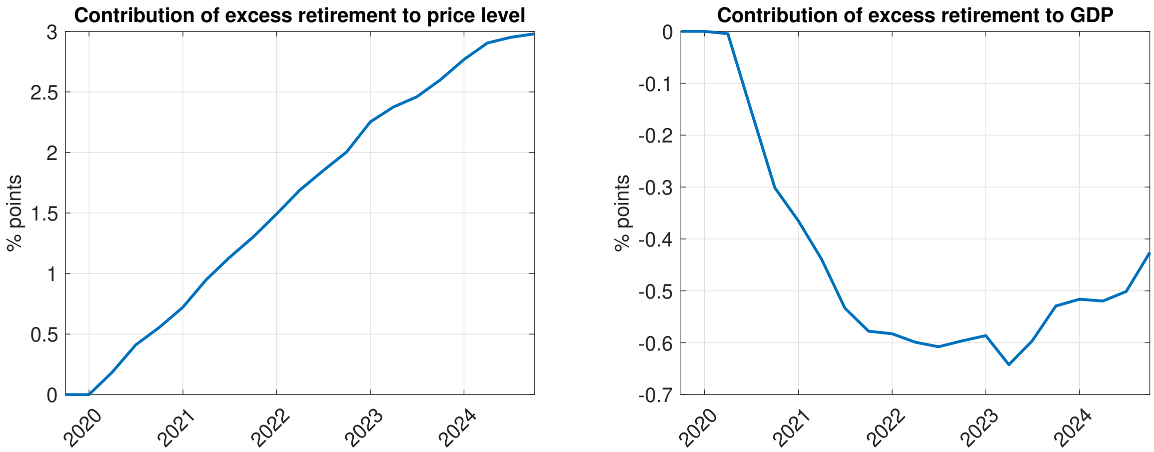

Figure 7. **Contribution of the Great Retirement to prices and output. Left**: Contribution to price level. **Right**: Contribution to real GDP.

shows the impact of the Great Retirement on aggregate variables.[23]

The upper-right panel of Figure 6 illustrates the dynamics of retirement. By construction, in the counterfactual model, retirement follows the pre-Covid-19 linear trend. Comparing the two lines, we observe a sharp increase in retirement around the onset of the pandemic. From 2021:Q1 onward, the blue line resumes growing roughly at the pre-Covid-19 trend rate, and the latest observations indicate a gradual narrowing of the retirement gap. In 2021:Q2, one year after the Covid-19 shock, the difference between the baseline and counterfactual retirement shares reaches 0.56%, corresponding to about 1.5 million additional retirees. The average gap between the two series after the initial jump (i.e., from 2021:Q1 onward) is about 0.42 percentage points. The Great Retirement had significant effects on the labor market, inflation, and to a lesser extent on output. In the absence of this phenomenon, nominal wages would have been approximately 1.7% lower in 2021:Q4, 2.2% lower in 2022:Q4, 2.6% lower in 2023:Q4, and 2.7% lower in 2024:Q4 compared to the actual data. This pattern aligns qualitatively with the estimated dynamic response of nominal wages in Figure 5.

Figure 7 illustrates the contribution of the Great Retirement to inflation and output by showing the cumulative percentage difference between the baseline and counterfactual economies from 2020:Q1 to 2024:Q4. According to our counterfactual analysis, the Great Retirement increased inflation by about 3 percentage (cumulative) points over this period, with yearly contributions of roughly 0.56 p.p. in 2020, 0.74 p.p. in 2021, 0.70 p.p. in 2022, 0.60

[23]It is worth stressing that, in this exercise, home-productivity shocks are used merely as a modeling device to reproduce the counterfactual retirement dynamics within our TANK framework and to assess their aggregate effects. They are not interpreted as the fundamental cause of the Great Retirement, which in our estimation arises from the combination of structural shocks identified by the model.

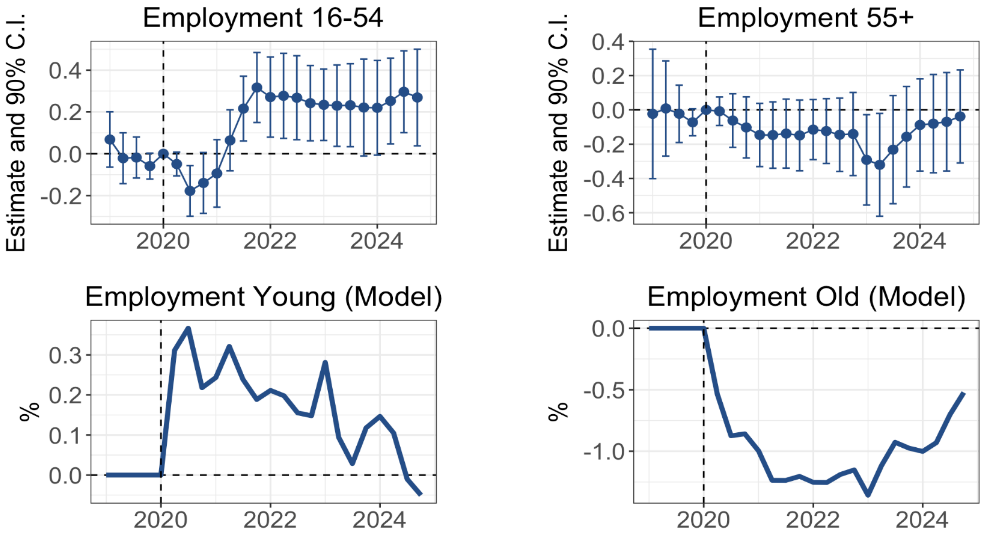

Figure 8. **Substitution between old retiree and young employees**. **Top**: Dynamic response of Employment by age to the Great Layoff (data: CPS- IPUMS, BLS and QCEW, BLS). **Bottom**: Difference of employment by age between baseline and counterfactual model: higher retirement causes higher employment of young agents and lower employment of old agents.

p.p. in 2023, and 0.38 p.p. in 2024. Given that total cumulative inflation between 2020:Q1 and 2024:Q4 was around 22.1%, the Great Retirement accounts for nearly 1/7 of the overall price increase. At the same time, the Great Retirement had a modest negative impact on output, peaking at a cumulative reduction of 0.64 percentage points in 2023:Q2. This decline can be decomposed into approximately 0.30 p.p. in 2020, 0.28 p.p. in 2021, and 0.02 p.p. in 2022, with the effect beginning to fade in the second half of 2023. Since cumulative GDP growth over the same period amounted to about 13%, the Great Retirement's impact on economic activity was relatively small.

The negligible effect on GDP growth is explained by the fact that the tightening of the labor market induced by the surge in retirements generated an increase in wages, which in turn stimulated younger individuals who were previously outside the labor force to enter employment and partially offset the initial loss of workers. Figure 8 compares the post-Covid reallocation of labor supply in the data and in the model. The two panels in the top row show the responses of employment for individuals aged 16–54 and 55+, respectively, using our shift-share regression (1) in Section 3.2. Employment of the younger group rises - after an initial, statistically insignificant decline - while employment of the older group falls, although the decline is significant only in a few periods. This empirical result mirrors the model's prediction, as illustrated in the two panels in the bottom row, which report the difference between the observed data and the counterfactual dynamics of employment for the younger and older groups. Employment for the younger group increases and that for the older group decreases, consistent with the mechanism in which younger workers substitute for retirees in employment.

Finally, our estimated impact of the Great Retirement on inflation may be interpreted as a lower bound once the aging composition of the labor force is considered. Participation typically declines at age 65 and falls steeply after 75. In 2020, the large baby-boom cohort (1945–1965) entered this age range, implying unusually high retirements over the past decade. This trend will gradually slow as the cohort ages beyond 65. Accordingly, our linear counterfactual trend may overstate future retirement dynamics, which are likely to decelerate, meaning that our counterfactual should have implied a higher retirement gap, and hence larger effects. This also underscores an important difference between the Covid-19 crisis and the Great Recession of 2008: while after the Great Recession substantial labor supply potential from baby boomers remained, this was no longer the case after the Covid-19 period.[24]

5 Model extension: heterogeneous workers' skills

The Covid-19 shock triggered a large number of layoffs concentrated in low-wage sectors such as Leisure and Hospitality (see Figure 4). The baseline model abstracted from such sectoral heterogeneity and, consequently, from heterogeneity in workers' productivities. However, one might suspect that the negligible effects on GDP obtained in the baseline model are precisely a consequence of ignoring worker heterogeneity: if most layoffs fell on relatively low-productivity workers, then the muted output response may simply reflect the low marginal product of those workers.[25] To address this possibility, we extend the model to incorporate heterogeneous productivities across workers to assess whether the composition of layoffs, rather than the aggregate magnitude alone, plays a key role in shaping the impact of the Covid-19 shock on post-pandemic output and inflation.

In this section, therefore, we extend the baseline model by considering another dimension of heterogeneity, namely workers' skills. Specifically, we distinguish four types of households based on age (*young* or *old*) and skill level (*skilled* or *unskilled*). The shares of young and old households in the economy are denoted by ζ_y and $\zeta_o = 1 - \zeta_y$, respectively, while the shares of skilled and unskilled households are denoted by ζ_H and $\zeta_L = 1 - \zeta_H$. We assume

[24]We thank Editor Ayşegül Şahin for this comment. Investigating how the age composition of the labor force shapes the business-cycle properties of labor market responses to shocks, especially in these two crisis, would be an interesting avenue for future research.

[25]We thank Editor Francesco Bianchi to push us to extend the model in this direction.

that skilled and unskilled workers are evenly distributed across the two age groups.

Apart from introducing four household types differentiated by age and skill, the model's structure remains largely consistent with the baseline described in Section 4.1. Accordingly, in what follows we simply highlight the key differences relative to the baseline model.

Workers' skills and intermediate-good production. In contrast to the baseline model presented in Section 4.1, where intermediate goods are produced solely using homogeneous labor as the single input, the current framework assumes that intermediate goods are produced using inputs supplied by both skilled and unskilled workers.

Let $X_{s,t}$ denote the input produced by workers of skill type $s \in \{H, L\}$, representing high-skilled and low-skilled labor, respectively. The aggregate production of input $X_{s,t}$ is given by

$$X_{s,t} = A_{s,t} E_{s,t} \; , \tag{26}$$

where $A_{s,t}$ is the productivity of type s following $\log(A_{s,t}) = \rho_{A,s} \log(A_{s,t-1}) + \epsilon_t^{A,s}$, and $E_{s,t}$ is total employment of workers with skill type s (both young and old).

Aggregate production of intermediate goods is then given by a CES aggregator that bundles inputs $X_{H,t}$ and $X_{L,t}$ according to

$$X_t = \left[\gamma_H (X_{H,t})^{\frac{\sigma_X - 1}{\sigma_X}} + \gamma_L (X_{L,t})^{\frac{\sigma_X - 1}{\sigma_X}} \right]^{\frac{\sigma_X}{\sigma_X - 1}} \; , \tag{27}$$

with $\gamma_H > \gamma_L$ ensuring that the real wage of skilled workers is higher than that of unskilled workers. Demand for input $X_{s,t}$ is given by

$$X_{s,t} = \left(\frac{P_{s,t}}{\gamma_s P_t^X} \right)^{-\sigma_X} X_t \; , \tag{28}$$

and the real price of the intermediate good P_t^X / P_t is

$$\frac{P_t^X}{P_t} = \left[\gamma_L^{\sigma_X} \left(\frac{P_{L,t}}{P_t} \right)^{1-\sigma_X} + \gamma_H^{\sigma_X} \left(\frac{P_{H,t}}{P_t} \right)^{1-\sigma_X} \right]^{\frac{1}{1-\sigma_X}} \; . \tag{29}$$

Job creation conditions are also differentiated by labor type s and given by

$$\frac{k}{q_{s,t}} = \frac{P_{s,t}}{P_t} A_{s,t} - \frac{W_{s,t}}{P_t} + \mathbb{E}_t \left[(1 - \rho_{s,t+1}) Q_{t,t+1}^H \frac{k}{q_{s,t+1}} \right] \; , \tag{30}$$

where we assumed that future values of filled vacancies are discounted according to the stochastic discount factor of skilled young agents (see Section 4.1 above for a discussion). Note also that workers of type s, regardless of age, receive the same wage $W_{s,t}/P_t$.

Finally, Nash bargaining over real wages results in constant splitting rules by type s, assuming that firms have the same relative bargaining power regardless of the wage type being negotiated, and that the extent of wage stickiness varies depending on the type s.

Rest of the model. The law of motion for employment by type, indexed by $a \in y, o$ and $s \in H, L$, is given by $E_{a,s,t} = (1 - \rho_{s,t})E_{a,s,t-1} + f_{s,t}S_{a,s,t}$, where $\rho_{s,t}$ denotes the separation rate and $f_{s,t}$ the job-finding rate for labor of type s. We assume that separation rates follow exogenous, skill-specific AR(1) processes of the form $\rho_{s,t} = (1 - \rho_{\rho,s})\bar{\rho}_s + \rho_{\rho,s}\rho_{s,t-1} + \epsilon_t^{\rho,s}$.

Unemployment benefits (b_s^u), utility function scaling parameters (ϕ_s), and home productivities ($A_{s,t}^h$) vary by skill type s. In contrast, elasticities ($\nu_{a,s}$) and pensions ($b_{a,s,t}^n$) are differentiated by both age a and skill s. As in the benchmark scenario, pensions are received exclusively by older agents, implying $b_{y,s,t}^n = 0$ and $b_{o,s,t}^n = b_{s,t}^n$. These pensions fluctuate with stock market performance, such that $b_{s,t}^n = b_s^n \Phi_t$, where $\Phi_t = A_t^{\varsigma}$. The aggregate productivity A_t is a weighted average of $A_{H,t}$ and $A_{L,t}$, with weights determined by the steady-state value shares of intermediate goods X_H and X_L in total intermediate good production.

Given that household types can borrow and lend each other subject to the same portfolio costs as in the baseline model, we can define optimality conditions for each households type as given by the Euler equations similar to Eq. (7)

$$R_t \mathbb{E}_t \left(Q_{t,t+1}^{a,s} \Pi_{t+1}^{-1} \right) + \lambda D_{a,s,t} = 1 \; , \tag{31}$$

as well as the participation condition

$$\begin{aligned} b_{a,s,t}^n + MRS_{a,s,t} = f_{s,t} \frac{W_{s,t}}{P_t} + (1 - f_{s,t})(b_s^u + (1 - \Gamma) MRS_{a,s,t}) + \\ \mathbb{E}_t \left[Q_{t,t+1}^{a,s} f_{s,t} (1 - \rho_{s,t+1}) \frac{1 - f_{s,t+1}}{f_{s,t+1}} (b_{a,s,t+1}^n + \Gamma MRS_{a,s,t+1} - b_s^u) \right] \; , \end{aligned} \tag{32}$$

which mirrors Eq. (8), but now applies to four distinct household groups, differentiated by both age a and skill type s.

The remainder of the model's supply side, along with the specified monetary policy rule, mirrors that of the baseline model discussed in Section 4.1.

	Param	Value	Target/Source
Discount factor	β	0.99	4% Average real return
Elasticity of substitution between consumption goods	ϵ	6	20% Price mark-up
Calvo Parameter	δ	0.67	Estimated mode in the baseline model
Home production function	α_h	1/3	Campolmi and Gnocchi (2016)
Firms' bargaining power	η	0.4	Campolmi and Gnocchi (2016)
Elasticity of matches to searchers	γ	0.6	Campolmi and Gnocchi (2016)
Households' search cost	Γ	0.368	ATUS
Firms' search cost	κ	2.6365	10% Vacancy cost per filled job over real wage of skilled workers
Unemployment benefit skilled workers	b_H^u	15.3663	96.8% Employment rate skilled workers
Relative preference for home over market goods skilled workers	ϕ	0.2151	76.7% Participation rate skilled
Pension skilled workers	b_H^n	33.6471	50.3% participation rate of old skilled workers
Unemployment benefit unskilled workers	b_L^u	2.2949	92.5% Employment rate unskilled workers
Relative preference for home over market goods skilled workers	ϕ_L	1.1683	58.8% Participation rate unskilled
Pension unskilled workers	b_L^n	7.2102	31.9% participation rate of old unskilled workers
Matching efficiency	ω	0.7993	2/3 Job filling rate skilled labor market
Share of young in skilled population	$\zeta_{H,y}$	0.707	Share of population over 16 and under 55 among skilled population
Share of young in unskilled population	$\zeta_{L,y}$	0.682	Share of population over 16 and under 55 among unskilled population
Share of skilled population	ζ_H	0.346	Share of skilled population
Portfolio costs	λ	0.01	Montoro and Ortiz (2023)
Elasticity of substitution skilled-unskilled	σ_X	1.4	Hornstein et al. (2005)
Importance of skilled workers in production of final good	γ_H	2.3	Ratio of skilled real wage and unskilled real wage ≈ 3
Importance of unskilled workers in production of final good	γ_L	1	Fixed

Table 4. Calibrated parameters in the heterogeneous workers' skills

5.1 Calibration and Estimation

As before, we calibrate some parameters and estimate the remaining ones using Bayesian techniques. The complete set of calibrated parameters is reported in Table 4. We maintain the same parameter values as in the baseline model for all parameters that are common across specifications, while introducing skill-specific parameters. Price stickiness is set equal to the estimated mode in the baseline model. As in the baseline case, labor market parameters are chosen to match steady state values consistent with features of U.S. data, but now these targets are differentiated by skill type. In particular, the unemployment benefit for skilled workers is set to reproduce their steady state employment rate; the scale parameter in the skilled workers' utility function is chosen to match their participation rate; and the pension benefit is calibrated to match the participation rate of old skilled workers. The same procedure applies to unskilled workers. We fix the population share of skilled workers, as well as the shares of young workers in both skilled and unskilled populations according to U.S. data. Parameters γ_H and γ_L measuring the relative contributions of intermediate input produced respectively by skilled and unskilled workers in the CES production function described in Eq. (27) are calibrated to replicate the relative wage between the two groups. Parameter σ_X, capturing the elasticity of substitution between inputs produced by skilled and unskilled workers is set as in Hornstein et al. (2005). Finally, the vacancy posting cost and the matching efficiency parameters are calibrated as in the baseline model, using skilled workers as the reference group.

For the estimation exercise, we use US quarterly data from 1998:Q1 to 2019:Q4 on real

GDP growth, CPI inflation, shadow policy rate from Wu and Xia (2016), change in labor force participation, real consumption growth, change in retirement rates of both skilled and unskilled workers, overall real wage growth as well as skilled workers real wage growth, and unemployment rate of workers older than 55, both skilled and unskilled (see Appendix A for a detailed data description).

		Prior			Posterior			
	Param	Dist	Mean	SD	Mode	Median	10%	90%
Inverse of intertemporal elasticity skilled young	$\nu_{H,y}$	IG	2	2	1.9353	2.2271	1.6257	3.1405
Inverse of intertemporal elasticity skilled old	$\nu_{H,o}$	IG	2	2	1.9871	2.2403	1.4800	3.6868
Inverse of intertemporal elasticity unskilled young	$\nu_{L,y}$	IG	2	2	1.7841	2.0969	1.3775	3.4557
Inverse of intertemporal elasticity unskilled old	$\nu_{L,o}$	IG	2	2	2.9710	3.5964	2.2941	5.8447
Consumption habits	ξ	B	0.5	0.05	0.6983	0.6975	0.6429	0.7467
Wage Stickiness Parameter skilled	$\theta_{w,H}$	B	0.5	0.1	0.3425	0.3501	0.2862	0.4117
Wage Stickiness Parameter unskilled	$\theta_{w,L}$	B	0.5	0.1	0.5558	0.5473	0.4557	0.6216
Job-separation rate skilled	ρ_H	B	0.12	0.1	0.3044	0.3352	0.2775	0.4195
Job-separation rate unskilled	ρ_L	B	0.12	0.1	0.3044	0.3289	0.2749	0.3970
Pension scaling parameter	ς	N	0.5	0.1	0.3315	0.3471	0.2223	0.4145
Monetary policy parameter	ϕ_π	N	1.5	0.1	1.4702	1.5020	1.3694	1.6345
Monetary policy parameter	ϕ_y	G	0.125	0.05	0.0791	0.1022	0.0553	0.1741
Persistence of policy rate	ρ_R	B	0.75	0.1	0.5825	0.6002	0.5389	0.7691
Persistence of technology shock (skilled)	ρ_{AH}	B	0.5	0.1	0.7265	0.6641	0.5356	0.7691
Persistence of technology shock (unskilled)	ρ_{AL}	B	0.5	0.1	0.6211	0.6233	0.4339	0.7320
Persistence of HP technology shock (skilled)	ρ_H^h	B	0.5	0.1	0.5167	0.5305	0.3917	0.6855
Persistence of HP technology shock (unskilled)	ρ_L^h	B	0.5	0.1	0.5583	0.5773	0.4339	0.7320
Persistence of preference shock	ρ_Z	B	0.5	0.1	0.8767	0.8777	0.8487	0.9025
Persistence of cost-push shock	ρ_μ	B	0.5	0.1	0.3414	0.3652	0.2589	0.4919
Persistence of tax redistribution shock	ρ_{tax}	B	0.5	0.1	0.4741	0.4741	0.3485	0.6017
Persistence of separation shock (skilled)	$\rho_{\rho H}$	B	0.5	0.1	0.6885	0.6401	0.4911	0.7575
Persistence of separation shock (unskilled)	$\rho_{\rho L}$	B	0.5	0.1	0.6254	0.6022	0.4649	0.7241
Std. technology shock (skilled)	σ_{AH}	IG	0.1	1	0.0138	0.0140	0.0123	0.0159
Std. technology shock (unskilled)	σ_{AL}	IG	0.1	1	0.0206	0.0212	0.0176	0.0256
Std. HP technology shock (skilled)	$\sigma_{H,h}$	IG	0.1	1	0.0352	0.0378	0.0270	0.0564
Std. HP technology shock (unskilled)	$\sigma_{L,h}$	IG	0.1	1	0.0199	0.0193	0.0155	0.0256
Std. preference shock	σ_Z	IG	0.1	1	0.0344	0.0362	0.0314	0.0419
Std. monetary shock	σ_{mp}	IG	0.1	1	0.0138	0.0137	0.0122	0.0156
Std. cost-push shock	σ_μ	IG	0.1	1	0.0185	0.0223	0.0194	0.0258
Std. tax redistribution shock	σ_{tax}	IG	0.1	1	0.0397	0.0530	0.0282	0.0580
Std. separation shock (skilled)	$\sigma_{\rho H}$	IG	0.1	1	0.0378	0.0374	0.0287	0.0480
Std. separation shock (unskilled)	$\sigma_{\rho L}$	IG	0.1	1	0.0258	0.0268	0.0216	0.0332
Std. Measurement Error LFP	σ_{lfp}	IG	0.05	1	0.0056	0.0057	0.0052	0.0064
Std. Measurement Error Retirement (skilled)	σ_{retH}	IG	0.05	1	0.0048	0.0049	0.0044	0.0054
Std. Measurement Error Retirement (unskilled)	σ_{retL}	IG	0.05	1	0.0046	0.0047	0.0042	0.0052
Std. Measurement Error Real wage	σ_{rw}	IG	0.05	1	0.0059	0.0059	0.0053	0.0066
Std. Measurement Error Real wage (skilled)	σ_{rwH}	IG	0.05	1	0.0057	0.0058	0.0042	0.0052
Std. Measurement Error Consumption	σ_c	IG	0.05	1	0.0057	0.0060	0.0052	0.0064
Std. Measurement Error Unemployment (old skilled)	σ_{UoH}	IG	0.05	1	0.0058	0.0061	0.0051	0.0066
Std. Measurement Error Unemployment (old unskilled)	σ_{UoL}	IG	0.05	1	0.0053	0.0048	0.0060	0.0063

Table 5. Estimated parameters. Codes B, IG, N, and G under prior distribution stand for Beta, Inverse Gamma, Normal, and Gamma respectively.

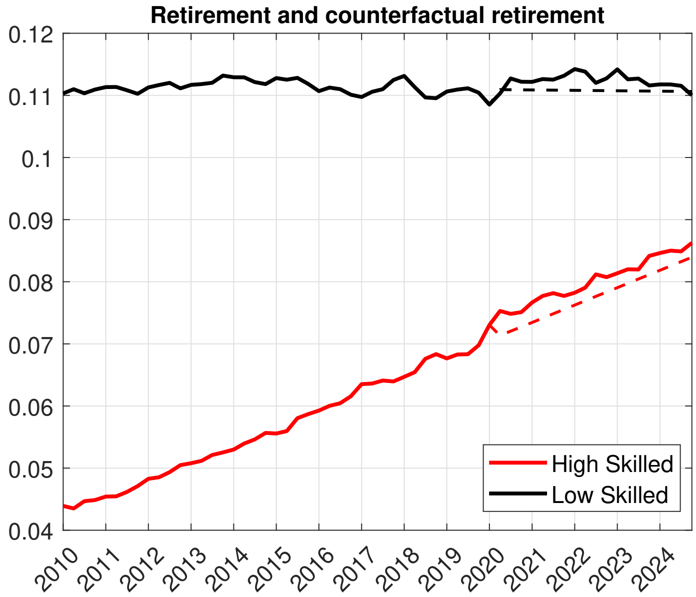

Figure 9. **Proportions of retired skilled and unskilled workers and the respective pre-Covid-19 linear trend.**

5.2 Results

Table 5 reports the list of estimated parameters, information on priors and the estimated posterior mode. The parameters are in line with the ones estimated for the baseline model. The intertemporal elasticity of labor supply is lower for old than for young workers, and it is particularly low for unskilled old workers. Consumption habit is lower with respect to the baseline. Wage stickiness is higher for unskilled workers but in both cases comparable to the baseline estimate. The monetary policy parameters are very close to the ones estimated for the baseline model. The shock parameters are comparable.

We then perform the same counterfactual exercise as described in the previous section for the baseline model. However, in the model with heterogeneous skills, there are two distinct types of older agents: skilled and unskilled, both of whom may choose to retire. Figure 9 displays retirement behavior for the two agent types from 2010 onward. Retirement among skilled workers exhibits a clear upward trend, whereas no such trend is evident for unskilled workers. In both cases, however, the Covid-19 shock led to a persistent increase in retirements, which has not yet been reabsorbed in the case of skilled workers. Building on the approach of the counterfactual presented in the previous section, we introduce shocks to home production for older agents in both skilled and unskilled households, ensuring that the Great Retirement does not take place for either group. Specifically, we simulate the model

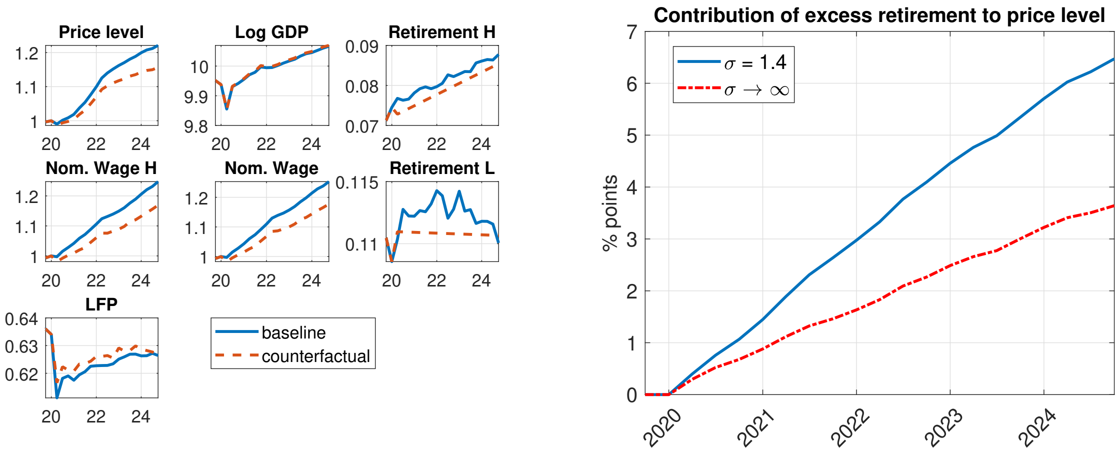

Figure 10. **The impact of the Great Retirement in the heterogeneous skills model. Left**: Counterfactual simulation from the baseline model (solid blue) and from the counterfactual economy (dashed orange) without the Great Retirement. **Right**: Contribution to the price level (blue), that is the difference between the solid blue and the dashed orange lines in the price level panel on the top right corner. The red dashed line shows the contribution to the price level of the Great Retirement in the heterogeneous skills model when the elasticity of substitution between high skilled sector goods and low skilled sector goods tend to be very high. This version of the model reproduces the results of the baseline model.

by applying shocks to the home production of older skilled and unskilled agents so that their retirement trajectories follow the estimated pre-Covid-19 trends (respectively dashed red and black lines in Figure 9).

Figure 10 shows the result of this counterfactual exercise. The effects are qualitatively the same as in our baseline model (see the panels on the left). In absence of the Great Retirement, the nominal wage and inflation would have been lower, while labor force participation and, slightly, output would have been higher in the counterfactual economy. Quantitatively, the effects on inflation are larger. The right panel of Figure 10 shows that in the model with heterogeneous skills, the cumulative contribution of the Great Retirement to inflation amounts to roughly 6%, rather than 3% as in the baseline model of Section 4.1. The negative effect on GDP is similar in profile and magnitude, being around 0.50 percentage points up to the end of 2022 and then marginally recovering from the second half of 2023.[26] Introducing heterogeneous worker productivity in the model increases the impact of the Great Retirement on inflation while leaving the effect on output largely unchanged. The mechanism operates through the labor market, because nominal wage inflation is amplified in this

[26]Figure C.1.2 in Appendix C.1 reports the historical decomposition for the period 2020 and 2021 for GDP, inflation and retirement of both skilled and unskilled workers. Again results align with the ones of the baseline model.

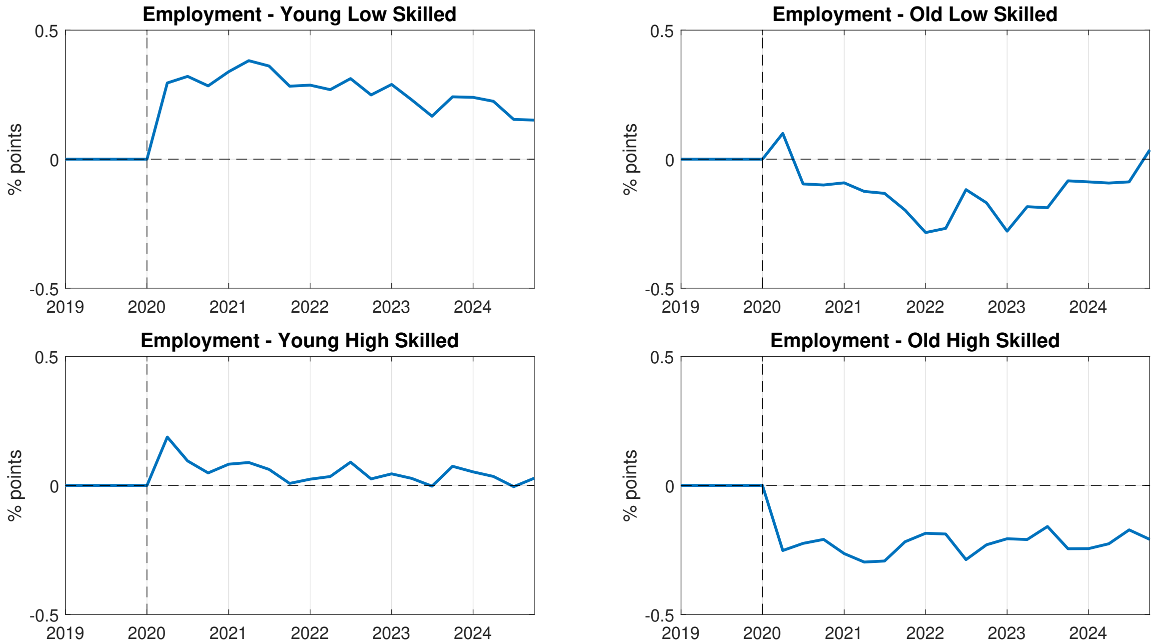

Figure 11. **Substitution between old retiree and young employees in the heterogeneous skills model**. Difference of employment by age and skills between baseline and counterfactual model.

version of the model. From a modeling standpoint, this occurs because imperfect substitution across worker types in the production function magnifies nominal wage inflation in this version of the model. The lower the degree of substitution across worker types, the more heterogeneous productivity matters; conversely, as workers become more substitutable, the model tends toward the homogeneous-productivity baseline.Indeed, when we set the elasticity of substitution between skilled and unskilled labor to a very high value - rather than 1.4 as in Hornstein et al. (2005) - the counterfactual delivers results that are quantitatively very close to those in the baseline model, as shown by the red dashed line in the right panel of Figure 10.[27] This result suggests that the inflation effect obtained in our baseline model can be interpreted as a lower bound.

Finally, as in Figure 8 for the baseline model, Figure 11 shows that the reallocation of labor supply between young and old individuals is also at the core of the mechanism in the heterogeneous-productivity version of the model. Employment of older agents - both skilled and unskilled - declines, whereas employment of younger agents rises. As in the

[27]Of course, the two versions of the model differ along additional dimensions, and parameter estimates also vary slightly. However, inspecting the mechanism suggests that these differences are not consequential: the key driver of the divergence between the two models is the value of the elasticity of substitution.

baseline case, this reallocation accounts for both the negligible effect on GDP growth and the increase in wages, and therefore inflation, that is required to induce younger individuals who were previously outside the labor force to enter employment.

6 Conclusions

The literature points to labor market tightness as an important determinant of post-Covid-19 inflation. This paper focuses on a specific channel through which labor market dynamics could have affected inflation, by investigating the role of retirement decisions and labor force participation. We show that, while the pandemic shock had transitory effects on output dynamics, it caused an unprecedented increase in retirees, i.e., a phenomenon labeled the Great Retirement.

First, we empirically show that the Great Layoff due to Covid-19 triggered the Great Retirement, not because there was something peculiar about Covid-19, but because retirement is countercyclical and the amount of layoffs was extraordinary. Second, we exploit differential exposure at the county level to the Covid-19 shock and show that counties most affected by the Great Layoff display a significantly higher increase in retirement and nominal wages, and that this effect is persistent over time. Our empirical results provide support to the idea that two months of Great Layoff in 2020 caused a surge in early retirements, ultimately causing inflationary pressures in the form of higher wages, required to draw younger individuals from outside the labor force into employment.

Finally, we build a quantitative New Keynesian model with endogenous labor market participation and retirement decision – consistent with the above empirical evidence – to quantify the impact of the Great Retirement on the post-Covid-19 recent inflation surge. Our findings suggest that the Great retirement had: (i) a positive impact on inflation equal to about 3 percentage (cumulative) points of inflation from 2020:Q1 up to 2024:Q4, divided roughly in 0.56 p.p. in 2020, 0.74 p.p. in 2021, 0.70 p.p. in 2022, 0.60 p.p. in 2023, and 0.38 p.p. in 2024. ; (ii) a modest negative impact on output, amounting to roughly 0.4 cumulative percentage points of GDP between 2020:Q1 and 2024:Q4, peaking at a cumulative reduction of 0.64 percentage points in 2023:Q2. This decline can be decomposed into approximately 0.30 p.p. in 2020, 0.28 p.p. in 2021, and 0.02 p.p. in 2022, with the effect beginning to fade in the second half of 2023.

Our paper focuses on the contribution of the Great Retirement to the post-Covid inflation surge. More generally, however, retirement may more broadly shape business cycle dynamics if it responds endogenously to economic conditions. Understanding retirement decisions then becomes relevant for interpreting the transmission of shocks and for assessing policy responses. We view this as a promising direction for future research, especially in light of population aging and the ongoing retirement of the baby-boom cohort.

Appendix

A Data

Section 1. Below we describe the data sources and definitions used in Figures 1 and 2.

Layoffs and Discharges is constructed using data from the SF Fed Data Explorer, Federal Reserve Bank of San Francisco. Data are based on most recent Job Openings and Labor Turnover Survey (JOLTS) collected by the Bureau of Labor Statistics and can be downloaded at https://www.frbsf.org/research-and-insights/data-and-indicators/sf-fed-data-explore

Labor Force is constructed using data from the Current Population Survey (CPS-IPUMS) collected by the Bureau of Labor Statistics. Data can be dowloaded at https://cps.ipums.org/cps/. Weights of respondents to the CPS have been adjusted to reflect population controls introduced in January 2022, January 2023, january 2024 and January 2025 by the Census Bureau and the Bureau of Labor Statistics (see e.g., "Adjustments to Household Survey Population Estimates in January 2025", US Bureau of Labor Statistics, Technical Documentation available at https://www.bls.gov/cps/methods/population-controls/population-control-adjustments-2025.pdf). To correct for the shifts introduced by new population weights, we follow guidance from the BLS (see Marisa L. DiNatale, "Creating Comparability in CPS Employment Series" available at https://www.bls.gov/cps/cpscomp.pdf) and adjust CPS respondent weights between 2010 and 2024 by linearly smoothing population controls over this time interval (see also Montes et al., 2022).

Retired Population is constructed using data from the Current Population Survey (CPS-IPUMS) collected by the Bureau of Labor Statistics. Data can be dowloaded at https://cps.ipums.org/cps/. Given that we do not have data to directly compute adjustment factors for retired individuals, we use data on adjustments for individuals over 55 who are not in the labor force. The underlying assumption is that the overall number of retired individuals changes as individuals in this category, and it is justified on the grounds that about 81% of individuals over 55 who are not in the labor force are retired (such percentage is about 0.5% and 7% for age groups 16-24 and 25-54 respectively). The smoothing procedure then follows the one outlined above for the variable *Labor Force*.

Labor Force Participation (LFP 16–24, 25–54, 55+) is constructed using data from the Current Population Survey (CPS-IPUMS) collected by the Bureau of Labor Statistics. Data can be dowloaded at https://cps.ipums.org/cps/. Weights of respondents to the CPS have been adjusted to reflect group-level revised population controls following the smoothing procedure outlined above for the variable *Labor Force*.

Section 3. Below we describe the data sources and definitions used in Table 1 and Figures 3, 4 and 5.

Regression results presented in Table 1 are based on the Atlanta Fed's Harmonized Variable and Longitudinally Matched (HVLM) dataset version of the monthly basic Current Population Survey (CPS). Data are available at https://cps.kansascityfed.org/.

Flow analysis is conducted using data from the Current Population Survey (CPS-IPUMS) collected by the Bureau of Labor Statistics. Data can be dowloaded at https://cps.ipums.org/cps/.

Layoffs and Discharges at the national level by supersector are constructed using data from the Job Openings and Labor Turnover Survey (JOLTS) collected by the Bureau of Labor Statistics and can be downloaded at https://www.bls.gov/jlt/data.htm.

Employment at the national level by supersector (Figure 4) is constructed using data from the Quarterly Census of Employment and Wages (QCEW) collected by the Bureau of Labor Statistics and can be downloaded at https://www.bls.gov/cew/downloadable-data-files.htm. Our analysis excludes supersectors labeled Public Administration and Unclassified, and considers Private Ownership only.

Employment at the county level by NAICS 4 sector (Figure 5) is constructed using data from the Quarterly Census of Employment and Wages (QCEW) collected by the Bureau of Labor Statistics and can be downloaded at https://www.bls.gov/cew/downloadable-data-files.htm. Our analysis excludes Private Household, Public Administration and Unclassified sectors, and considers Private Ownership only.

Retirement and *Other Not-In-Labor-Force* at the county level are constructed using data from the Current Population Survey (CPS-IPUMS) collected by the Bureau of Labor Statistics. Data can be dowloaded at https://cps.ipums.org/cps/. Since there are no data about population adjustments at the county level, we apply the same national-level adjustment factors described above to county-level total number of individuals who are retired, individuals who are not in the labor force and not retired, as well as to county-level total population. The underlying assumption is that county-level aggregates change in the same way as national aggregates.

Nominal Wages at the county level by NAICS 4 sector are constructed using data from the Quarterly Census of Employment and Wages (QCEW) collected by the Bureau of Labor Statistics and can be downloaded at https://www.bls.gov/cew/downloadable-data-files.htm. Our analysis excludes Private Household, Public Administration and Unclassified sectors, and considers Private Ownership only. Nominal wages refer to average weekly wages in each quarter. Moreover, when weighting 2022, 2023 and 2024 county-level sectoral wages by 2019 shares, we take into account the NAICS revision occurred in 2022 following correspondence tables provided by the Bureau of Labor Statistics and available at `https://www.bls.gov/ces/naics/naics-2022.htm`.

Section 4. Below we describe the data sources and definitions of the observables used to estimate the TANK model developed in Section 4.1 and run the counterfactual exercise, as well as data used

Real GDP Growth is constructed using quarterly real GDP data [GDPC1] from the Bureau of Economic Analysis, 1998:Q1 – 2024:Q4. Data were retrieved from FRED, Federal Reserve Bank of St. Louis, and can be downloaded at `https://fred.stlouisfed.org/series/GDPC1`. Growth rates are constructed by taking first differences of HP-filtered log real GDP.

CPI Inflation is constructed using quarterly data on CPI for All Urban Consumers: All Items in US City Average [CPIAUCSL] from the Bureau of Economic Analysis, 1998:Q1 – 2024:Q4. Data were retrieved from FRED, Federal Reserve Bank of St. Louis, and can be downloaded at `https://fred.stlouisfed.org/series/CPIAUCSL`. Inflation is constructed by taking de-meaned first differences of log CPI.

Shadow Policy Rate is the Wu-Xia Shadow Federal Funds Rate (Wu and Xia, 2016), 1998:Q1 – 2024:Q4. Data are de-meaned and can be downloaded at `https://sites.google.com/view/jingcynthiawu/shadow-rates`.

Change in Labor Force Participation is constructed using data from the Current Population Survey (CPS-IPUMS) collected by the Bureau of Labor Statistics. Data can be dowloaded at `https://cps.ipums.org/cps/`. Weights of respondents to the CPS have been adjusted to reflect group-level revised population controls following the smoothing procedure outlined above for the variable *Labor Force*. Monthly data are aggregate over quarters 1998:Q1 – 2024:Q4 and changes are obtained by taking first differences of the HP-filtered labor force participation series.

Change in Retirement Rate is constructed using data on *Retired Population* described above. Monthly data are aggregate over quarters 1998:Q1 – 2024:Q4 and changes are obtained by taking first differences of the HP-filtered retired over population series.

Real Wage Growth is constructed using monthly data from the Atlanta Fed's Wage Growth Tracker, which is a measure of the nominal wage growth of individuals and can be dowloaded at `https://www.atlantafed.org/chcs/wage-growth-tracker`. It is constructed using microdata from the Current Population Survey (CPS), and is the median percent change in the hourly wage of individuals observed 12 months apart. Real wage growth is then obtained as the de-meaned difference between the growth rates of nominal wages and CPI, aggregated at quarterly frequency over the time span 1998:Q1 – 2024:Q4.

Real Consumption Growth is constructed using quarterly real personal consumption expenditures [PCECC96] from the Bureau of Economic Analysis, 1998:Q1 – 2024:Q4. Data were retrieved from FRED, Federal Reserve Bank of St. Louis, and can be downloaded at https://fred.stlouisfed.org/series/PCECC96. Growth rates are constructed by taking first differences of HP-filtered log real consumption.

Unemployment of people 55+ is constructed using quarterly data 1998:Q1 – 2024:Q4 from the Labor Force Statistics from the Current Population Survey built by the Bureau of Labor Statistics. Data can be dowloaded at https://www.bls.gov/data/home.htm#unemployment. Our variable is constructed by dividing the number of unemployed over 55 by the civilian noninstitutional population over 55. detrending ?

B Additional Empirical Results

B.1 Estimates of individual controls

Figure B.1.1 reports estimates and 95% confidence intervals for regressions in Table 1, columns (3) and (6). Reference categories for education, ethnicity and wage decile are respectively Education: High, Black non-Hispanic and Wage decile 1.

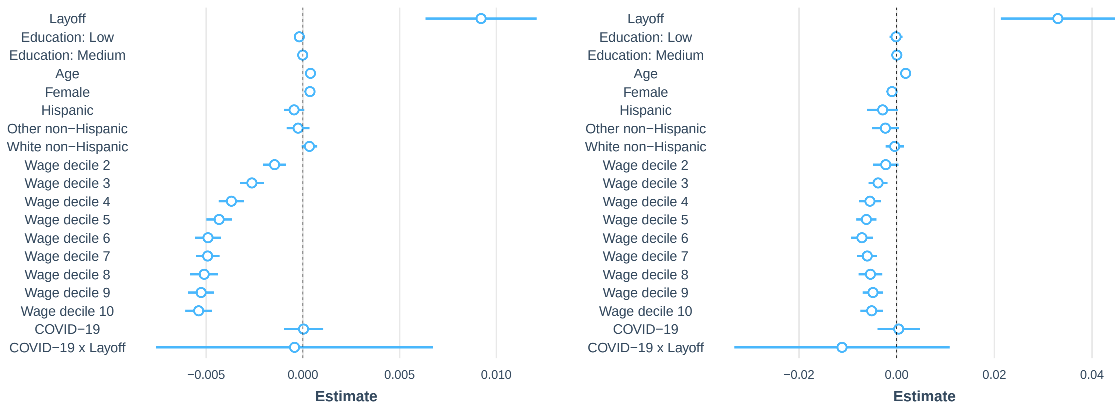

Figure B.1.1. **Estimated coefficients and 95% confidence intervals for regressions in Table 1.** Reference categories for education, ethnicity and wage decile are respectively Education: High, Black non-Hispanic and Wage decile 1. **Left panel:** full sample including all ages above 16. **Right panel:** subsample of respondents above 55.

B.2 Composition effects on county-level wages

Figure B.2.1 plots the percentage change in employment between February and April 2020 against average weekly wages in 2019 (left panel) and against the percentage change in average weekly wages between 2020 and 2019 (right panel) for each BLS supersector. The left panel shows that layoffs were concentrated in supersector characterized by relatively lower wages, thus suggesting a between-industries composition effect on county-level average wage. The right panel shows that supersectors with relatively higher layoffs are not systematically associated to larger increases in average wages between 2019 and 2020, thus suggesting the absence of a within-industry composition effect on county-level average wage.

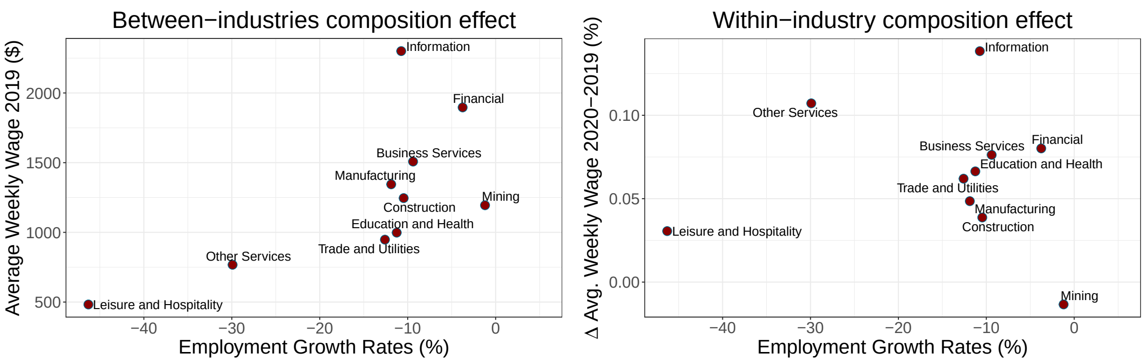

Figure B.2.1. **Composition effects on county-level wages. Left panel:** Employment growth rates between February 2020 and April 2020 vs. average weekly wages in 2019 by BLS supersector (data: QCEW, BLS). **Right panel:** Employment growth rates between February 2020 and April 2020 vs. change in average weekly wages between 2020 and 2019 by BLS supersector (data: QCEW, BLS).

C Features of the model

C.1 Historical and Variance Decomposition

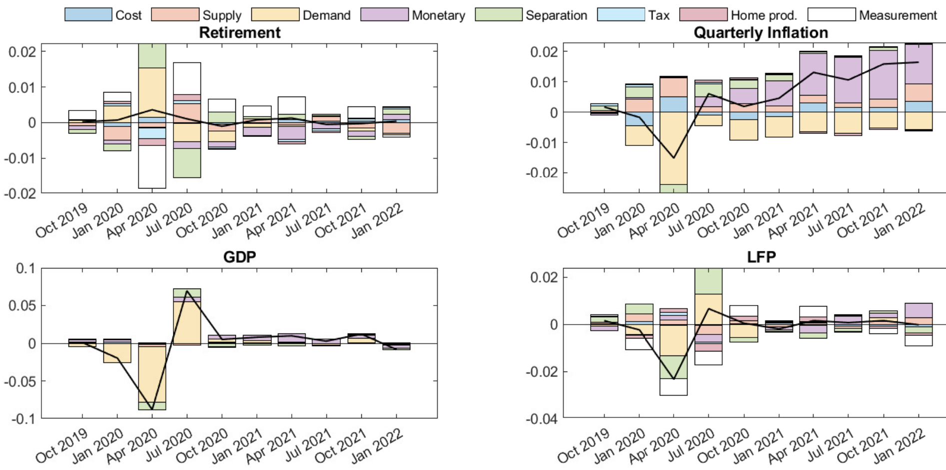

Figure C.1.1. **Historical decomposition from 2019:Q4 to 2022:Q2.** The Figure shows how the various shocks in the model affected the dynamics of key variables in the post-Covid period.

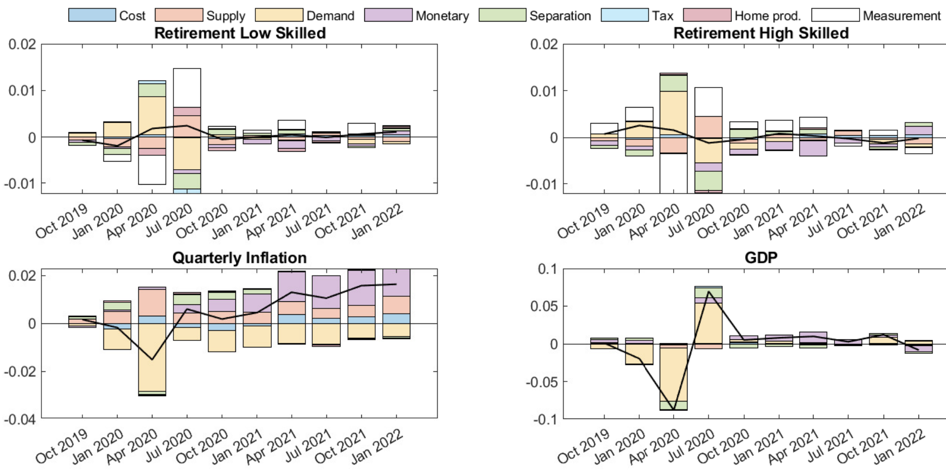

Figure C.1.2. **Historical decomposition for the heterogeneous productivity model.** The Figure shows how the various shocks in the model affected the dynamics of key variables in the post-Covid period.

	Supply	Home prod. young	Home prod. old	Preference	Monetary	Cost–push	Separation	Tax
Y	13.85	0.01	0.16	66.22	17.34	0.82	0.89	0.71
Inflation	28.79	0.03	0.47	23.75	19.30	22.99	3.40	1.28
Retirement	22.40	0.22	0.80	38.26	16.38	3.29	2.29	16.36
LFP	30.15	0.11	1.70	37.00	8.12	6.63	7.93	8.37

Table C.1.1. **Variance decomposition of the key macroeconomic variables.** Percent contribution to unconditional variance.

C.2 Cyclical behavior of retirement

Table C.2.1 reports the business cycle moments of retirement, participation and GDP to document some business cycle facts on retirement. Retirement is countercyclical in our sample, while labor force participation is procyclical. Interestingly, this does not hold anymore if we exclude the Covid years from the sample. This is consistent with our HD above.

	Full Sample 1998–2024			No-Covid Sample 1998–2019		
	σ_x	σ_x/σ_Y	corr(x_t,Y_t)	σ_x	σ_x/σ_Y	corr(x_t,Y_t)
GDP	1.25	1	1	0.59	1	1
Retirement	0.09	0.07	-0.19	0.08	0.13	0.08
LFP	0.27	0.22	0.72	0.14	0.24	-0.02
U old	0.63	0.53	-0.24	0.61	1.03	-0.21
U young	1.50	1.20	-0.22	1.42	2.39	-0.20
LFP young	0.34	0.28	0.72	0.18	0.30	0.05

Table C.2.1. Business cycle moments. The moments are computed using GDP growth, detrended growth of Retirement, Labor Force Participation (LFP), and Labor Force Participation of young (age 16–54) as a percentage of total population, and demeaned unemployment rates of the older population (age 55+) and younger population (age 16–54).

Figure C.2.1 shows the impulse response functions to an aggregated demand shock and an aggregate supply shock (i.e., a TFP shock). A aggregate demand shock induce a countercyclical response of retirement and procyclical of labor force participation, while the opposite is true for an aggregate supply shock. hence, the business cycle behavior of these two variables depend on the type of shocks hitting the economy, and the very large demand demand shock during the Covid period dominate the cyclical behavior of these two variable sin our sample.

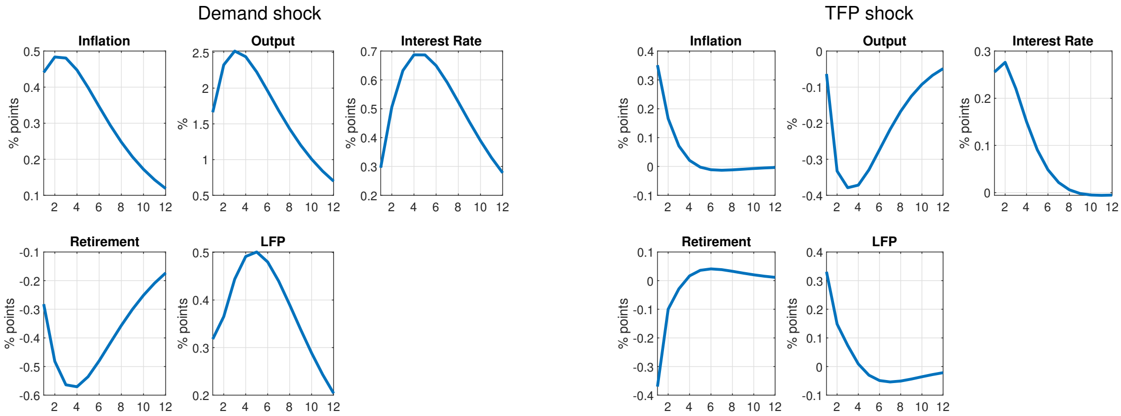

Figure C.2.1. **Impulse response functions.** The Figure shows the IRFs to demand shock (left) and TFP shock (right).

C.3 Impulse-Response functions (IRFs)

Monetary policy shock. Figure C.3.1 illustrates the dynamic responses to monetary policy shocks. The left-hand panels present the model-implied impulse response functions (IRFs), while the right-hand panels display the empirical IRFs, estimated using monthly-frequency local projections and monetary policy shocks from Jarociński and Karadi (2020). The empirical model adopts a standard specification that includes 12 lags of control variables: the Wu-Xia shadow rate (interest rate), the logarithm of industrial production (output), the inflation rate, the unemployment rate, the excess bond premium, the logarithm of the Commodity Research Bureau Index of global commodity prices, and the shock variable. For the IRFs of (log) retirement and (log) labor force, the model additionally controls for 12 lags of these respective variables. Shaded areas represent 68% confidence intervals. The empirical IRFs broadly align with those generated by the model. Both retirement and labor force participation rise on impact, consistent with model predictions, and the response of retirement is notably persistent. Inflation declines immediately, whereas the output response exhibits a delayed decrease.

Figure C.3.2 shows the IRFs to a monetary policy shock for different relative share of old and young people, to show how the effects of monetary policy shocks in our framework depend on the age structure of the population.

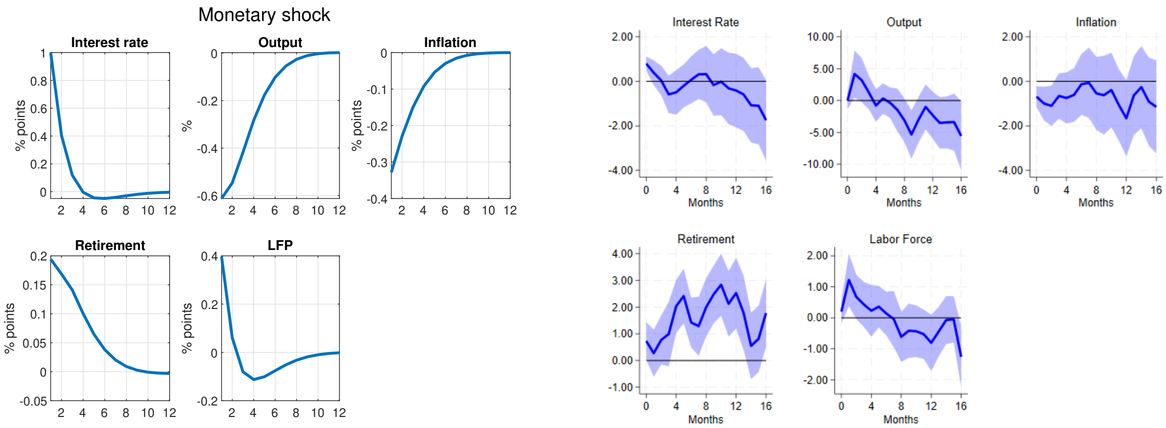

Figure C.3.1. **Left panels:** Model-implied IRFs to a 1% monetary policy tightening. **Right panels:** IRFs to a monetary policy tightening estimated using local projections with Jarociński and Karadi (2020) shocks.

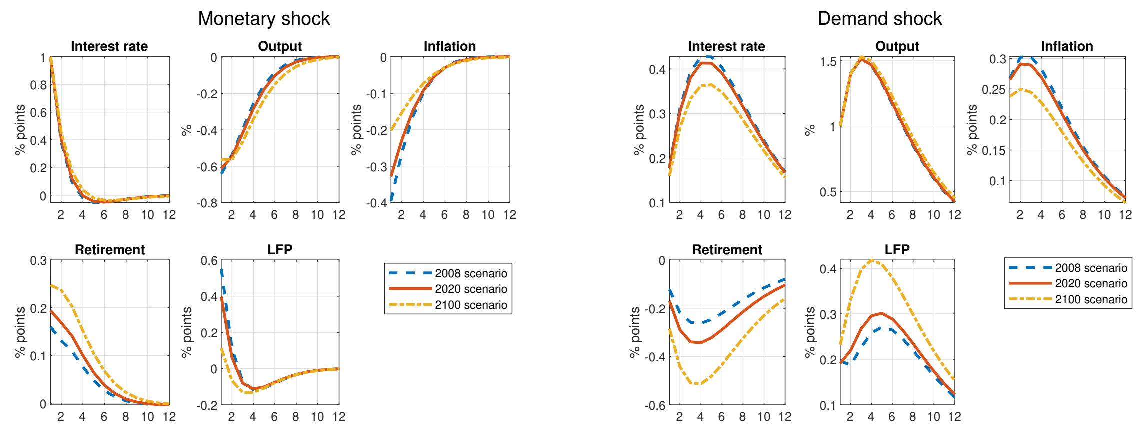

Figure C.3.2. The impact of shocks with different calibrations of the share of 55+. In the *2008 scenario* the share of 55+ is 30%; the *2020 scenario* corresponds to our baseline calibration with 37% of 55+; in the *2100 scenario* the share of 55+ is 48%, coherent with the projections of Census U.S. **Left panels**: Dynamic responses to a restrictive monetary shock. **Right panels**: Dynamic responses to a positive demand shock.

Home-productivity shock. Figure C.3.3 reports dynamic responses to a shock to home-productivity of old agents $A^h_{o,t}$. Such shock has a direct impact on the labor market participation of old agents and is used to control the dynamic path of retirement. In fact, a change in productivity at home has a direct effect on the marginal value of home-produced goods and thus on the benefit of being out of the labor force. The innovation to $A^h_{o,t}$ in Figure C.3.3

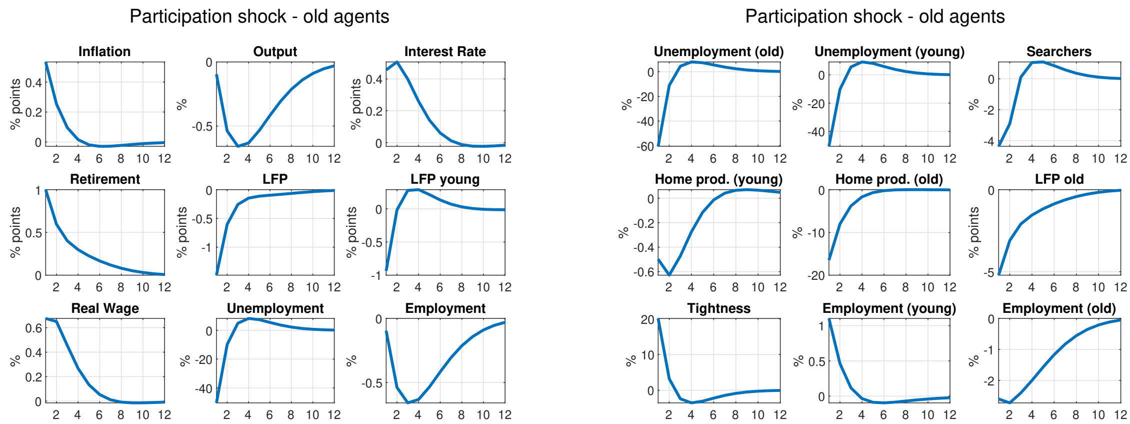

Figure C.3.3. **Dynamic responses to home-productivity shock for old agents.**

has been normalized to produce an increase in the retirement rate of 1 percentage point at impact. This increase corresponds to a rise of 0.4 percentage points in inflation at impact. The mechanism linking retirement to inflation is as follows. An increase in retirement leads to a decline in labor force participation, which in turn increases labor market tightness. In a tighter labor market the probability of finding a job for the fewer searching agents increases, thus explaining the increase in employment and decrease in unemployment of young agents. Moreover, when tightness increases, the vacancy filling rate drops, thus leading to an increase in the value of a filled vacancy. The latter effect, coupled with the increase in households' outside option when deciding whether to participate in the labor market (i.e., higher value of home-produced goods generated by the marginal non-participant for both young and old agents), puts upward pressure on wages. Intermediate-good producers, operating in perfect competition, increase their price causing higher marginal costs for final-goods producers and ultimately resulting in higher inflation.

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