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* Views expressed are those of the authors and do not necessarily reflect official positions of De Nederlandsche Bank.

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De Nederlandsche Bank NV
P.O. Box 98
1000 AB AMSTERDAM
The Netherlands

Great Layoff, Great Retirement and Post-pandemic Inflation*

Guido Ascari†
De Nederlandsche Bank, University of Pavia, CEPR, RCEA

Jakob Grazzini‡
University of Pavia

Domenico Massaro§
University of Milan

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Abstract

The Covid-19 shock caused a dramatic spike in the number of retirees – a phenomenon dubbed the "Great Retirement" – and a prolonged contraction in the labor force. This paper investigates the impact of the Great Retirement on the post-pandemic surge of inflation, via the labor market. First, retirement is generally countercyclical, and the peculiarity of the pandemic shock was just in its size: the "Great Layoff" in March and April 2020 triggered the Great Retirement. Hence, a transitory labor demand shock generated a persistent labor supply shock. Second, counties more exposed to the Great Layoff exhibit a relatively higher increase in wages. Finally, an estimated model with endogenous labor market participation quantitatively assesses the overall contribution of the Great Retirement to inflation from 2020:Q1 up to 2023:Q2 to be roughly equal to 3.7 percentage (cumulative) points.

Keywords: Great Retirement, Labor Force, Wages, Inflation.

JEL classification: E30, E24, J21.

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†Guido Ascari, De Nederlandsche Bank, Sparkelweg 4, 1096BA Amsterdam, Netherlands, and Department of Economics and Management, University of Pavia, Via San Felice 5, 27100 Pavia, Italy, Email: g.ascari@dnb.nl, guido.ascari@unipv.it.

‡Department of Economics and Management, University of Pavia, Via San Felice 5, 27100 Pavia, Italy, Email: jakob.grazzini@unipv.it.

§Domenico Massaro, Department of Economics, Management and Quantitative Methods, University of Milan, Via Conservatorio 7, 20122 Milan, Italy. Email: domenico.massaro1@unimi.it.

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 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 and increased labor market tightness, ultimately causing 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 we apply it 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). 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 labor force drop is very persistent and it has only partially recovered since then. In fact, the labor force in the US has reached the pre-pandemic level but it has not come back to the pre-pandemic trend. 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

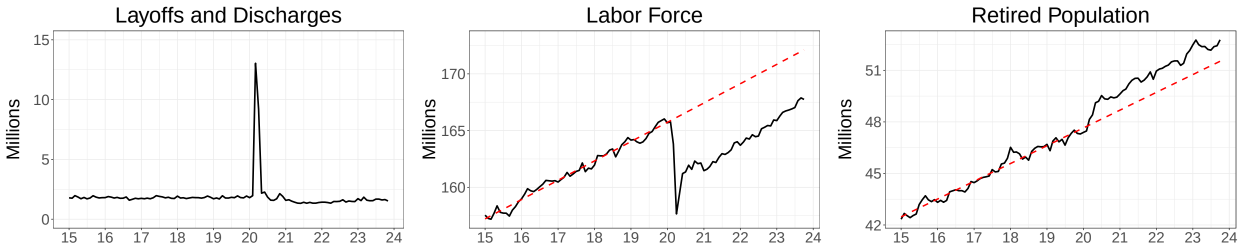

Figure 1. **Unprecedented surge in layoffs, persistent drop in the labor force and increase in retirement. Left**: Layoffs and discharges in million (data: FRB San Francisco, based on JOLTS, BLS). **Middle:** The solid black line is the labor force (age 16+) in millions, while the dashed red line is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

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

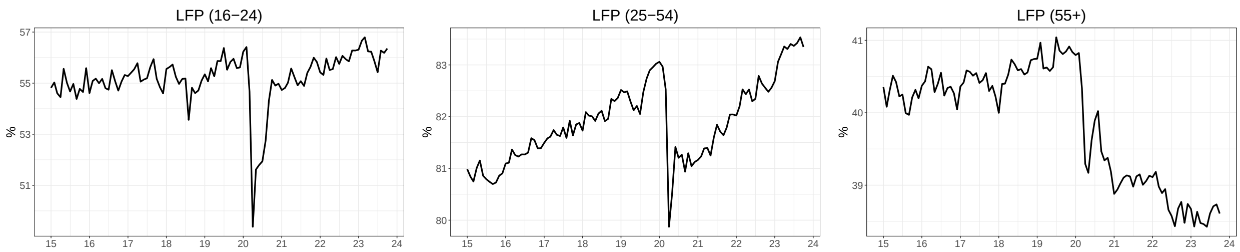

Figure 2. **Labor force participation by age group. Left**: Age group 16 – 24. **Middle:** Age group 25 – 55. **Right:** Age group 55+ (data: CPS-IPUMS, BLS).

months of the Covid-19 pandemic, LFP recovered for individuals in both 16–24 and 25–54 age groups. The former quickly recovered 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.

[1]Note that also the share of retired population persistently remained above the pre-pandemic trend by about 0.5 percentage points (see Figure 5). 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.

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.

The empirical 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.

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' members, *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] Our findings suggest that the Great retirement had: (i) a positive

[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

impact on inflation equal to roughly 3.7 percentage (cumulative) points of inflation from 2020:Q1 up to 2023:Q2, divided roughly in 1% in 2020, 1.3% in 2021, 0.9% in 2022 and the rest in the first two quarters of 2023; (ii) a negative impact on output equal to roughly 0.38 percentage (cumulative) points of GDP growth from 2020:Q1 up to 2023:Q2, divided roughly in 0.12% in 2020, 0.17% in 2021, 0.06% in 2022 and the rest in the first two quarters of 2023.

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 model to quantitatively assess the role played by the Great Retirement in the post-pandemic inflation surge. Finally, Section 5 concludes.

2 Related Literature

The US experienced a sharp and mostly unexpected surge in inflation following the Covid-19 pandemic. This has spurred an intense debate aimed at understanding why inflation has risen. Blanchard and Bernanke (2023) analyze the causes of post-pandemic inflation by estimating a simple dynamic model. They find that the initial increase in inflation is mostly explained by shocks to commodity prices, reflecting strong aggregate demand, and sectoral price spikes, resulting from changes in the sectoral composition of demand together with constraints on sectoral supply. Their results suggest that labor market tightness played a smaller role and it had a positive impact on inflation only starting from late 2021. Ferrante et al. (2023) study the inflationary effects of sectoral reallocation. They estimate a multi-sector model featuring sticky prices, input-output linkages, and labor reallocation costs, finding that a demand reallocation shock explains a large portion of the increase in US inflation after the pandemic. Comin et al. (2023) focus on constraints in the supply chain and argue that the post-pandemic behavior of the US economy is consistent with a negative shock to production capacity. Using a multisector, open economy, New Keynesian framework, they show that binding production constraints account for half of the increase in inflation during 2021-2022. 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

many other forces that contributed – some much more forcefully – to the post-pandemic inflation surge, see Section 2.

headline shocks – mainly changes in energy and in auto-related industries prices and supply chain disruptions – into core 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, given the observed increase in both job-openings and inflation after the pandemic. In particular, 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. On the contrary, 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., 2023) 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, either through an expected decrease in the natural rate of unemployment rate or an increase in the unemployment rate. Koch and Noureldin (2023) study the inflation forecast errors over the period 2021:Q1-2022:Q3 and find that, ex-post, core inflation forecast errors in 2021 are explained by strong demand recovery, pressures on supply chains, demand shift from services to goods and labor market tightness. Using an estimated New Keynesian model featuring oil as a complementary good for households and as a complementary input for firms, Gagliardone and Gertler (2023) show that a combination of oil price shocks and accomodative monetary policy mainly accounts for the post-pandemic surge in inflation. Bianchi et al. (2023) incorporate unfunded fiscal shocks in a quantitative New Keynesian model and show that fiscal inflation plays a major role in explaining the post-pandemic rise in inflation. di Giovanni et al. (2023) estimate a multi-country multi-sector New Keynesian model to quantify the drivers of the recent inflation surge. Their findings show that inflation was sparkled by pandemic-related supply shocks in factor markets and increased further due to expansionary fiscal and monetary policies that stimulated aggregate demand. Moreover, such shocks have been amplified by the sectoral reallocation of consumption combined with energy shocks. Amiti et al. (2023) use a calibrated two-sector New Keynesian model with multiple factors of production, endogenous markups and foreign competition to investigate the drivers of post-pandemic inflation. More specifically, they focus on supply chain disruptions, sectoral shift of consumption from goods to services coupled with accomodative monetary policy, and labor supply constraints. Their results show that the interaction between supply chain and labor disutility shocks had an amplification effect on price inflation due to diminishing firms' ability to minimize costs by substituting across inputs.[4]

The contributions in the literature are numerous and hence here we have to focus on a subset of them. However, the debate shows that the post-pandemic inflation has been a complicated phenomenon that involved multiple sources and complex interactions. Our analysis focuses on the labor market. Even if its relative importance is a matter of debate, there is no doubt that high labor market tightness has played a role in the recent inflation burst. We add to the literature on post-pandemic inflation by quantifying the marginal effect that the Great Retirement had on inflation dynamics.

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. Nie and Yang (2021) argue that the large increase in retirement due to the pandemic was mainly driven by a sharp reduction of the flow rate from retirement to employment, while the flow rate from unemployment to retirement actually decreased during the pandemic years.[5] The data in Figure 1 suggests that

[4]Other contributions to this debate are, e.g., Harding et al. (2023), Grazzini et al. (2023), and Cecchetti et al. (2023), among others.

[5]However, it is difficult to assess the relative contribution of the flow from unemployment to retirement looking just at the flow rate because, as the Nie and Yang (2021) argue, the steep increase in the unem-

the Great Layoff occurred in March and April 2020 induced an abrupt step increase in the number of retirees – that has to come from an increase in the transition into retirement – that became very persistent due to the fact that retirees did not get back to the labor force, consistently with the evidence in Nie and Yang (2021), thus contributing to the persistent contraction in the labor force. Finally, our counterfactual in the model with endogenous labor force participation decision in Section 4 is in line with this evidence because it is based on artificial shocks that will make retired agents to choose to counterfactually go back to the labor force. In the model, these two decisions – from retirement to unemployment or from unemployment to retirement – are two faces of the same coins because they are both based on the comparison between the value of being retired and the value of being unemployed.

Our paper confirms the finding that workers – especially the older ones – who are unemployed because of a layoff are more likely to retire and adds the following contributions. First, we show that this relationship between layoff and retirement has not changed during the Covid-19 pandemic and, thus, that the Great Retirement is simply the consequence of the Great Layoff due to the magnitude of the Covid-19 shock. Second, focusing on the pandemic period, we leverage on differential counties' exposure to layoffs to provide further evidence that this mechanism has been at play during the Covid-19 crisis. Counties more exposed to the Great Layoff in March and April 2020 show a stronger increase in retirement in the following quarters. Finally, we also show that such counties display a higher growth in nominal wages, thus linking the temporary shift in labor demand to a more persistent effect on labor supply that increased inflationary pressures.

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 de-

ployment level from February to April 2020 largely explains the decline in the unemployment-to-retirement transition rate.

mographic 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 November 2023, 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]

	Dependent variable: Retired					
	Age over 55			Full sample		
	(1)	(2)	(3)	(4)	(5)	(6)
Layoff	0.055***	0.030***	0.033***	0.014***	0.009***	0.009***
Covid-19 × Layoff	–	–	−0.010	–	–	−0.000
Controls	no	yes	yes	no	yes	yes
n.obs	3,119,539	317,772	317,772	15,379,309	1,461,912	1,461,912

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

Table 1. **Laid off workers are more likely to retire, and Covid-19 was not special in this respect.** OLS estimation with state × 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 × year fixed effects.

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 of employment (12 months before the survey) and assign each respondent to a wage decile

[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.

(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 interacted state and year 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. Finally, in columns 3 and 6 we interact the employment status of respondents with a Covid-19 dummy, taking value 1 if the survey is conducted after February 2020.[8] Results show that retirement decisions did not change during the Covid-19 era, but the size of the pandemic-induced layoff shock made it quantitatively relevant.

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 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 a new employer might offer could be well below the worker's previous wage, reducing the likelihood of an offer being accepted. In Appendix C we add to this literature by developing a very simple partial equilibrium life-cycle model where the relative values of labor market states (employed, unemployed and retired) depend on a worker's age. Layoffs change a worker's state from employed to unemployed, and this change triggers a retirement when the worker is old enough, that is when the value of retirement is higher than the value of unemployment. This mechanism is not peculiar to the pandemic crisis but it is general and it explains the counter-cyclical behavior of retirement found in, e.g., Gorodnichenko et al. (2013), Coile and Levine (2009, 2011). However, the unprecedented amount of layoffs occurred in March and April 2020, i.e., about 22 millions workers – more than 13% of the total labor force – made this phenomenon particularly evident. In the following section we provide evidence that the temporary labor demand shock causing the Great Layoff had a persistent effect on labor supply, causing the Great Retirement and upward pressures on nominal wages.

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

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 3 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.[9,10] The rationale for presenting this result 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 3, Leisure, and Hospitality 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

[9] Supersectors are derived from the BLS aggregation of NAICS sectors. We excluded from the analysis supersectors labeled Public Administration and Unclassified.

[10] 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).

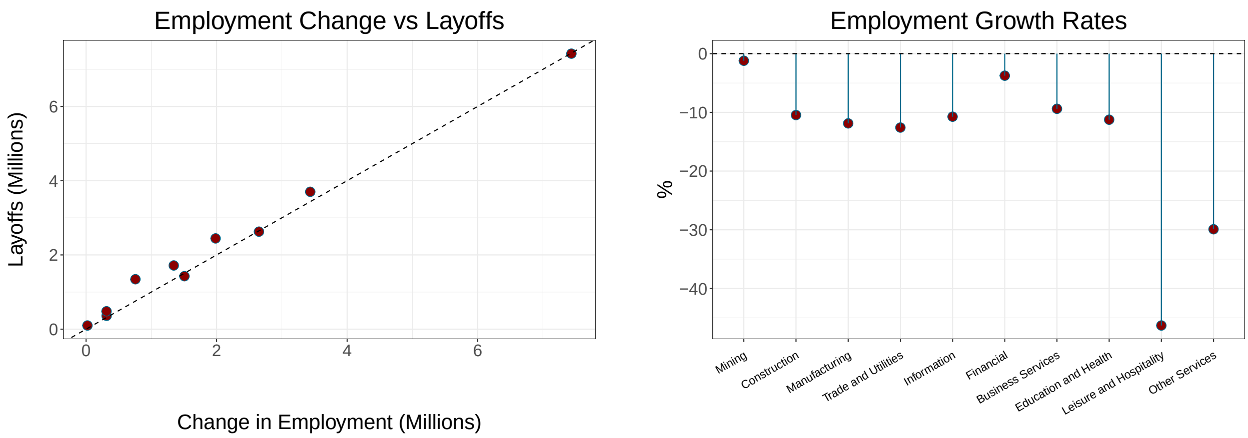

Figure 3. **Employment changes are mostly layoffs and they are asymmetric across sectors. Left**: Change in national employment level between February 2020 and April 2020 (in absolute value) and sum of layoffs occurred in March and April 2020 by BLS supersector (data: JOLTS, BLS and QCEW, BLS). **Right**: National employment growth rate between February 2020 and April 2020 by BLS supersector (data: QCEW, BLS).

of the state in which county ℓ is located.[11] In our empirical exercise we set $t_0 = 2019$, so that industry shares are fixed to an initial time period prior to the Covid-19 shock,[12] 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.[13]

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 2023:Q3

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

The labor market outcomes (y) of interest are the retired-to-population ratio, individuals not in labor force and not retired over total population, and (log) nominal wages. We thus

[11] 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 our results.

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

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

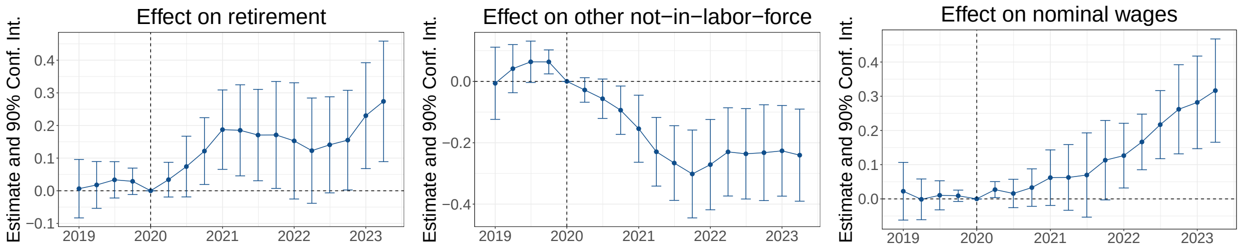

Figure 4. **Counties more exposed to the Great Layoff display higher retirement and higher wages. Left**: Dynamic response of retirement to the Great Layoff (data: CPS-IPUMS, BLS and QCEW, BLS). **Middle**: Dynamic response of individuals not in labor force and not retired to the Great Layoff (data: CPS-IPUMS, BLS and QCEW, BLS). **Right**: Dynamic response of nominal wages to the Great Layoff (data: QCEW, BLS).

estimate separate regressions for each outcome and for each quarter between 2019:Q1 and 2023:Q3, so that $\Delta y_{\ell,q}$ is the change in an outcome for county ℓ between 2020:Q1 and quarter q.[14] 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.[15]

Results of the estimation of Eq. (2) are reported in Figure 4. 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 4 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. The estimated response of retirement (Figure 4, left panel) confirms our previous findings: the Great Layoff triggered early retirement of the older segment of displaced workers, we 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 4, middle 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

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

[15] 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.

individuals not in labor force and not retired, i.e., younger workers flowing into the labor force. The response of nominal wages (Figure 4, right 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 persistent shift in the labor supply due to the Great Retirement. Eventually, re-entry of displaced younger workers in the labor force together with the entry of new workers that were outside the labor force (Figure 4, middle panel) are making up for the gap, but the process takes time, as suggested by Figures 1 and 2, such that a transitory labor demand shock determined a persistent supply shock.

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 3, layoffs were concentrated in Leisure and Hospitality and Other Services supersectors, which are characterized by relatively lower wages (see Figure B.2, 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 (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.

What is the effect of this persistent labor supply shock on the post-pandemic inflation? Unfortunately, there are no data on inflation at the county level that we could use to perform the same analysis we did above for wages, so we need to resort to a model to assess the quantitative effect of the Great Retirement on aggregate inflation.

4 The impact of Great Retirement on post-pandemic inflation

This section presents a model to rationalize these empirical findings 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 Appendix D contains the detailed 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. Unemployed, non-participants and separated workers at the end of period $t - 1$, i.e. $U_{t-1} + N_{t-1} + \rho E_{t-1}$ 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

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

with $S_t \geq 0$. As in Campolmi and Gnocchi (2016), we assume instantaneous hiring, so that 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 $E_t = (1 - \rho)E_{t-1} + f_t S_t$.[16] 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^n only if old. Therefore, the benefit from being out of the labor force is equal 0 for young agents, $b^n_y = 0$, and equal to b^n for old agents, $b^n_o = b^n$.

Income is pooled across across households 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). The nominal budget constraint of type a agents is given by

$$\int_0^1 P_{i,t}C_{i,t}di + R_t^{-1}D_t \leq D_{t-1} + E_{a,t}W_t + P_t b^u U_{a,t} + P_t b^n_a N_{a,t} + T_t \ , \tag{3}$$

where $\int_0^1 P_{i,t}C_{i,t}di$ is the expenditure on consumption goods, D_t is the stock of bonds, R_t is the gross nominal interest rate, P_t is the aggregate price level and T_t is a lump sum tax.

Following Campolmi and Gnocchi (2016), both household types derive utility from consumption of market-produced as well as home-produced goods. Consumption of market-produced goods is common across households and the composite bundle that enters the utility function is defined as $C_t \equiv \left[\int_0^1 C_{i,t}^{\frac{\epsilon-1}{\epsilon}} di\right]^{\frac{\epsilon}{\epsilon-1}}$ with $\epsilon \geq 1$. The corresponding aggregate price index is $P_t \equiv \left(\int_0^1 P_{i,t}^{1-\epsilon} di\right)^{\frac{1}{1-\epsilon}}$. Home-produced goods are the result of housework time, which can be heterogeneous across household types. Home-produced goods are thus indexed by a and defined as $h_{a,t}$. For each household type, the housework time foregone

[16] 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., ρE_{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., $L_t \geq (1 - \rho)E_{t-1}$.

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

$$h_{a,t} = \left[A^h_{a,t}(1 - E_{a,t} - \Gamma U_{a,t})\right]^{1-\alpha_h} , \tag{4}$$

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 $\log(A^h_{a,t}) = \rho^h_a \log(A^h_{a,t-1}) + \epsilon^h_{a,t}$ with $\epsilon^h_{a,t}$ i.i.d. with zero mean and variance $\sigma^2_{a,h}$.

The flow utility function is defined as

$$\mathcal{U}_{a,t} \equiv Z_t \log(C_t - \xi C_{t-1}) + \phi \frac{(h_{a,t})^{1-\nu_a}}{1-\nu_a} , \tag{5}$$

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 common across types and written as

$$R_t \mathbb{E}_t \left(Q_{t,t+1} \Pi^{-1}_{t+1}\right) = 1 , \tag{6}$$

where $Q_{t,t+1} \equiv \beta \left(\frac{C_t - \xi C_{t-1}}{C_{t+1} - \xi C_t} \frac{Z_{t+1}}{Z_t} \right)$ is the stochastic discount factor and $\Pi_{t+1} \equiv \frac{P_t}{P_{t+1}}$ is gross inflation. The participation condition may 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

$$\begin{aligned} f_t \frac{W_t}{P_t} + (1-f_t) b^u + \mathbb{E}_t \left[Q_{t,t+1} f_t (1-\rho) \frac{1-f_{t+1}}{f_{t+1}} (\Gamma MRS_{a,t+1} - b^u + b^n_a) \right] = \\ b^n_a + MRS_{a,t} \left[f_t + (1-f_t)\Gamma \right] , \end{aligned} \tag{7}$$

where $MRS_{a,t} \equiv \frac{C_t - \xi C_{t-1}}{Z_t} \phi A^h_{a,t} (1-\alpha_h)(h_{a,t})^{-\frac{\alpha_h}{1-\alpha_h} - \nu_a}$ denotes the value of home-produced goods generated by the marginal non-participant in terms of market consumption goods. The participation condition in Eq. (7) requires equating the benefits of allocating the marginal non-employed agent (at the beginning of period t) between S_t and N_t. Let us first consider the left-hand side of Eq. (7), representing the expected benefit of marginally increasing the pool of searchers S_t. The first two terms represent direct benefits given by the probability of becoming employed times the real wage plus the probability of not being hired times the unemployment compensation. To interpret the term between square brackets, start by noticing that employment in t also has an impact on unemployment in $t+1$. In fact, a marginal increase in $E_{a,t}$, occurring with probability f_t, reduces job searchers in $t+1$ by a factor $1/f_{t+1}$ with probability $(1-\rho)$, i.e., if there is no exogenous separation. When fewer households members are allocated to S_{t+1}, future unemployment U_{t+1} decreases by a factor $(1-f_{t+1})$. This leads to a benefit in terms of home production, net of the loss of unemployment compensation b^u, given by the saving in searching time Γ times the value of home-produced goods generated by the marginal non-participant. Moreover, this benefit is increased by the pension b^n_a, equal to b^n if the agent is of type old and zero otherwise. Now consider the right-hand side of Eq. (7), representing the expected benefit of marginally increasing the pool of non-participating agents N_t. The first term is the direct benefit in terms of real pension, b^n_a. The second term represents the direct benefit in terms of home production. The amount of time gained for home production by a non-participant with respect to a searcher is equal to 1 with probability f_t and Γ with probability $(1-f_t)$, and needs to be multiplied by the value of home-produced goods generated by the marginal non-participant, i.e., $MRS_{a,t}$.

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 $\log(A_t) = \rho_A \log(A_{t-1}) + \epsilon^A_t$ with ϵ^A_t i.i.d. with zero mean and variance σ^2_A. 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 the value of a filled vacancy is given by

$$V^J_t = \frac{P^X_t}{P_t} A_t - \frac{W_t}{P_t} + (1-\rho)\mathbb{E}_t[Q_{t,t+1} V^J_{t+1}] \ . \tag{8}$$

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

$$k = q_t V^J_t \ , \tag{9}$$

where q_t denotes the probability of filling the vacancy. Substituting Eq. (9) into (8) we obtain the job creation condition

$$\frac{k}{q_t} = \frac{P_t^X}{P_t} A_t - \frac{W_t}{P_t} + (1-\rho)\mathbb{E}_t \left[Q_{t,t+1} \frac{k}{q_{t+1}} \right] . \tag{10}$$

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 technology

$$Y_{i,t} = X_{i,t}^{1-\alpha} \tag{11}$$

in a monopolistically competitive market. Defining the price of firm i in period t as $P_{i,t}^*$, the downward sloping demand function faced by the firm is

$$Y_{i,t} = \left(\frac{P_{i,t}^*}{P_t} \right)^{-\epsilon} Y_t \ , \tag{12}$$

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 $RMC_t \equiv \frac{P_t^X}{P_t} \frac{1}{1-\alpha} Y_t^{\frac{\alpha}{1-\alpha}}$, with weights depending on expected future demand and the discount factor. In each period t, the average price level is given by the aggregator

$$P_t^{1-\epsilon} = \delta P_{t-1}^{1-\epsilon} + (1-\delta)(P_t^*)^{1-\epsilon} \ , \tag{13}$$

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

$$\Pi_t = \left(\frac{1-(1-\delta)\left(\frac{P_t^*}{P_t}\right)^{1-\epsilon}}{\delta} \right)^{\frac{1}{\epsilon-1}} . \tag{14}$$

For the sake of estimation, we add a cost-push shock to this last equation (see Appendix D).

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 $V^w_{a,t}$ resulting from reaching an agreement for the household is determined by the net benefit of having an additional member employed instead of unemployed, for a chosen level of participation $L_t = \bar{L}$, that is

$$V^w_{a,t} = \frac{W_t}{P_t} - b^u - (1-\Gamma)MRS_{a,t} + \mathbb{E}_t\left[Q_{t,t+1}(1-\rho)(1-f_{t+1})V^w_{a,t+1}\right] \ . \tag{15}$$

According to Eq. (15), the surplus of moving an additional member from unemployment to employment is given by the real wage net of the unemployment compensation, minus the cost of the additional foregone time dedicated to home production, plus discounted future surplus times the amount by which future employment is increased due to a marginal increase in current employment. The surplus from a match between a job searcher and a firm is split according to Nash bargaining

$$\eta V^w_t = (1-\eta)V^J_t \ , \tag{16}$$

where the union considers average surplus given by

$$V^w_t \equiv \zeta V^w_{y,t} + (1-\zeta)V^w_{o,t} = \frac{W_t}{P_t} - b^u - (1-\Gamma)MRS_t + \mathbb{E}_t\left[Q_{t,t+1}(1-\rho)(1-f_{t+1})V^w_{t+1}\right] \ , \tag{17}$$

and $MRS_t \equiv \zeta MRS_{y,t} + (1-\zeta)MRS_{o,t}$. Substituting the definitions of V^w_t and V^J_t into Eq. (16), together with the free entry and the job creation conditions, and using that $\theta_t = f_t/q_t$, we can write the wage equation above as

$$\frac{W_t}{P_t} = (1-\eta)\frac{P^X_t}{P_t}A_t + \eta[b^u + (1-\Gamma)MRS_t] + (1-\eta)(1-\rho)\mathbb{E}_t\left[Q_{t,t+1}k\theta_{t+1}\right] \ . \tag{18}$$

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

$$X_t = \int_0^1 X_{j,t}dj = A_tE_t \ , \tag{19}$$

while the standard aggregate resource constraint can be written as

$$Y_t = C_t + kV_t \ , \tag{20}$$

where aggregate output is defined by the standard aggregator

$$Y_t = \left(\int_0^1 Y_{i,t}^{\frac{\epsilon-1}{\epsilon}} di \right)^{\frac{\epsilon}{\epsilon-1}} . \tag{21}$$

Using Eqs. (11) and (12), we can write the aggregate production function as

$$Y_t = X_t^{1-\alpha} \Delta_t^{\alpha-1} , \tag{22}$$

where Δ_t is a measure of price dispersion defined as

$$\Delta_t = \int_0^1 \left(\frac{P_{i,t}}{P_t} \right)^{-\frac{\epsilon}{1-\alpha}} di . \tag{23}$$

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

$$\log(R_t) = \rho_R \log(R_{t-1}) + (1-\rho_R)[-\log(\beta) + \phi_\pi \log(\Pi_t) + \phi_y \log(\tilde{Y}_t)] , \tag{24}$$

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.

4.2 Calibration and estimation

We calibrate some parameters and estimate the others using Bayesian techniques. The model is calibrated to match steady state values in the literature and in US data. Specifically, the values of unemployment benefit, pension and scale parameter in the utility function are calibrated in order to match the employment rate, the overall participation rate and the participation rate of old workers. The share of young population is set to reflect demographic data in the US. The full list of calibrated parameters is shown in Table 2. 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 and real consumption growth (see Appendix A for a detailed data description). Table 3 reports the list of estimated parameters, information on priors and the estimated posterior mode.

	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	2/3	Price duration
Job-separation rate	ρ	0.12	Campolmi and Gnocchi (2016)
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	0.44	Campolmi and Gnocchi (2016)
Firms' search cost	κ	0.0196	Campolmi and Gnocchi (2016)
Unemployment benefit	b^u	0.3836	96.5% Employment rate
Relative preference for home over market goods	ϕ	0.0426	63% Participation rate
Matching efficiency	ω	0.66	2/3 Job filling rate
Pension	b^n	0.6328	40% participation rate of old workers
Share of young population	w	0.63	Share of population over 16 and under 55

Table 2. Calibrated parameters

		Prior			Posterior			
	Param	Dist	Mean	SD	Mode	Median	10%	90%
Final goods production function	α	B	0.33	0.2	0.0168	0.0325	0.0087	0.0773
Inverse of intertemporal elasticity young	ν_y	IG	5	2	4.6005	4.6822	3.8850	5.7644
Inverse of intertemporal elasticity old	ν_o	IG	5	2	4.3614	4.1881	3.0482	6.0696
Consumption habits	ξ	B	0.5	0.1	0.9391	0.9432	0.9189	0.9618
Monetary policy parameter	ϕ_π	N	1.5	0.12	1.6320	1.6344	1.4874	1.7840
Monetary policy parameter	ϕ_y	G	0.125	0.05	0.1051	0.1132	0.0639	0.1838
Persistence of policy rate	ρ_R	B	0.75	0.1	0.5377	0.5727	0.4826	0.6749
Persistence of technology shock	ρ_A	B	0.5	0.2	0.5458	0.5499	0.4234	0.6504
Persistence of HP technology shock (young)	ρ_y^h	B	0.5	0.2	0.6329	0.6028	0.3294	0.8292
Persistence of HP technology shock (old)	ρ_o^h	B	0.5	0.2	0.4077	0.4258	0.1934	0.6824
Persistence of preference shock	ρ_Z	B	0.5	0.2	0.9087	0.9037	0.8466	0.9376
Persistence of monetary shock	ρ_{mp}	B	0.5	0.2	0.8380	0.8221	0.7006	0.8776
Persistence of cost-push shock	ρ_{cp}	B	0.5	0.2	0.1085	0.1447	0.0600	0.2690
Std. technology shock	σ_A	IG	0.1	2	0.0165	0.0169	0.0145	0.0197
Std. HP technology shock (young)	$\sigma_{y,h}$	IG	0.1	2	0.0276	0.0288	0.0226	0.0375
Std. HP technology shock (old)	$\sigma_{o,h}$	IG	0.1	2	0.0324	0.0366	0.0262	0.0548
Std. preference shock	σ_Z	IG	0.1	2	0.0662	0.0653	0.0483	0.0863
Std. monetary shock	σ_{mp}	IG	0.1	2	0.0105	0.0104	0.0093	0.0117
Std. cost-push shock	σ_{cp}	IG	0.1	2	0.0095	0.0096	0.0087	0.0107
Std. Measurement Error GDP	σ_y	IG	0.1	2	0.0098	0.0099	0.0090	0.0110
Std. Measurement Error Inflation	σ_π	IG	0.1	2	0.0113	0.0112	0.0101	0.0126
Std. Measurement Error LFP	σ_{lfp}	IG	0.1	2	0.0108	0.0111	0.0100	0.0125
Std. Measurement Error Retirement	σ_{ret}	IG	0.1	2	0.0110	0.0114	0.0102	0.0128
Std. Measurement Error Real wage	σ_{rw}	IG	0.1	2	0.0104	0.0104	0.0094	0.0116
Std. Measurement Error Consumption	σ_c	IG	0.1	2	0.0093	0.0094	0.0086	0.0104

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

4.3 Results

The posterior mode of the estimated structural parameters shows that the data calls for almost constant returns to scale in the production function for the final goods producers, a relatively high value of the habit persistence parameter, and very standard monetary policy parameters. The intertemporal elasticity parameters are comparable across types, with the estimated posterior mode being slightly higher for young agents. The preference and the monetary policy shock are the most persistence ones, while the cost-push shock has very low persistence.

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. 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 estimation 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. 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 out of the labor force.[17] We then perform the following counterfactual exercise. First, we compute the smoothed values of endogenous variables and exogenous shocks from 1998:Q1 to 2023:Q3 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 value of home-production productivity 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 5 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

[17] Figure D.4 in Appendix D.2 reports the dynamic responses to a shock to home-productivity of old agents.

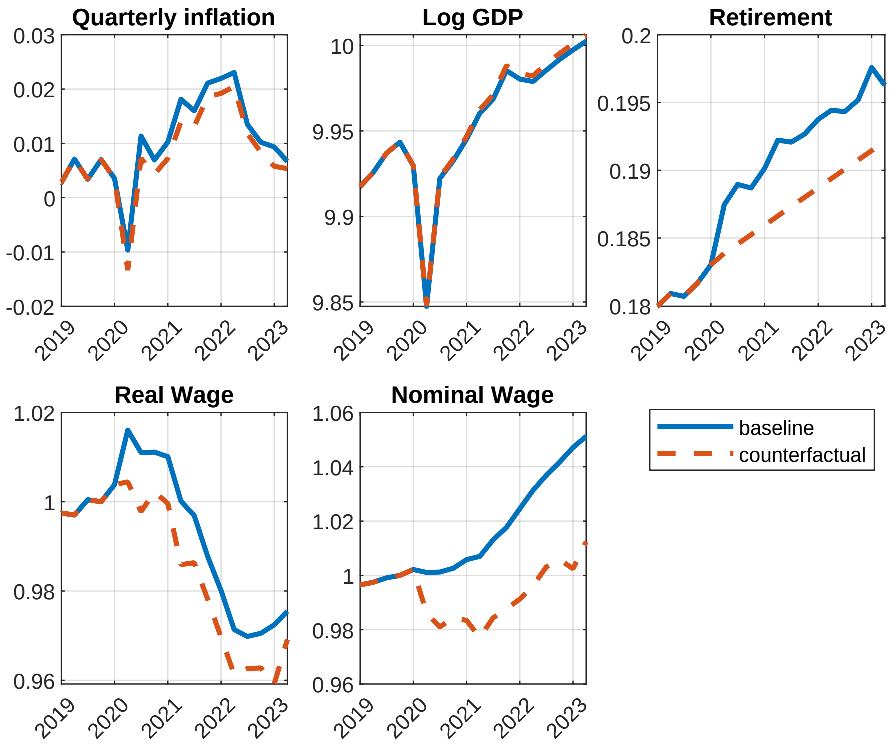

Figure 5. **A counterfactual economy where the Great Retirement never happened.** The Figure shows the simulation from the baseline model (continuous blue) and from the counterfactual economy (dashed orange) without the Great Retirement. The baseline is the smoothed values produced using the estimated model and coincides with the actual data. The dashed line are the simulated values from a counterfactual exercise where home-production productivity of old agents is engineered in order to put retirements on the 2011:Q1 - 2019:Q4 linear trend.

actual data of the observed variables. The difference between baseline and counterfactual shows the impact of the Great Retirement on aggregate variables.[18]

The right-upper panel of Figure 5 displays the dynamics of retirement. By design, in the counterfactual model, retirement follows the pre-Covid-19 linear trend. Looking a the difference between the two lines, we see a jump in retirement and, then, from 2021:Q1 the blue line goes back – more or less – to the pre-Covid-19 growth trend . The average difference between the two lines after the initial jump – more specifically, from 2021:Q1 onward – is of

[18]It is worth stressing that, in this exercise, home-productivity shocks are merely a device to engineer the counterfactual retirement behavior in our TANK model, and thus to evaluate the impact of retirement on macroeconomic aggregates, and not as the source of the Great Retirement, which in our estimation will be due to a combination of the estimated structural shocks.

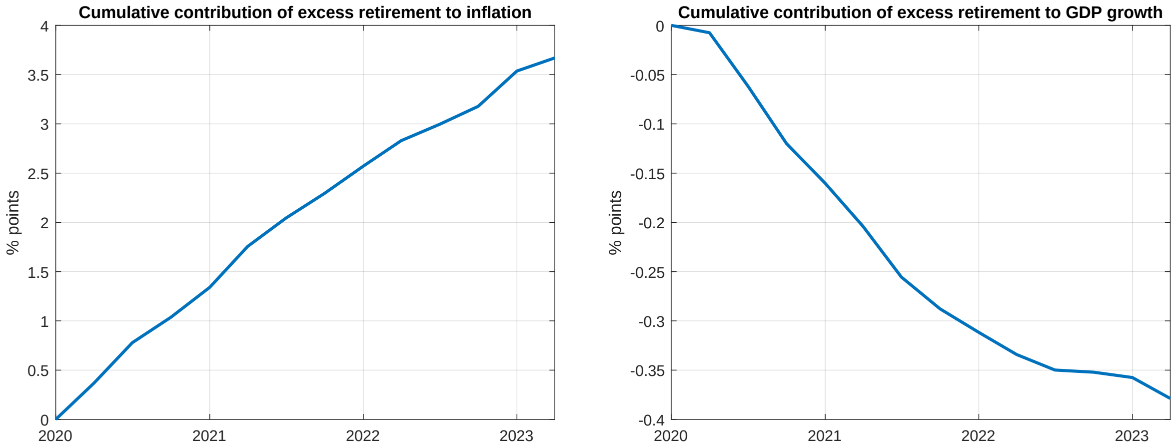

Figure 6. **Cumulative contribution of the Great Retirement to inflation and to output growth. Left**: Cumulative contribution to inflation. **Right**: Cumulative contribution to real GDP growth.

0.5 percentage points. This figure shows – as Figure 1 in Section 1 – that a very large, but temporary, shock as Covid-19 (see the behavior of GDP in the middle-top panel) translated into a very persistent labor supply shock. The Great Retirement had important consequences on the labor market, inflation and output. In absence of the Great Retirement, the nominal wage would have been about 2% lower in 2021:Q1, 3% lower in 2022:Q1 and 4% lower in 2023:Q1 with respect to actual data. This is qualitatively coherent with the estimated dynamic response of nominal wages in Figure 4. As a result, inflation – as well as the real wage – would have been lower, while output would have been higher in the counterfactual economy.

While judging from Figure 5 it might seem that the effects on inflation and output are immaterial, it is actually not so. Figure 6 highlights the contribution of the Great Retirement on inflation and output, by showing the cumulative percentage difference between the baseline and the counterfactual economy from 2020:Q1 to 2023:Q2. According to our counterfactual the Great retirement had a positive impact on inflation equal to roughly 3.7 percentage (cumulative) points of inflation from 2020:Q1 up to 2023:Q2, divided roughly in 1% in 2020, 1.3% in 2021, 0.9% in 2022 and the rest in the first quarters of 2023. Moreover, it had a negative impact on output equal to roughly 0.38 percentage (cumulative) points of GDP growth from 2020:Q1 up to 2023:Q2, divided roughly in 0.12% in 2020, 0.17% in 2021, 0.06% in 2022 and the rest in the first quarters of 2023.

Finally, as a validation exercise, we plot in Figure 7 the smoothed value of $N_{y,t}$, i.e., the percentage of young population who is not in the labor force, implied by the estimated model using parameters at the posterior mode against CPS-IPUMS data on the percentage of individuals of age between 16 and 54, who are not in the labor force over the total population of that age range. The model does a good job in reproducing the qualitative pattern of observed 16 – 54 individuals out of the labor force, with a statistically significant correlation between simulated and actual data of approximately 0.68.

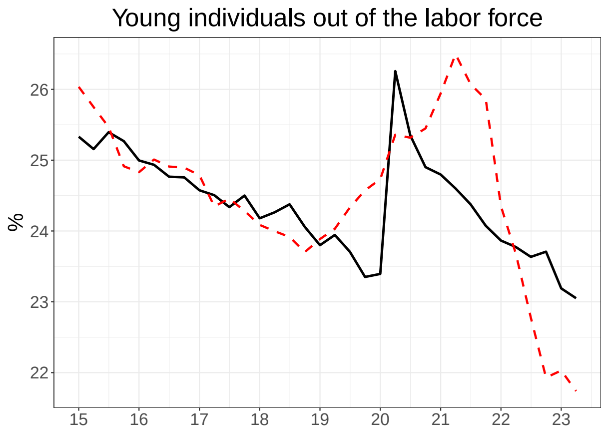

Figure 7. **Simulated and actual data on young individuals out of the labor force.** The black solid line denotes the percentage of individuals between 16 and 54 who are not in the labor force (data: CPS-IPUMS). The red dashed line denotes smoothed values of young non-participant $N_{y,t}$ using model parameters at their posterior mode.

5 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 a persistent decrease in the labor force due to 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, for an exposure research design empirical investigation, which shows 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 persistent reduction of the labor supply, via a surge in early retirements, ultimately causing inflationary pressures in the form of higher wages.

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 roughly 3.7 percentage (cumulative) points of inflation from 2020:Q1 up to 2023:Q2, divided roughly in 1% in 2020, 1.3% in 2021 and 0.9% in 2022; (ii) a negative impact on output equal to roughly 0.38 percentage (cumulative) points of GDP growth from 2020:Q1 up to 2023:Q2, divided roughly in 0.12% in 2020, 0.17% in 2021 and 0.06% in 2022.

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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 were retrieved in February 2024 and 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-explorer/.

Labor Force is constructed using data from the Current Population Survey (CPS-IPUMS) collected by the Bureau of Labor Statistics. Data were retrieved in January 2024 and 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 and January 2023 by the Census Bureau and the Bureau of Labor Statistics (see e.g., "Adjustments to Household Survey Population Estimates in January 2023", US Bureau of Labor Statistics, Technical Documentation available at https://www.bls.gov/cps/population-control-adjustments-2023.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 2023 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 were retrieved in January 2024 and 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 were retrieved in January 2024 and 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 and 4.

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/.

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 3) 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 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 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 were retrieved in January 2024 and 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 and 2023 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.

Real GDP Growth is constructed using quarterly real GDP data [GDPC1] from the Bureau of Economic Analysis, 1998:Q1 – 2023:Q3. 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 – 2023:Q3. 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 – 2023:Q3. 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 were retrieved in January 2024 and 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 – 2023:Q3 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 – 2023:Q3 and changes are obtained by taking first differences of the HP-filtered retired over population series.

Real Wage Growth is constructed using 1998:Q1 – 2023:Q3 quarterly data on the Employment Cost Index collected by the Bureau of Labor Statistics. In particular, we consider the growth rate in total compensation for all civilian workers in all industries and occupations (current dollar index) as the growth rate of nominal wages. Data until 2001:Q1 are based on SIC industry classification, while data from 2001:Q2 are based on NAICS industry classification. Real wage growth is then obtained as the de-meaned difference between the growth rates of nominal wages and CPI.

Real Consumption Growth is constructed using quarterly real personal consumption expenditures [PCECC96] from the Bureau of Economic Analysis, 1998:Q1 – 2023:Q3. 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.

B Additional figures

B.1 Estimates of individual controls

Figure B.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.

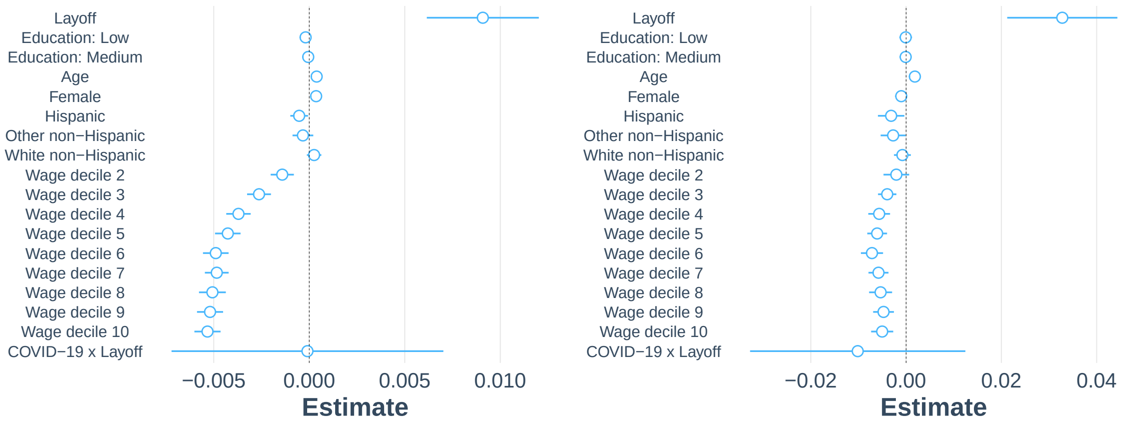

Figure B.1. **Estimated coefficients and 95% confidence intervals for regressions in Table 1.** Reference categories for education, ethnicity and wage decile are respectively Education: High, Black non-Hispanic and Wage decile 1. **Left panel:** full sample including all ages above 16. **Right panel:**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

B.2 Composition effects on county-level wages

Figure B.2 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. **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 Simple partial equilibrium model

To rationalize the empirical findings in Table 1, we build a very simple deterministic partial equilibrium life-cycle model. The economy is populated by individuals with discrete ages ranging from 16 to 80. At the age of 80, agents leave the economy. Individuals are homogeneous in every other characteristic but their age and they may be in three possible states: employed, unemployed and retired. Since the model aims at just being illustrative about the impact of a layoff on the decision of retiring versus remaining in the labor force, we simplify it by assuming that it is not possible to go back from retirement to labor force, and to be out of the labor force without being retired.

We now describe the lifetime value of each state as a function of age. The value of being retired is

$$V_r(a) = \sum_{t=a}^{T} \beta^{(t-a)}(p(a) + h) \; , \tag{C.1}$$

where a is the age, $T = 80$ is the maximum age, β is the discount factor, h is home-production, and $p(a)$ is the pension accruing to the retired worker. The pension is increasing with the retirement age, so that $p'(a) > 0$, and it is constant once retired. This provides an incentive to delay the retirement date. In particular, we assume that every agent has the right to a minimum pension and that the pension will be paid only once agents reach the age of 55. This means that every agent that stops working at an age smaller than, or equal to, 55, will receive the minimum pension from age 55 onward. We set the minimum pension (in real terms) to 80% of the - constant and normalized to 1 - real wage. After the age of 55, the pension increases by 0.004 each year. If an agent decides to retire at age 56, they will receive a pension of 0.804 for the rest of their life. Similarly, if an agent decides to retire at 65, they will get a pension of 0.84 for the rest of their life.

The value of being unemployed can be written as

$$V_u(a) = b + \Gamma h + \beta(fV_e(a+1) + (1-f)N(a+1)) \ , \tag{C.2}$$

where b is a constant unemployment real benefit, Γh is the cost of job searching in terms of home production, with $0 \leq \Gamma \leq 1$. Parameter f is the exogenous job finding rate, $V_e(a+1)$ is the value of finding a job in the next period-age and $N(a+1)$ is the value of not finding a job. Since workers can decide whether to retire or to be part of the labor force, the value of not finding a job depends on such decision. Therefore, we write $N(a+1)$ as the maximum between the value of being unemployed and the value of being retired:

$$N(a) = \max(V_u(a), V_r(a)) \ . \tag{C.3}$$

The value of being employed is

$$V_e(a) = w + \beta\left(\rho N(a+1) + (1-\rho)V_e(a+1)\right) \ , \tag{C.4}$$

where w is the exogenous real wage and ρ is the exogenous separation probability. If a separation shock hits, the worker may decide to stay unemployed or to retire. Therefore, the continuation value of separation is given by $N(a+1)$. If the separation shock does not hit, the continuation value is the value of the employment state in $a+1$.

We set parameter values so that the value of employment is always greater than the value of unemployment and retirement. In particular, we set $\beta = 0.96, \rho = 0.035, f = 0.6, b = 0.4, h = 0.1, w = 1$, and $\Gamma = 0.2$. The value of each possible state as a function of age is plotted in Figure C.3. The stylized model yields the following insight about retirement decisions of laid off workers. A layoff causes the displaced worker to jump from the value of the employment state – dashed yellow line – to the one of the unemployment state – dotted

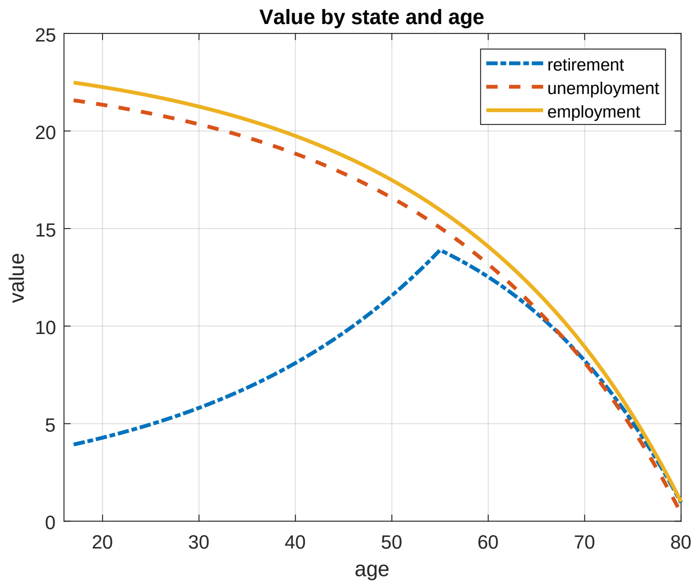

Figure C.3. **Value of being employed, unemployed and retired by age.**

red line. After a certain age, the model implies that the value of the retirement state – solid blue line – becomes larger than the value of being unemployed, because of the assumption that the accruing pension is a positive function of age. Hence, for old enough workers, the layoff triggers a retirement, as the micro-evidence suggests.

D TANK model

D.1 Derivation of model equations

Households. To derive first-order conditions for the household problem, write the value function for type a as

$$\mathcal{V}_{a,t} = \max_{E_{a,t},D_t} \mathcal{U}_{a,t} + \beta \mathbb{E}_t \mathcal{V}_{a,t+1} \ . \tag{D.5}$$

As discussed in Section 4.1, income is pooled and consumption of market-produced goods is decided collectively. Rewriting the aggregate budget constraint as

$$C_t = \frac{D_{t-1}}{P_t} - R_t^{-1} \frac{D_t}{P_t} + E_t \frac{W_t}{P_t} + b^u U_t + b^n N_{o,t} + \frac{T_t}{P_t} \ , \tag{D.6}$$

where we considered that $b^n_y = 0$, we can write the first-order condition for optimal consumption choices as

$$\begin{aligned}\frac{\partial \mathcal{V}_{a,t}}{\partial D_t} &= \frac{\partial \mathcal{U}_{a,t}}{\partial D_t} + \beta \mathbb{E}_t \frac{\partial \mathcal{V}_{a,t+1}}{\partial D_t} = 0 \\ &= Z_t \frac{1}{C_t - \xi C_{t-1}} \left(R_t^{-1} \frac{1}{P_t} \right) + \beta \mathbb{E}_t \left(Z_{t+1} \frac{1}{C_{t+1} - \xi C_t} \frac{1}{P_{t+1}} \right) = 0 \; ,\end{aligned}$$

yielding the conventional Euler equation

$$R_t \mathbb{E}_t \left(Q_{t,t+1} \Pi_{t+1}^{-1} \right) = 1 \; . \tag{D.7}$$

Consider now the households' labor supply decision. Differently from consumption, labor supply choices may differ across types due to different elasticities ν_a, home productivities $A^h_{a,t}$ and outside options $b^n_{a,t}$. The derivative with respect to employment is given by

$$\frac{\partial \mathcal{V}_{a,t}}{\partial E_{a,t}} = \frac{\partial \mathcal{U}_{a,t}}{\partial E_{a,t}} + \beta \mathbb{E}_t \frac{\partial \mathcal{V}_{a,t+1}}{\partial E_{a,t}} \; . \tag{D.8}$$

Using that $\partial \mathcal{V}_{a,t+2} / \partial E_{a,t} = 0$, we have that

$$\frac{\partial \mathcal{V}_{a,t+1}}{\partial E_{a,t}} = \frac{Z_{t+1}}{C_{t+1} - \xi C_t} \frac{\partial C_{t+1}}{\partial E_{a,t}} + \phi (h_{a,t+1})^{-\nu_a} \frac{\partial h_{a,t+1}}{\partial E_{a,t}} \; . \tag{D.9}$$

By substituting Eq. (D.9) in Eq. (D.8) and computing $\frac{\partial \mathcal{U}_{a,t}}{\partial E_{a,t}}$ we have that

$$\frac{\partial \mathcal{V}_{a,t}}{\partial E_{a,t}} = \frac{Z_t}{C_t - \xi C_{t-1}} \frac{\partial C_t}{\partial E_{a,t}} + \phi (h_{a,t})^{-\nu_a} \frac{\partial h_{a,t}}{\partial E_{a,t}} + \beta \mathbb{E}_t \left(\frac{Z_{t+1}}{C_{t+1} - \xi C_t} \frac{\partial C_{t+1}}{\partial E_{a,t}} + \phi (h_{a,t+1})^{-\nu_a} \frac{\partial h_{a,t+1}}{\partial E_{a,t}} \right) \; .$$

Rewriting the dynamics of employment as

$$E_t = (1 - \rho) E_{t-1} + f_t S_t = (1 - \rho) E_{t-1} + \frac{f_t}{1 - f_t} U_t \; , \tag{D.10}$$

and computing derivatives

$$\begin{aligned}
\frac{\partial C_t}{\partial E_{a,t}} &= \frac{W_t}{P_t} + \frac{b^u(1-f_t)}{f_t} - \frac{b^n_a}{f_t} \\
\frac{\partial h_{a,t}}{\partial E_{a,t}} &= (1-\alpha_h)(h_{a,t})^{-\frac{\alpha_h}{1-\alpha_h}} A^h_{a,t}\left(-1-\Gamma\frac{1-f_t}{f_t}\right) \\
\frac{\partial C_{t+1}}{\partial E_{a,t}} &= -\frac{1-f_{t+1}}{f_{t+1}}(1-\rho)b^u + \frac{1-f_{t+1}}{f_{t+1}}(1-\rho)b^n_a \\
\frac{\partial h_{a,t+1}}{\partial E_{a,t}} &= (1-\alpha_h)(h_{a,t+1})^{-\frac{\alpha_h}{1-\alpha_h}} A^h_{a,t+1}\left(\Gamma\frac{1-f_{t+1}}{f_{t+1}}(1-\rho)\right) \ ,
\end{aligned}$$

we can rewrite the equation for $\partial\mathcal{V}_{a,t}/\partial E_{a,t}$ as

$$\begin{aligned}
\frac{\partial\mathcal{V}_{a,t}}{\partial E_{a,t}} = \frac{Z_t}{C_t-\xi C_{t-1}}&\left[\left(\frac{W_t}{P_t} + \frac{b^u(1-f_t)}{f_t} - \frac{b^n_a}{f_t}\right) - MRS_{a,t}\left(1+\Gamma\frac{1-f_t}{f_t}\right)\right] + \\
+\beta\mathbb{E}_t&\left[\frac{Z_{t+1}}{C_{t+1}-\xi C_t}\left(\frac{1-f_{t+1}}{f_{t+1}}(1-\rho)(b^n_a - b^u + \Gamma MRS_{a,t+1})\right)\right] \ ,
\end{aligned} \tag{D.11}$$

where $MRS_{a,t} \equiv \frac{C_t-\xi C_{t-1}}{Z_t}\phi A^h_{a,t}(1-\alpha_h)(h_{a,t})^{-\frac{\alpha_h}{1-\alpha_h}-\nu_a}$ denotes the value of home-produced goods generated by the marginal non-participant in terms of market consumption goods. Setting the derivative of Eq. (D.11) to zero, we obtain the participation condition for households

$$\begin{aligned}
f_t\frac{W_t}{P_t} + (1-f_t)b^u + \mathbb{E}_t\left[Q_{t,t+1}f_t(1-\rho)\frac{1-f_{t+1}}{f_{t+1}}(\Gamma MRS_{a,t+1} - b^u + b^n_a)\right] = \\
b^n_a + MRS_{a,t}\left[f_t + (1-f_t)\Gamma\right] \ .
\end{aligned} \tag{D.12}$$

Final-good producers. Denote by $1-\delta$ the probability of resetting prices, and define the reset price of firm i as P^*_i. The downward sloping demand function, for any period $k \geq 0$ in which the firm does not reset its price, is given by

$$Y_{i,t+k} = \left(\frac{P^*_{i,t}}{P_{t+k}}\right)^{-\epsilon} Y_{t+k} \ , \tag{D.13}$$

where ϵ is the elasticity of substitution and Y_t is aggregate income. The optimization problem of the firm is given by

$$\max_{P^*_{i,t}} \sum_{k=0}^{\infty} \delta^k \mathbb{E}_t\left[Q_{t,t+k}\frac{1}{P_{t+k}}\left(P^*_{i,t}Y_{i,t+k} - TC(Y_{i,t+k})\right)\right] \ , \tag{D.14}$$

where $Q_{t,t+k}$ is the stochastic discount factor described before and $TC(Y_{i,t+k})$ is the total cost in period $t+k$ as a function of output $Y_{i,t+k}$. Differentiating Eq. (D.14) with respect to price $P^*_{i,t}$ we can derive the first-order condition

$$\begin{aligned}
&\sum_{k=0}^{\infty} \mathbb{E}_t \left[\delta^k Q_{t,t+k} \frac{1}{P_{t+k}} \left(Y_{i,t+k} + P^*_{i,t} \frac{\partial Y_{i,t+k}}{\partial P^*_{i,t}} - \frac{\partial TC}{\partial Y_{i,t+k}} \frac{\partial Y_{i,t+k}}{\partial P^*_{i,t}} \right) \right] = 0 \\
&\sum_{k=0}^{\infty} \mathbb{E}_t \left[\delta^k Q_{t,t+k} \frac{1}{P_{t+k}} \left(Y_{i,t+k} + \frac{\partial Y_{i,t+k}}{\partial P^*_{i,t}} \left(P^*_{i,t} - \frac{\partial TC}{\partial Y_{i,t+k}} \right) \right) \right] = 0 \\
&\sum_{k=0}^{\infty} \mathbb{E}_t \left[\delta^k Q_{t,t+k} \frac{1}{P_{t+k}} \left(Y_{i,t+k} - \epsilon \left(\frac{P^*_{i,t}}{P_{t+k}} \right)^{-\epsilon-1} \frac{1}{P_{t+k}} Y_{t+k} \left(P^*_{i,t} - MC_{i,t+k} \right) \right) \right] = 0 \\
&\sum_{k=0}^{\infty} \mathbb{E}_t \left[\delta^k Q_{t,t+k} \frac{1}{P_{t+k}} \left(Y_{i,t+k} - \epsilon Y_{i,t+k} \frac{1}{P^*_{i,t}} (P^*_{i,t} - MC_{i,t+k}) \right) \right] = 0 \\
&\sum_{k=0}^{\infty} \mathbb{E}_t \left[\delta^k Q_{t,t+k} Y_{i,t+k} \frac{1}{P_{t+k}} \left(1 - \epsilon + \epsilon MC_{i,t+k} \frac{1}{P^*_{i,t}} \right) \right] = 0 \\
&\sum_{k=0}^{\infty} \mathbb{E}_t \left[\delta^k Q_{t,t+k} Y_{i,t+k} \frac{1}{P_{t+k}} \left(P^*_{i,t} + \frac{\epsilon}{\epsilon - 1} MC_{i,t+k} \right) \right] = 0 \\
&\sum_{k=0}^{\infty} \mathbb{E}_t \left[\delta^k Q_{t,t+k} Y_{i,t+k} \frac{1}{P_{t+k}} \left(P^*_{i,t} + \frac{\epsilon}{\epsilon - 1} RMC_{i,t+k} P_{t+k} \right) \right] = 0 \,,
\end{aligned} \tag{D.15}$$

where $MC_{i,t+k}$ denotes marginal costs and $RMC_{i,t+k} \equiv MC_{i,t+k}/P_{t+k}$ are real marginal costs. Using the production function, $TC(Y_{i,t}) = P^X_t X_{i,t} = P^X_t Y_{i,t}^{\frac{1}{1-\alpha}}$, so that we can write firm's marginal costs as

$$MC_{i,t} = \frac{P^X_t}{1-\alpha} Y_{i,t}^{\frac{\alpha}{1-\alpha}} \,.$$

Substituting the individual demand faced by firm i in the equation above we can write

$$RMC_{i,t+k} = \frac{P^X_{t+k}}{P_{t+k}} \frac{1}{1-\alpha} Y_{t+k}^{\frac{\alpha}{1-\alpha}} \left(\frac{P^*_{i,t}}{P_{t+k}} \right)^{\frac{-\alpha\epsilon}{1-\alpha}} \,.$$

Defining $RMC_t \equiv \frac{P^X_t}{P_t} \frac{1}{1-\alpha} Y_t^{\frac{\alpha}{1-\alpha}}$, we can write the equation for individual real marginal costs above as

$$RMC_{i,t+k} = RMC_{t+k} \left(\frac{P^*_{i,t}}{P_{t+k}} \right)^{\frac{-\alpha\epsilon}{1-\alpha}} \,. \tag{D.16}$$

To derive a recursive formulation of the pricing equation, rewrite Eq. (D.15) as

$$\sum_{k=0}^{\infty}\mathbb{E}_t\left[\delta^k Q_{t,t+k}\left(\frac{P^*_{i,t}}{P_{t+k}}\right)^{-\epsilon}Y_{t+k}\frac{1}{P_{t+k}}\left(P^*_{i,t}+\frac{\epsilon}{\epsilon-1}RMC_{i,t+k}P_{t+k}\right)\right]=0$$
$$\sum_{k=0}^{\infty}\mathbb{E}_t\left[\delta^k Q_{t,t+k}\left(\frac{P_t}{P_{t+k}}\right)^{-\epsilon}\left(\frac{P^*_{i,t}}{P_t}\right)^{-\epsilon}Y_{t+k}\frac{P_t}{P_{t+k}}\left(\frac{P^*_{i,t}}{P_t}+\frac{\epsilon}{\epsilon-1}RMC_{i,t+k}\frac{P_{t+k}}{P_t}\right)\right]=0$$
$$\sum_{k=0}^{\infty}\mathbb{E}_t\left[\delta^k Q_{t,t+k}\left(\frac{P_t}{P_{t+k}}\right)^{1-\epsilon}\left(\frac{P^*_{i,t}}{P_t}\right)^{-\epsilon}Y_{t+k}\left(\frac{P^*_{i,t}}{P_t}+\frac{\epsilon}{\epsilon-1}RMC_{i,t+k}\frac{P_{t+k}}{P_t}\right)\right]=0$$
$$\sum_{k=0}^{\infty}\mathbb{E}_t\left[\delta^k Q_{t,t+k}Y_{t+k}\left(\frac{P_t}{P_{t+k}}\right)^{1-\epsilon}\left(\frac{P^*_{i,t}}{P_t}\right)^{1-\epsilon}\right]=$$
$$\sum_{k=0}^{\infty}\mathbb{E}_t\left[\delta^k Q_{t,t+k}Y_{t+k}\left(\frac{P_t}{P_{t+k}}\right)^{-\epsilon}\left(\frac{P^*_{i,t}}{P_t}\right)^{-\epsilon}\frac{\epsilon}{\epsilon-1}RMC_{i,t+k}\right],$$

and substitute in Eq. (D.16) for $RMC_{i,t+k}$ to get

$$\sum_{k=0}^{\infty}\mathbb{E}_t\left[\delta^k Q_{t,t+k}Y_{t+k}\left(\frac{P_t}{P_{t+k}}\right)^{1-\epsilon}\left(\frac{P^*_{i,t}}{P_t}\right)^{1-\epsilon}\right]=$$
$$\frac{\epsilon}{\epsilon-1}\sum_{k=0}^{\infty}\mathbb{E}_t\left[\delta^k Q_{t,t+k}Y_{t+k}\left(\frac{P_t}{P_{t+k}}\right)^{-\epsilon}\left(\frac{P^*_{i,t}}{P_t}\right)^{-\epsilon}RMC_{t+k}\left(\frac{P^*_{i,t}}{P_{t+k}}\right)^{\frac{-\alpha\epsilon}{1-\alpha}}\right]$$
$$\sum_{k=0}^{\infty}\mathbb{E}_t\left[\delta^k Q_{t,t+k}Y_{t+k}\left(\frac{P_t}{P_{t+k}}\right)^{1-\epsilon}\left(\frac{P^*_{i,t}}{P_t}\right)^{1-\epsilon}\right]=$$
$$\frac{\epsilon}{\epsilon-1}\sum_{k=0}^{\infty}\mathbb{E}_t\left[\delta^k Q_{t,t+k}Y_{t+k}\left(\frac{P_t}{P_{t+k}}\right)^{-\epsilon}\left(\frac{P^*_{i,t}}{P_t}\right)^{-\epsilon}RMC_{t+k}\left(\frac{P^*_{i,t}}{P_t}\right)^{\frac{-\alpha\epsilon}{1-\alpha}}\left(\frac{P_t}{P_{t+k}}\right)^{\frac{-\alpha\epsilon}{1-\alpha}}\right].$$

Dividing both sides by $\left(\frac{P^*_{i,t}}{P_t}\right)^{-\epsilon}\left(\frac{P^*_{i,t}}{P_t}\right)^{\frac{-\alpha\epsilon}{1-\alpha}}$ we get

$$\sum_{k=0}^{\infty}\mathbb{E}_t\left[\delta^k Q_{t,t+k}Y_{t+k}\left(\frac{P_t}{P_{t+k}}\right)^{1-\epsilon}\left(\frac{P^*_{i,t}}{P_t}\right)^{\frac{1-\alpha+\alpha\epsilon}{1-\alpha}}\right]=\frac{\epsilon}{\epsilon-1}\sum_{k=0}^{\infty}\mathbb{E}_t\left[\delta^k Q_{t,t+k}Y_{t+k}\left(\frac{P_t}{P_{t+k}}\right)^{\frac{-\epsilon}{1-\alpha}}RMC_{t+k}\right].$$

Factoring out and defining $\Pi_{t+k}\equiv P_{t+k}/P_t$ yields

$$\left(\frac{P^*_{i,t}}{P_t}\right)^{\frac{1-\alpha+\alpha\epsilon}{1-\alpha}}\sum_{k=0}^{\infty}\mathbb{E}_t\left[\delta^k Q_{t,t+k}Y_{t+k}\Pi_{t+k}^{\epsilon-1}\right]=\frac{\epsilon}{\epsilon-1}\sum_{k=0}^{\infty}\mathbb{E}_t\left[\delta^k Q_{t,t+k}Y_{t+k}\Pi_{t+k}^{\frac{\epsilon}{1-\alpha}}RMC_{t+k}\right]. \tag{D.17}$$

Define the right-hand side of Eq. (D.17) as K_t, that is

$$K_t = \frac{\epsilon}{\epsilon - 1} \sum_{k=0}^{\infty} \mathbb{E}_t \left[\delta^k Q_{t,t+k} Y_{t+k} \Pi_{t+k}^{\frac{\epsilon}{1-\alpha}} RMC_{t+k} \right] ,$$

and take the first term of the summation out to get

$$K_t = \frac{\epsilon}{\epsilon - 1} Y_t RMC_t + \frac{\epsilon}{\epsilon - 1} \sum_{k=1}^{\infty} \mathbb{E}_t \left[\delta^k Q_{t,t+k} \Pi_{t+k}^{\frac{\epsilon}{1-\alpha}} Y_{t+k} RMC_{t+k} \right] .$$

Noticing that K_{t+1} is given by

$$K_{t+1} = \frac{\epsilon}{\epsilon - 1} \sum_{k=0}^{\infty} \mathbb{E}_t \left[\delta^k Q_{t+1,t+k} \Pi_{t+1+k}^{\frac{\epsilon}{1-\alpha}} Y_{t+1+k} RMC_{t+1+k} \right] ,$$

we can then write K_t recursively as

$$K_t = \frac{\epsilon}{\epsilon - 1} Y_t RMC_t + \delta \mathbb{E}_t \left[Q_{t,t+1} \Pi_{t+1}^{\frac{\epsilon}{1-\alpha}} K_{t+1} \right] .$$

Similarly, defining F_t as

$$F_t = \sum_{k=0}^{\infty} \delta^k \mathbb{E}_t \left[Q_{t,t+k} \Pi_{t+k}^{\epsilon-1} Y_{t+k} \right] ,$$

and writing it recursively in a similar fashion as

$$F_t = Y_t + \delta \mathbb{E}_t \left[Q_{t,t+1} \Pi_{t+1}^{\epsilon-1} F_{t+1} \right] ,$$

we can finally use Eq. (D.17) write the optimal relative price in a symmetric equilibrium where $P_{i,t}^* = P_t^*$ for all resetting firms as

$$\left(\frac{P_t^*}{P_t} \right)^{\frac{1-\alpha+\alpha\epsilon}{1-\alpha}} = \frac{K_t}{F_t} . \tag{D.18}$$

In each period t, the average price level is given by the aggregator

$$P_t^{1-\epsilon} = \delta P_{t-1}^{1-\epsilon} + (1-\delta)(P_t^*)^{1-\epsilon} . \tag{D.19}$$

Dividing both sides of Eq. (D.19) by $P_t^{1-\epsilon}$ we get

$$1 = \delta \Pi_t^{\epsilon-1} + (1-\delta)\left(\frac{P_t^*}{P_t}\right)^{1-\epsilon} ,$$

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

$$\Pi_t = \left(\frac{1-(1-\delta)\left(\frac{P_t^*}{P_t}\right)^{1-\epsilon}}{\delta}\right)^{\frac{1}{\epsilon-1}} . \tag{D.20}$$

Search frictions and equilibrium wages, Let $V_{a,t}^w$ denote the surplus of having an additional member employed rather than unemployed, for a chosen level of participation $L_t = \bar{L}$. In this case we have that employment is given by

$$E_t = (1-\rho)E_{t-1} + f_t S_t = (1-\rho)E_{t-1} + f_t L_t - f_t(1-\rho)E_{t-1} = (1-\rho)(1-f_t)E_{t-1} + f_t \bar{L} ,$$

and the surplus $V_{a,t}^w$ can be written as

$$\begin{aligned} V_{a,t}^w = \frac{\partial \mathcal{V}_{a,t}}{\partial E_{a,t}} \frac{C_t - \xi C_{t-1}}{Z_t} &= \frac{\partial \mathcal{U}_{a,t}}{\partial E_{a,t}} \frac{C_t - \xi C_{t-1}}{Z_t} + \beta \mathbb{E}_t \frac{\partial \mathcal{V}_{a,t+1}}{\partial E_{a,t}} \frac{C_t - \xi C_{t-1}}{Z_t} \\ &= \frac{W_t}{P_t} - b^u - (1-\Gamma) MRS_{a,t} + \mathbb{E}_t \left[Q_{t,t+1} (1-\rho)(1-f_{t+1}) V_{a,t+1}^w \right] . \end{aligned} \tag{D.21}$$

The surplus from a match between a job searcher and a firm is split according to Nash bargaining

$$\eta V_t^w = (1-\eta) V_t^J , \tag{D.22}$$

where the union considers average surplus given by

$$V_t^w \equiv \zeta V_{y,t}^w + (1-\zeta) V_{o,t}^w = \frac{W_t}{P_t} - b^u - (1-\Gamma) MRS_t + \mathbb{E}_t \left[Q_{t,t+1}(1-\rho)(1-f_{t+1}) V_{t+1}^w \right] , \tag{D.23}$$

and $MRS_t \equiv \zeta MRS_{y,t} + (1-\zeta) MRS_{o,t}$. Substituting the definitions of V_t^w and V_t^J into Eq. (D.22), together with the free entry and the job creation conditions, we get

$$\begin{aligned} &\eta \left\{ \frac{W_t}{P_t} - b^u - (1-\Gamma) MRS_t + \mathbb{E}_t \left[Q_{t,t+1} (1-\rho)(1-f_{t+1}) \frac{1-\eta}{\eta} \frac{k}{q_{t+1}} \right] \right\} \\ &= (1-\eta) \left\{ \frac{P_t^X}{P_t} A_t - \frac{W_t}{P_t} + (1-\rho) \mathbb{E}_t \left[Q_{t,t+1} \frac{k}{q_{t+1}} \right] \right\} . \end{aligned}$$

Using that $\theta_t = f_t/q_t$, we can write the wage equation above as

$$\frac{W_t}{P_t} = (1-\eta)\frac{P_t^X}{P_t}A_t + \eta[b^u + (1-\Gamma)MRS_t] + (1-\eta)(1-\rho)\mathbb{E}_t\left[Q_{t,t+1}k\theta_{t+1}\right] \ . \tag{D.24}$$

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

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

while the standard aggregate resource constraint is given by

$$Y_t = C_t + kV_t \ ,$$

where aggregate output is defined by the standard aggregator

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

Moreover, market clearing in the labor market requires

$$E_t = \int_0^1 E_{i,t}di \ ,$$

where $E_{i,t}$ denotes labor used to produce $X_{i,t}$, in turn used for the production of $Y_{i,t}$. Using the production function of final-good firms we get

$$E_t = \int_0^1 \frac{Y_{i,t}^{\frac{1}{1-\alpha}}}{A_t} di \ ,$$

and substituting in the individual demand faced by firm i yields

$$\begin{aligned} E_t &= \frac{1}{A_t} Y_t^{\frac{1}{1-\alpha}} \int_0^1 \left(\frac{P_{i,t}}{P_t}\right)^{-\frac{\epsilon}{1-\alpha}} di \\ &= \frac{1}{A_t} Y_t^{\frac{1}{1-\alpha}} \Delta_t \ , \end{aligned}$$

where the last equality follows from the definition of price dispersion

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

The aggregate production function can thus be written as

$$Y_t = X_t^{1-\alpha} \Delta_t^{\alpha-1} \ ,$$

while the law of motion for Δ_t is

$$\begin{aligned}
\Delta_t &= (1-\delta)\left(\frac{P_{i,t}^*}{P_t}\right)^{-\frac{\epsilon}{1-\alpha}} + \delta \int_0^1 \left(\frac{P_{i,t-1}}{P_t}\right)^{-\frac{\epsilon}{1-\alpha}} di \\
&= (1-\delta)\left(\frac{P_{i,t}^*}{P_t}\right)^{-\frac{\epsilon}{1-\alpha}} + \delta \left(\frac{P_{t-1}}{P_t}\right)^{-\frac{\epsilon}{1-\alpha}} \int_0^1 \left(\frac{P_{i,t-1}}{P_{t-1}}\right)^{-\frac{\epsilon}{1-\alpha}} di \\
&= (1-\delta)\left(\frac{P_{i,t}^*}{P_t}\right)^{-\frac{\epsilon}{1-\alpha}} + \delta \Pi_t^{\frac{\epsilon}{1-\alpha}} \Delta_{t-1} \ .
\end{aligned}$$

D.2 Impulse-Response functions

Figure D.4 reports dynamic responses to a shock to home-productivity of old agents $A_{o,t}^h$. 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 $A_{o,t}^h$ in Figure D.4 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.

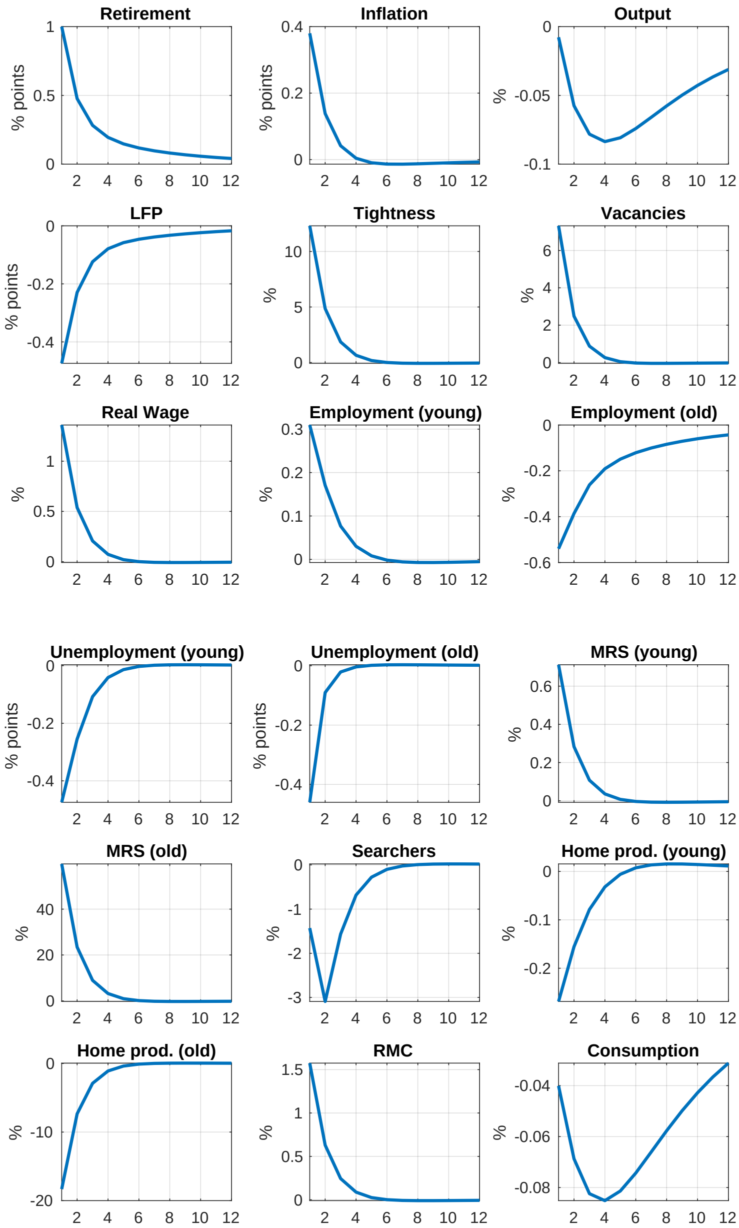

Figure D.4. **Dynamic responses to home-productivity shock for old agents.**

D.3 List of model and measurement equations

Below we report the full list of model and measurement equations.

Model equations

$$E_{y,t} = (1-\rho)\ (1-f_t)\ E_{y,t-1} + f_t\, L_{y,t} \tag{D.25}$$

$$E_{o,t} = (1-\rho)\ (1-f_t)\ E_{o,t-1} + f_t\, L_{o,t} \tag{D.26}$$

$$E_t = E_{y,t}\,\zeta + E_{o,t}\ (1-\zeta) \tag{D.27}$$

$$q_t = \omega\,\theta_t^{(-\gamma)} \tag{D.28}$$

$$f_t = q_t\,\theta_t \tag{D.29}$$

$$h_{y,t} = \left(\exp\left({A^h}_{y,t}\right)\ (N_{y,t} + (1-\Gamma)\ U_{y,t})\right)^{1-\alpha_h} \tag{D.30}$$

$$h_{o,t} = \left(\exp\left({A^h}_{o,t}\right)\ (N_{o,t} + (1-\Gamma)\ U_{o,t})\right)^{1-\alpha_h} \tag{D.31}$$

$$L_{y,t} = E_{y,t} + U_{y,t} \tag{D.32}$$

$$L_{o,t} = E_{o,t} + U_{o,t} \tag{D.33}$$

$$L_t = L_{y,t}\,\zeta + L_{o,t}\ (1-\zeta) \tag{D.34}$$

$$U_t = \zeta\,U_{y,t} + (1-\zeta)\ U_{o,t} \tag{D.35}$$

$$sdf_t = \frac{\beta\ \exp\left(Z_{t+1}\right)}{\exp\left(Z_t\right)}\,\frac{muc_{t+1}}{muc_t} \tag{D.36}$$

$$muc_t = \frac{1}{C_t - \xi\,C_{t-1}} \tag{D.37}$$

$$\frac{sdf_t\,R_t}{\Pi_{t+1}} = 1 \tag{D.38}$$

$$\frac{1-f_t}{f_t}\;\left(\Gamma\, MRS_{y,t}-b^u\right)=W_t/P_t-MRS_{y,t}+\frac{\left(1-\rho\right)\;sdf_t\;\left(1-f_{t+1}\right)}{f_{t+1}}\;\left(\Gamma\, MRS_{y,t+1}-b^u\right) \tag{D.39}$$

$$\begin{aligned}\frac{1-f_t}{f_t}\;\left(\Gamma\, MRS_{o,t}-b^u\right)+\frac{b^n}{f_t}&=W_t/P_t-MRS_{o,t}\\&+\frac{\left(1-\rho\right)\;sdf_t\;\left(1-f_{t+1}\right)}{f_{t+1}}\;\left(b^n+\Gamma\, MRS_{o,t+1}-b^u\right)\end{aligned} \tag{D.40}$$

$$muh_{y,t}=\phi\, h_{y,t}^{(-\nu)} \tag{D.41}$$

$$muh_{o,t}=\phi\, h_{o,t}^{(-v2)} \tag{D.42}$$

$$MRS_{y,t}=\frac{\frac{\left(1-\alpha_h\right)\;\exp\left({A^h}_{y,t}\right)\, muh_{y,t}\, h_{y,t}^{\frac{(-\alpha_h)}{1-\alpha_h}}}{muc_t}}{\exp\left(Z_t\right)} \tag{D.43}$$

$$MRS_{o,t}=\frac{\frac{\left(1-\alpha_h\right)\;\exp\left({A^h}_{o,t}\right)\, muh_{o,t}\, h_{o,t}^{\frac{(-\alpha_h)}{1-\alpha_h}}}{muc_t}}{\exp\left(Z_t\right)} \tag{D.44}$$

$$\frac{k}{q_t}=P_t^X/P_t\;\exp\left(A_t\right)-W_t/P_t+\frac{\left(1-\rho\right)\;sdf_t\, k}{q_{t+1}} \tag{D.45}$$

$$W_t/P_t=\exp\left(A_t\right)\;P_t^X/P_t\;\left(1-\eta\right)+\eta\;\left(b^u+\left(1-\Gamma\right)\;MRS_t\right)+k\, sdf_t\;\left(1-\rho\right)\;\left(1-\eta\right)\;\theta_{t+1} \tag{D.46}$$

$$MRS_t=\zeta\, MRS_{y,t}+\left(1-\zeta\right)\;MRS_{o,t} \tag{D.47}$$

$$Y_t=C_t+k\, V_t \tag{D.48}$$

$$Y_t=\left(E_t\;\exp\left(A_t\right)\right)^{1-\alpha}\;\Delta_t^{\alpha-1} \tag{D.49}$$

$$\Delta_t=\left(1-\delta\right)\;\left(P_t^*/P_t\right)^{\frac{(-\epsilon)}{1-\alpha}}+\delta\,\Pi_t^{\frac{\epsilon}{1-\alpha}}\;\Delta_{t-1} \tag{D.50}$$

$$\Pi_t=\left(\frac{1-\left(1-\delta\right)\;\left(P_t^*/P_t\right)^{1-\epsilon}}{\delta}\right)^{\frac{1}{\epsilon-1}}\;\exp\left(cp_t\right) \tag{D.51}$$

$$(P_t^*/P_t)^{\frac{1-\alpha+\alpha\,\epsilon}{1-\alpha}} = \frac{K_t}{F_t} \tag{D.52}$$

$$K_t = Y_t\,\frac{\epsilon}{\epsilon-1}\,RMC_t + sdf_t\,\delta\,\Pi_{t+1}^{\frac{\epsilon}{1-\alpha}}\,K_{t+1} \tag{D.53}$$

$$F_t = Y_t + sdf_t\,\delta\,\Pi_{t+1}^{\epsilon-1}\,F_{t+1} \tag{D.54}$$

$$RMC_t = P_t^X/P_t\,\frac{1}{1-\alpha}\,Y_t^{\frac{\alpha}{1-\alpha}} \tag{D.55}$$

$$\tilde{Y}_t = (E_t\,\exp(A_t))^{1-\alpha} \tag{D.56}$$

$$\log(R_t) = \rho_R\,\log(R_{t-1}) + (1-\rho_R)\left(\phi_\pi\,\log(\Pi_t) - \log(\beta) + \phi_y\,\log\left(\frac{Y_t}{\tilde{Y}_t}\right)\right) + mp_t \tag{D.57}$$

$$\theta_t = \frac{V_t}{S_t} \tag{D.58}$$

$$S_{y,t} = L_{y,t} - (1-\rho)\,E_{y,t-1} \tag{D.59}$$

$$S_{o,t} = L_{o,t} - (1-\rho)\,E_{o,t-1} \tag{D.60}$$

$$S_t = \zeta\,S_{y,t} + (1-\zeta)\,S_{o,t} \tag{D.61}$$

$$N_{y,t} = 1 - L_{y,t} \tag{D.62}$$

$$N_{o,t} = 1 - L_{o,t} \tag{D.63}$$

$$A_t = \rho_A\,A_{t-1} + \sigma_A\,{\varepsilon^A}_t \tag{D.64}$$

$${A^h}_{y,t} = \rho_y^h\,{A^h}_{y,t-1} + \sigma_{y,h}\,\varepsilon_{y,t}^h \tag{D.65}$$

$${A^h}_{o,t} = \rho_o^h\,{A^h}_{o,t-1} + \sigma_{o,h}\,{\varepsilon^h}_{o,t} \tag{D.66}$$

$$Z_t = \rho_z\,Z_{t-1} + \sigma_Z\,{\varepsilon^Z}_t \tag{D.67}$$

$$mp_t = \rho_{mp}\,mp_{t-1} + \sigma_{mp}\,{\varepsilon^{mp}}_t \tag{D.68}$$

$$cp_t = \rho_{cp}\,cp_{t-1} + \sigma_{cp}\,{\varepsilon^{cp}}_t \tag{D.69}$$

Measurement equations

$$delta.out_t = \frac{Y_t - Y_{t-1}}{Y_{t-1}} + \sigma_y \, \varepsilon^y{}_t \tag{D.70}$$

$$infl_t = \log\left(\Pi_t\right) + \sigma_\pi \, \varepsilon^\pi{}_t \tag{D.71}$$

$$rate_t = \log\left(R_t\right) \tag{D.72}$$

$$delta.lfp_t = L_t - L_{t-1} + \sigma_L \, \varepsilon^L{}_t \tag{D.73}$$

$$delta.ret_t = (1-\zeta)\, \left(N_{o,t} - N_{o,t-1}\right) + \sigma_{N_o} \, \varepsilon^{N_o}{}_t \tag{D.74}$$

$$delta.rw_t = \frac{W_t/P_t - W_{t-1}/P_{t-1}}{W_{t-1}/P_{t-1}} + \sigma_w \, \varepsilon^w{}_t \tag{D.75}$$

$$delta.cons_t = \frac{C_t - C_{t-1}}{C_{t-1}} + \sigma_C \, \varepsilon^C{}_t \tag{D.76}$$

DeNederlandscheBank
EUROSYSTEEM

De Nederlandsche Bank N.V.
Postbus 98, 1000 AB Amsterdam
020 524 91 11
dnb.nl