Demographic Trends and the Transmission of Monetary Policy

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Abstract

This paper studies the impact of demographic trends on the effectiveness of monetary policy. I propose and quantify a novel channel to explain how population aging affects the transmission of monetary policy: older individuals devote a larger share of their consumption bundle to product categories with higher levels of price rigidity – categories that adjust their prices less often – so the aggregate frequency of price adjustment decreases as the population ages. Using micro data on consumer expenditure, I document that the main driver of the negative relationship between age and the frequency of price adjustment is the higher share of services consumed by old households. At the macro level, if prices are more rigid output should respond more to monetary shocks. To test this hypothesis, I exploit the cross-sectional variation in demographic structures among U.S. states, and I show that the economic activity in states with a higher old-age dependency ratio reacts more to monetary shocks. I rationalize these findings using a two-sector OLG New Keynesian model. Combining the model with population projections for the U.S., I find that changes in the age distribution between 1980 and 2010 increased the contemporaneous response of output to monetary shocks by 6% and will increase it by 10% by 2050. Moreover, demographic trends explain around 10% of the observed decrease in the slope of the Phillips curve.

Keywords: Monetary policy, age structure, consumption heterogeneity, Phillips curve
JEL classification: E31, E52, J11

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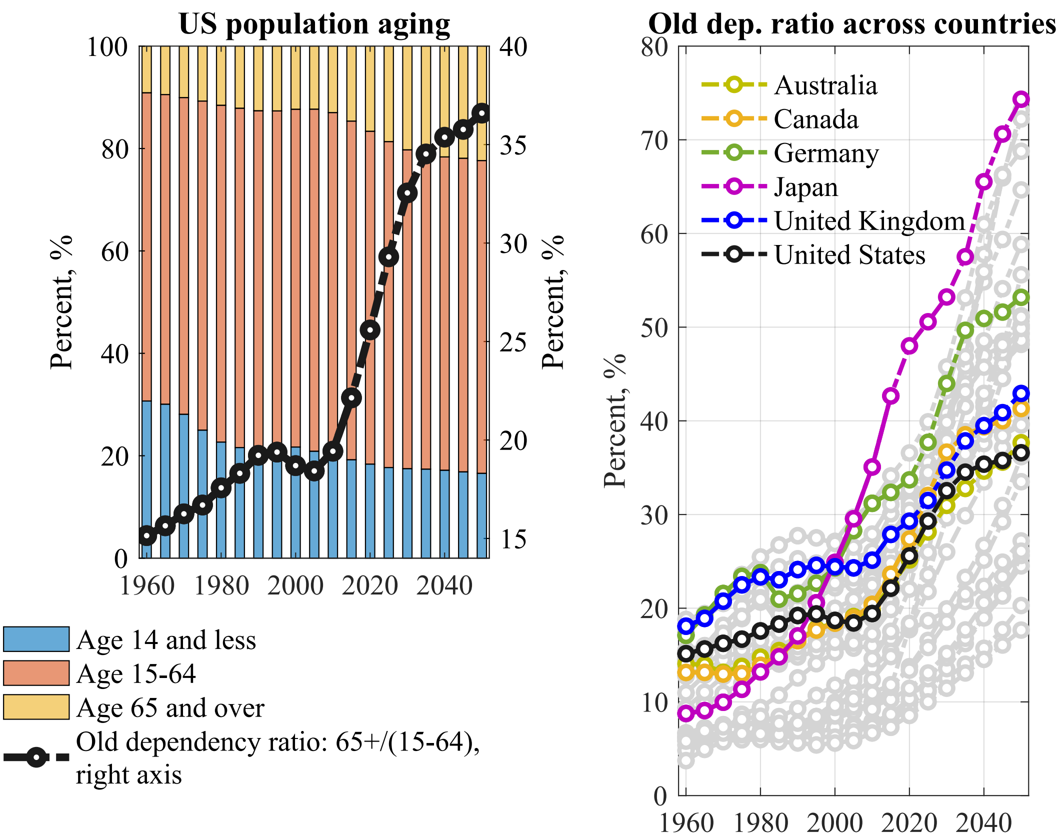
1 Introduction

The world population has aged rapidly over the past half-century. In the United States, lower fertility rates and longer life expectancies have already increased the share of retired people and reduced the size of the working population. As shown in the left panel of Figure 1, the ratio of these two groups, defined as the old-age dependency ratio, has significantly grown since 1960 and it is projected to rise even further in the following decades. The U.S. is not alone in this demographic transition. Every country is expected to experience similar demographic trends as the U.S. These trends influence many central aspects of the economy and are not limited to the pension system sustainability or labor market participation. Monetary authorities are also not immune to the effects of the changes in the population distribution. Given the magnitude and the increasing pace of these trends, it is of great importance for the monetary authorities to understand the extent to which demographic trends might affect their abilities to achieve their mandates.

Figure 1: Demographic trends



Notes: The left panel of the plot shows the age composition evolution over time for the U.S. population as well as the relative old-age dependency ratio from 1960 to 2050. The right panel compares the time series of the old-age dependency ratio across major economies. The source of the data is the World Bank Population Estimates And Projections.

This paper studies the impact of population aging on the effectiveness of monetary policy. I propose a novel channel to explain how the transmission of monetary policy might be influenced by demographic trends. Older individuals devote a larger share of their expenditures to services, and services tend to adjust their prices less often than goods. As the population ages, the relative importance of services rises leading to an increase in price stickiness. Since fewer firms can adjust their price in response to a monetary shock, output responds more strongly. Using household-level data for the U.S., I document that the negative relationship between age and the frequency of price adjustment of the consumption bundle is driven by significant differences in sectoral expenditure shares across age groups. In line with this micro evidence, I show that the economic activity of U.S. states with an older demographic structure is more responsive to monetary shocks. I then use a theoretical model to quantify how much of the change in the effectiveness of U.S. monetary policy from 1980 to 2050 can be accounted for by population aging.

To study the relationship between age and price stickiness, I combine household-level data from the U.S. Consumer Expenditure Survey (CEX) for the period 1982-2018 with the sectoral frequency of price adjustment computed by Nakamura and Steinsson (2008). I find that older households spend significantly more on services. The services expenditure share of households over 80 years old is 20 percentage points higher compared to the one of households in their early 30s. At the same time, services adjust their prices on average every 13 months, whereas goods every 3 months. The average frequency at which the price of the consumption bundle is adjusted is highly heterogeneous across age groups ranging from 8.2 months for young households to almost 10 months for older households. This relationship is stable over the sample period and when controlling for other households' characteristics.

Through the lens of a standard 3-equation New Keynesian model, I evaluate how changes in price stickiness affect the responsiveness of output and inflation to monetary shocks. A decrease in the frequency of price adjustment results in a more muted response of inflation, since fewer firms adjust their price, but a more substantial response of output, since firms would need to adjust their production more vigorously. However, output and inflation are not equally sensitive to changes in the price stickiness parameter. The response of output is significantly influenced by the frequency of price adjustment, whereas inflation is only marginally affected. This is due to the fact that with higher price stickiness fewer firms can adjust their price every period. Inflation responds less to shocks and also becomes less sensitive to changes in the other macroeconomic variables. Since prices cannot be adjusted, firms respond by adjusting their production more. Moreover, firms anticipate that on average they might not be able to adjust their price for a longer time period. The expectations channel results in a further increase in output responsiveness. Due to the lower sensitivity of inflation to changes in the economy, the increase in output responsiveness has only a marginal impact on the responsiveness of inflation.

The theoretical framework delivers two key predictions on how monetary policy transmission is influenced by demographic trends. An increase in the share of older individuals increases the demand for services resulting in a lower frequency of price adjustment at the aggregate level. Therefore, the first prediction is a stronger response of output following a monetary shock because fewer firms can adjust their price. The second prediction is that the response of inflation in older economies is only slightly more muted because the sensitivity of inflation to changes in the economy is lower. I test these macroeconomic predictions by exploiting the cross-sectional variation in demographic structures among U.S. states from 1980 to 2010. I compute the responses of state-level real personal income and GDP from the Bureau of Economic Analysis (BEA) as well as inflation rates from Hazell et al. (2021) to a monetary shock adopting a panel local projection approach à la Jordà (2005). Exogenous variations in interest rate are captured using the Romer and Romer (2004) monetary shocks series. By interacting the responses with state-level demographic characteristics, I confirm that the economic activity of states with a relatively higher share of older individuals responds more to monetary shocks. In contrast, the response of inflation is not significantly influenced by the different demographic structures.

This empirical evidence motivates the last part of the paper, where I develop a two-sector overlapping generations New Keynesian model to investigate how monetary policy shock propagation is influenced by population aging. The model incorporates a rich demographic structure with age-specific mortality rates, labor productivity, and consumption preferences over the services and goods sectors. The sectors differ in their degree of price stickiness, and only the output from the goods sector can be stored and invested. I calibrate the model to match the realized and projected population distribution and the different sectoral preferences across age groups observed in the data.

The theoretical model is then used to answer the following questions: What is the relationship between monetary policy effectiveness and demographic trends? To what extent does the new channel proposed in this paper contribute to changes in this relationship? And, finally, did population aging play any role in the observed decrease in the sensitivity of inflation to changes in economic activity (i.e., on the flattening of the Phillips curve)?

In line with the empirical evidence, the model implies that the change in the U.S. population distribution and mortality rate between 1980 and 2010 increased the contemporaneous response of output to monetary shocks but only marginally affected the response of inflation. Demographic trends alone increased the output response by 6% in 2010 relative to 1980 (approximately one-third of the overall change) and in 2050 the response is expected to be up to 10% higher relative to 1980. Moreover, through the shift in aggregate demand, demographic trends explain around 10% of the decrease in the slope of the Phillips curve.

Understanding how and through which channels the shifts in demographic structure influence the transmission of monetary policy shocks is crucial for policymakers and central bankers to conduct optimal monetary policy. While in the recent literature, much attention has been dedicated to studying the effects of aging on government debt and fiscal policy, the focus on the implications for monetary policy has been limited. Most of these studies concentrate on the long-term consequences on the level of the interest rate and inflation. Indeed, given the slow-moving pace of demographic trends, the impact of population aging on the transmission of monetary policy shocks has been considered negligible. However, the results of this paper show that population aging can significantly influence the effectiveness of short-term monetary policy.

Related literature. This paper contributes to three strands of the literature. First, the results complement the large body of empirical evidence on the time-varying effects of monetary policy shocks on real activity and inflation. Reforms in the institutional structure of the credit markets (Boivin et al., 2010), stronger anchoring of expectations as well as demographic trends (Imam, 2014, Kronick and Ambler, 2019) have been proposed as potential explanations for the fact that the responses of output and inflation to shocks have changed in the last decades. I contribute by suggesting and quantifying a new channel: the decrease in the frequency of price adjustment due to a shift in demand towards the services sector partially caused by population aging. As Galesi and Rachedi (2018) illustrate, the response of inflation to monetary shocks in countries with a larger share of services consumption is more muted.

The second strand is the literature on the relationship between monetary policy and demographic trends. As previously mentioned, most of the literature has focused on the effects on the long-term steady-state level of the interest rates and inflation[1] rather than on the short-term implications. Few exceptions include Fujiwara and Teranishi (2008), Kantur (2013), and Yoshino and Miyamoto (2017), which use a two-agents model with workers and retirees to study the effectiveness of monetary policies from a theoretical perspective. Bielecki et al. (2021) develop a life-cycle model calibrated on the Euro Area to show that demographic trends have contributed to the decline in the natural interest rate and have exacerbated the risk of hitting the lower bound and that the pressure is expected to continue. Finally, Brzoza-Brzezina and Kolasa (2021) study the importance of asset distribution across generations for the redistributive effects of monetary policy.

From an empirical point of view, Wong (2014) and Wong (2021) find that the consumption of younger households tends to respond more to monetary shocks since they refinance or enter new loans as interest rates change. Leahy and Thapar (2020) show that the responses of private employment and personal income are stronger the greater the share of the population between 40 and 65 years of age. In contrast, Kimberly et al. (2021) demonstrate that the consumption of older households is more responsive to monetary policy shocks because of their portfolio composition. Kopecky (2022) provides empirical evidence that population age structure plays an essential role in the relationship between excess money growth and inflation. Using a cointegrated VAR approach for the U.S. and Euro Area, Bobeica et al. (2017) find a positive long-run relationship between inflation and the growth rate of the working-age population. Similarly, de Albuquerque et al. (2020) document in a panel of 24 countries that the 35-64 years old group creates disinflationary pressure while very old population groups appear to contribute strongly to inflation. I contribute by documenting a new channel that also leads to a stronger response to shocks of the economic activity of U.S. states with a higher share of older adults, in line with this literature.

Finally, this paper relates to the literature that studies the Phillips curve's flattening (a positive relation between inflation and the output gap). The empirical disconnect between inflation and economic activity has been interpreted as potential evidence that the Phillips curve has weakened or even disappeared (Coibion and Gorodnichenko, 2015, Blanchard et al., 2015, Laurence and Mazumder, 2011). Potential explanations include the successful anchoring of expectations (Bernanke, 2010), the increase in central bank credibility (McLeay and Tenreyro, 2019), global forces (Jorda et al., 2019), and the change in the input-output network (Rubbo, 2020). Related to this last channel, I show that population aging shifts

[1] See, among others, Carvalho et al. (2016), Aksoy et al. (2019), Eggertsson et al. (2019), Papetti (2019), Lis et al. (2020), Papetti (2021), Bielecki et al. (2020), Lisack et al. (2021) and Auclert et al. (2021).

aggregate demand towards the services sector, which has a lower slope of the Phillips curve, resulting in an overall decrease in the sensitivity of inflation to real activity.

Road map. The remaining paper is organized as follows. Section 2 uses household-level expenditure data to document the negative relationship between age and the frequency of price adjustment. In section 3, I derive which are the theoretical predictions of a change in price stickiness using a standard 3-equation New Keynesian model. Section 4 studies the heterogeneous effects of monetary policy shocks across U.S. states according to their demographic structures. In section 5, I develop the two-sector OLG NK model to assess how the transmission of monetary policy shocks in the U.S. has been influenced by demographic trends and to what extent consumption heterogeneity explains this. Finally, section 6 concludes.

2 Micro-level evidence

Using household-level data for the U.S., I document significant heterogeneity in price stickiness across the consumption bundles of different age groups. In particular, older people purchase more services rather than goods and the firms in the services sector tend to adjust less often their prices. Therefore, an increase in the share of old people puts downward pressure on the aggregate frequency of price adjustment.

2.1 Heterogeneity in the frequency of price adjustment

2.1.1 Data

I now show how the frequency of price adjustment varies with household age using micro-data for the U.S. To do so, I combine data on expenditure shares from the Consumer Expenditure Survey (CEX) run by the Bureau of Labor Statistics (BLS)[2] for the 1982-2018 period with the item-level frequency of price adjustment data from Nakamura and Steinsson (2008), which is computed as the fraction of the number of times an item changes its price over the number of times the item is observed[3]. The expenditure data from the CEX are available at Universal Classification Code (UCC) level for about 600 categories whereas the frequency of price adjustment from Nakamura and Steinsson (2008) at the Entry Level Items (ELI) level for 272

[2]The CEX survey respondents are asked about their expenditures for the full consumption basket. The CEX is made up of two separate surveys: the Interview and the Diary. The first one covers the full range of expenditures on a quarterly basis, while the second provides more detailed information at a weekly frequency for certain product categories like food and clothing. A set of demographic characteristics are reported in both surveys. Overall, in the two modules, there are questions regarding around 600 Universal Classification Code (UCC) categories.

[3]Figure 23 reports heterogeneity in price rigidities across 19 categories and between goods and services.

categories. Therefore, as in Clayton et al. (2018) and Cravino et al. (2020a), I implement a "many-to-one" merge from UCCs to ELIs by summing up the expenditures of all UCCs linked to the same ELI. Because a few ELIs do not find a linked UCC (e.g., rent), the final dataset covers 263 ELIs out of 272[4].

I then aggregate households into age groups based on the reference person's age, that is the age of the household head[5], and compute the average frequency of price changes for age group a, $\bar{\theta}_t^a = \sum_j \omega_{t,j}^a \theta_j$, as the weighted average of the product-specific frequencies of price changes θ_j from Nakamura and Steinsson (2008) using as weights the age group-specific expenditure shares $\omega_{t,j}^a$ from the CEX[6].

As an alternative measure of price stickiness, I compute the mean implied duration. I define for each ELI category the mean implied duration as $d = \frac{-1}{ln(1-f)}$, where f is the frequency of price adjustment, which measures after how many months, on average, a firm in sector j adjusts its price. I then compute the mean implied duration for each age group a similarly to the frequency of price changes.

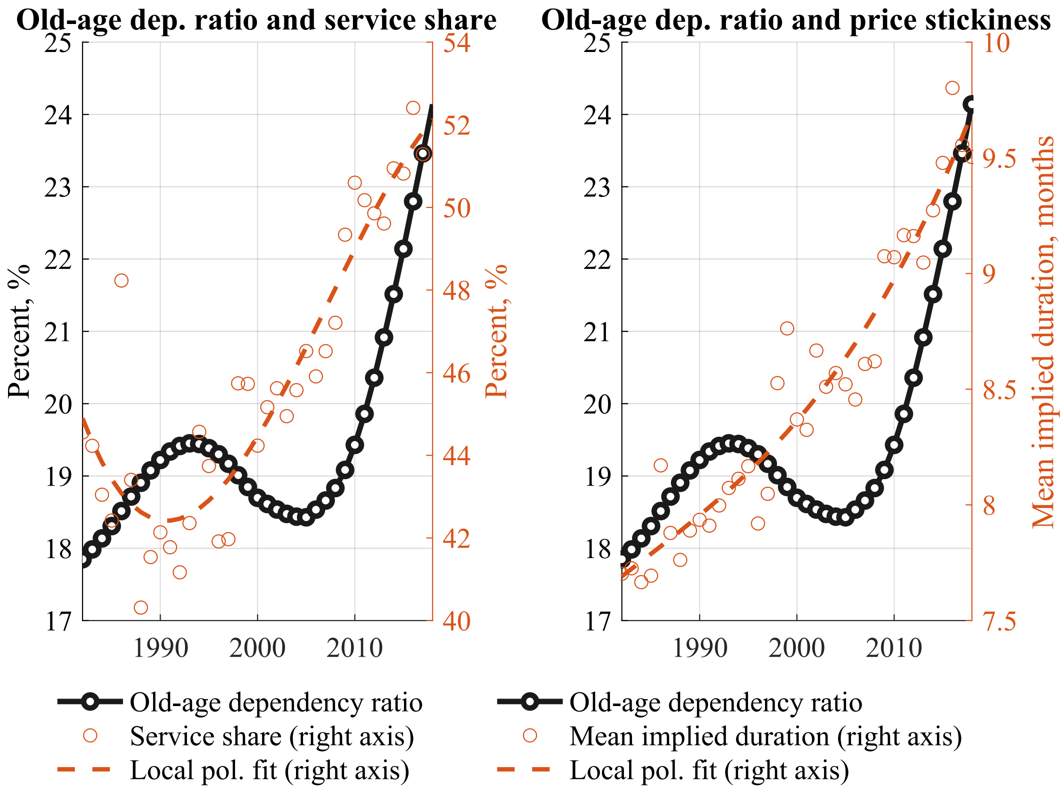
Before presenting the price stickiness heterogeneity across age groups, it is useful to see how it evolved over time and how it relates to demographic trends. The core idea of this paper is well summarized in Figure 2. On the left panel, I compare the time series from 1980 to 2018 for the U.S. old-age dependency ratio (left axis) with the scatterplot of the share of consumption devoted to services as well as the relative polynomial fit (right axis). The distinction between goods and services, which I will discuss more in detail later, is extremely important for my analysis since the share of services consumed increases over the life-cycle (with the share for older households being around 20 percentage points more than for younger households) and because the two categories have remarkably different frequencies of price adjustments (goods adjust on average every 3 months whereas services every 13 months). On the right panel, I compare the same time series of the U.S. old-age dependency ratio (left axis) with the scatterplot of the mean implied duration as well as the relative polynomial fit (right axis). The old-age dependency ratio in the U.S. increased throughout the 80s and until the mid-90s. It slightly decreased in the subsequent 10 years and then it significantly rose again (and is expected to keep rising in the next decades as shown in Figure 1).

[4]See Appendix A.1 for more details about the data.

[5]The results are similar if it is used the average age across all household members.

[6]The implicit assumption I make is that the frequency of price adjustment at sectoral level θ_j is constant over time. This assumption is partly tested by Nakamura and Steinsson (2008) who compare the frequency of price adjustment over two different periods, 1988-1997 and 1998-2005, and they show that the parameters are rather stable over time.

Figure 2: Old-age dependency ratio, service share, and price stickiness



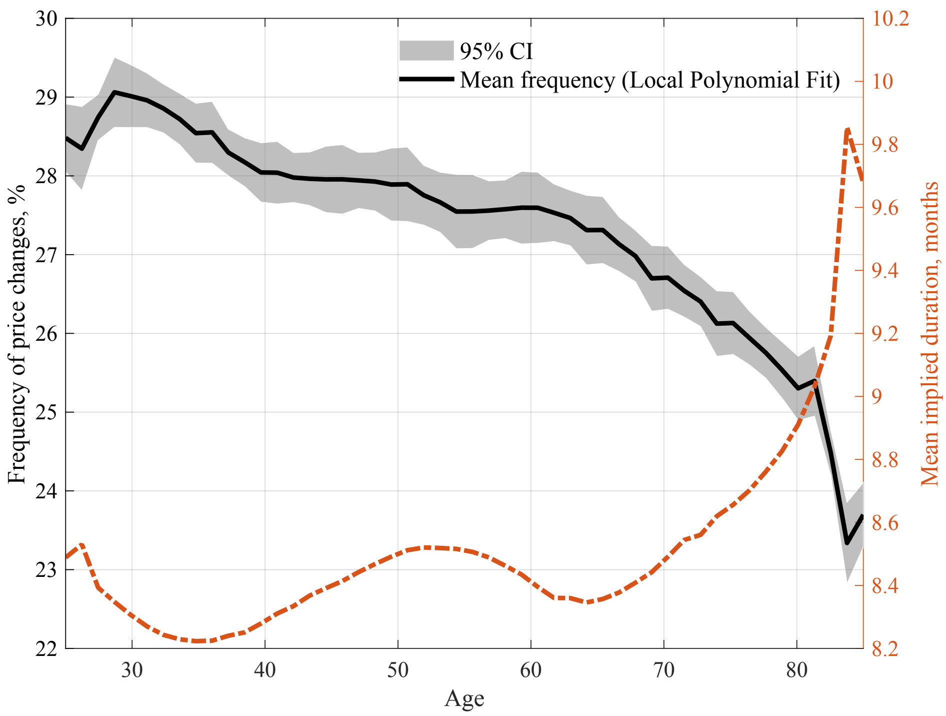
Notes: The left panel of the plot shows the evolution of the U.S. old-age dependency ratio over time (left axis) alongside the time series of the share of consumption devoted to services (right axis). The right panel compares the time series of the U.S. old-age dependency ratio with the mean implied duration of prices (right axis). The source of the data is the World Bank Population Estimates And Projections as well as the CEX data.

The evolution of the demographic structure can be considered to some extent exogenous but, despite being rather slow-moving, it is likely to have non-negligible effects on the overall economy. In particular, as shown in Cravino et al. (2020b), population aging explains around a fifth of the increase in the share of services consumed (which overall rose from 44% to 52%) over the last 40 years. Moreover, given that firms in the services sector adjust their prices much less frequently than firms in the goods sector, the rise in the share of services resulted in a decrease in the overall frequency of price adjustment with the mean implied duration increasing from around 8 months to 9.5 months. Therefore, since demographic trends contributed to the change in the share of services, they are also partially responsible for the observed decrease in the frequency of price adjustment. As every standard New Keynesian model predicts, the lower the frequency of price adjustment, the stronger the response of output and the more muted the response of inflation to monetary policy shocks.

2.1.2 Price stickiness across age groups

In this section, I document significant heterogeneity in price stickiness across age groups due to the different expenditure categories they consume. Figure 3 plots the weighted average frequency of price adjustment for each age group, $\bar{\theta}^a$. There is a clear and significant negative correlation between age and frequency of price adjustment. Given their heterogeneity in consumption bundles, the expenditures of older households are characterized by a much stronger price stickiness relative to young households. The average frequency of price adjustment for households above the age of 80 years is more than 20% lower than that of households between the ages of 15 and 25 years. Figure 3 also reports the mean implied duration for each age group (right axis). The mean implied duration significantly increases over the life cycle from around 8.4 months to almost 9.8 months.

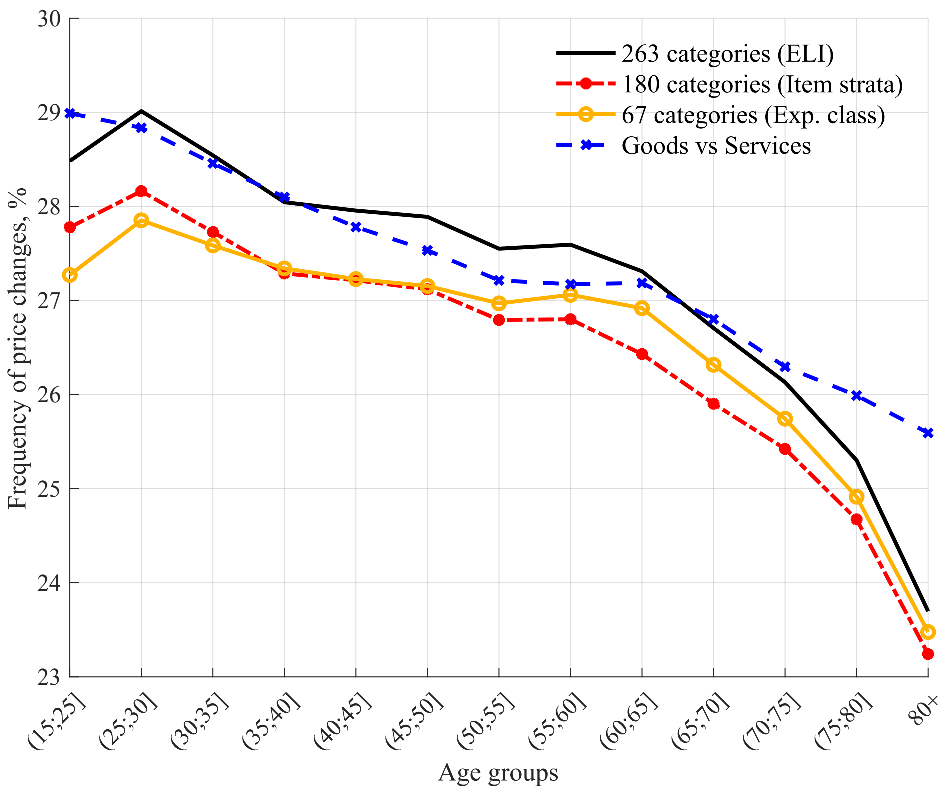
Figure 3: Frequency of price adjustment across age groups



Notes: The figure plots the weighted average frequency of price adjustment across age groups (left axis) alongside the mean implied duration (right axis). The shaded area is the 95% confidence band. The frequency of price adjustment is computed as the fraction of the number of times an item changes its price over the number of times the item is observed and expressed in percent per month. The mean implied duration captures after how many months, on average, a firm in sector j adjusts its price. The expenditure shares are computed using data from the CEX whereas the sectoral price stickiness parameters are retrieved from Nakamura and Steinsson (2008).

Which expenditure categories are mainly responsible for the observed pattern? Figure 4 shows that aggregating the 263 items into less and less granular groups does not remarkably affect the observed negative relationship between age and frequency of price adjustment. In particular, the classification of each expenditure category into goods or services almost entirely captures the relationship of interest[7]. This last classification is particularly important since services adjust their prices more than four times less frequently than goods (every 13 months versus every 3 months). Additionally, the expenditure share on services of old households is around 15 to 20 percentage points higher than that of young households. Therefore, in the theoretical model, I will focus on this distinction.

Figure 4: Frequency of price adjustment across age groups, alternative aggregation



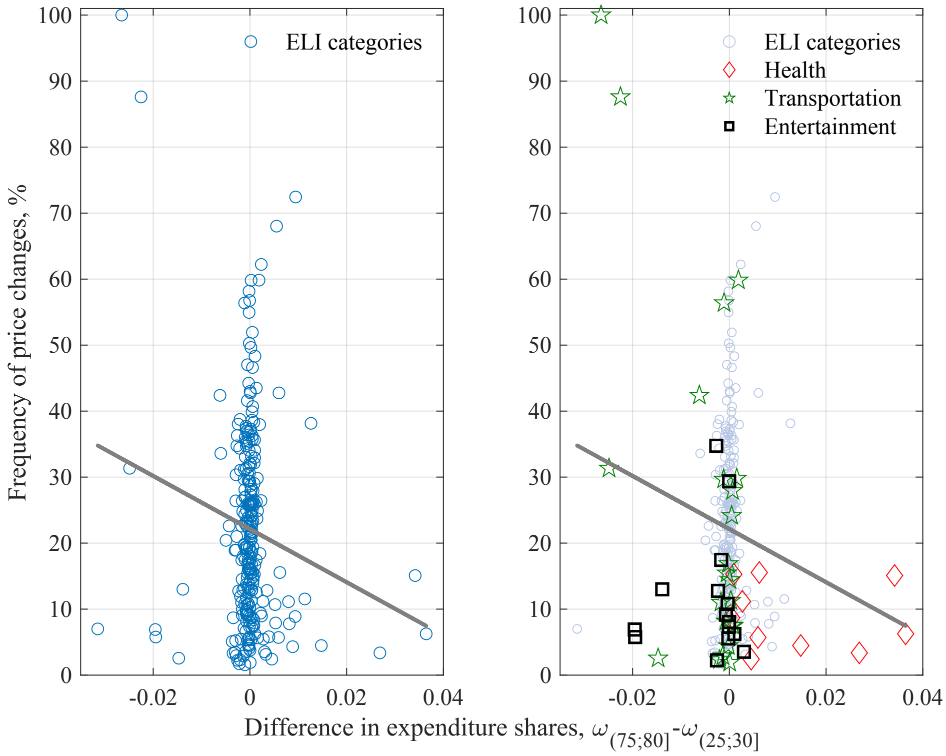
Notes: The figure plots the weighted average frequency of price adjustment across age groups when the expenditure categories are aggregated at ELI, Item Stata, and Expenditure Class level as well as Goods and Services. The frequency of price adjustment is computed as the fraction of the number of times an item changes its price over the number of times the item is observed and expressed in percent per month.

To shed further light on which categories mainly drive the relationship between age and price stickiness, I focus now on more granular expenditure categories. Table 6 shows the expenditure shares across some age groups for twenty of the main consumption categories.

[7] I classify as Goods the following expenditure categories: Food at home, Vehicle purchasing, Gas, Entertainment equipment, Appliances, furniture and fixtures, Alcoholic beverages, Clothing and other apparel, Tobacco, Personal care goods. I classify them as Services: Health, Utilities, Car maintenance, Repairs and insurance, Food away from home, Domestic services and childcare, Education, Entertainment services, Public transport, and Personal care services.

In line with previous findings, the largest disparity can be observed in health expenditures where the average consumption share of households above the age of 80 years is almost 16 percentage points larger than that of households below the age of 25 years. Moreover, younger households tend to spend relatively more on categories like Education, Entertainment, and Private Transportation. In contrast, Energy and Household Furnishings and Operations constitute a larger component of the older household consumption bundle.

Figure 5: Expenditure differences across age group



Notes: The left panel plots the frequency of price adjustment against the difference in sectoral expenditure shares for the age groups (75; 80] and (25; 30]. The right panel shows the same plot highlighting some important categories: Entertainment, Health, and Transportation. The fitted linear regression line of the data is included in both panels.

The left panel of Figure 5 plots the frequency of price change on the y-axis against the difference in the expenditure shares between the age groups (75; 80] and (25; 30] on the x-axis. A positive value means that the older group has higher expenditure shares in that category. Most of the categories gather around zero suggesting that the two age groups have similar expenditure shares. However, the categories more intensively brought by older households tend to be characterized by a lower frequency of price adjustment while the opposite holds for the categories mainly purchased by younger households. The correlation between the x-axis and y-axis variables is -0.153.

On the right panel of Figure 5 I highlight some of the categories for which expenditure heterogeneity is more evident. As previously mentioned, medical expenses are a major component of the elderly consumption bundle and at the same time, they are characterized by an extremely low frequency of price adjustment. The opposite is true for Transportation: younger households spend more on these categories and the firms in this sector are able to adjust their prices more frequently.

2.2 Decomposing the rise in service share

Since older people allocate a larger share of their consumption towards services, and since services tend to adjust their price much less frequently, an increase in the share of old people will increase the aggregate demand for services resulting in a lower frequency of price adjustment.

In order to quantify the contribution of observed changes in the age distribution to the observed changes in service shares in the U.S. between 1982 and 2018, I carry out a shift-share decomposition similar to Cravino et al. (2020b). This exercise allows us to quantify to what extent the increase in the share of services is due to the change in expenditure shares within age groups (i.e., each age group consumes more services but the share of aggregate expenditure of each age group is the same) and to what extent is due to reallocation of expenditures between groups (i.e., the share of services for each age group is unchanged but the age groups which have a higher share of services now account for a larger share of aggregate expenditure).

The share of services in aggregate consumption can be written as:

$$\alpha_t^s = \frac{\sum_a C_t^{s,a}}{\sum_a \sum_j C_t^{j,a}} = \sum_a \alpha_t^{s,a} s_t^a \tag{1}$$

where $\alpha_t^{s,a} = \frac{C_t^{s,a}}{\sum_j C_t^{j,a}}$ is the within age group share of expenditure devoted to services and $s_t^a = \frac{\sum_j C_t^{j,a}}{\sum_a \sum_j C_t^{j,a}}$ is the share of age group a in aggregate expenditure.

I can then decompose the change in services between two periods t_1 and t_2 as:

$$\Delta\alpha_t^s = \underbrace{\sum_a \Delta\alpha^{s,a}\bar{s}^a}_{\text{Within}} + \underbrace{\sum_a \bar{\alpha}^{s,a}\Delta s^{s,a}}_{\text{Between}} \tag{2}$$

with $\Delta x = x_{t_2} - x_{t_1}$ and $\bar{x} = \frac{x_{t_2} - x_{t_1}}{2}$ for any variable x. The term "Within" captures changes in the age-specific expenditure shares keeping age distribution fixed whereas the term

Table 1: Within-between decomposition, 1982 to 2018

	Service share	Contribution	Implied duration, months
Within	0.058	80 %	1.44 (+18.70 %)
Between	0.015	20 %	0.36 (+4.68 %)
Total	0.073 (44.95 % to 52.23 %)	100 %	1.80 (+23.38 %) (7.70 to 9.50)

"Between" captures changes in the share of age group a in aggregate expenditures keeping the preferences fixed.

I compute the within-between decomposition using the CEX data for 1982 and 2018 and report the results in Table 1. The service share increased by 7.3 percentage points between the two periods considered (first column) and 20% of the increase is attributed to between age group changes in expenditures (second column). The remaining 80% is due to changes in expenditure shares within groups. This result is in line with the findings in Cravino et al. (2020b).

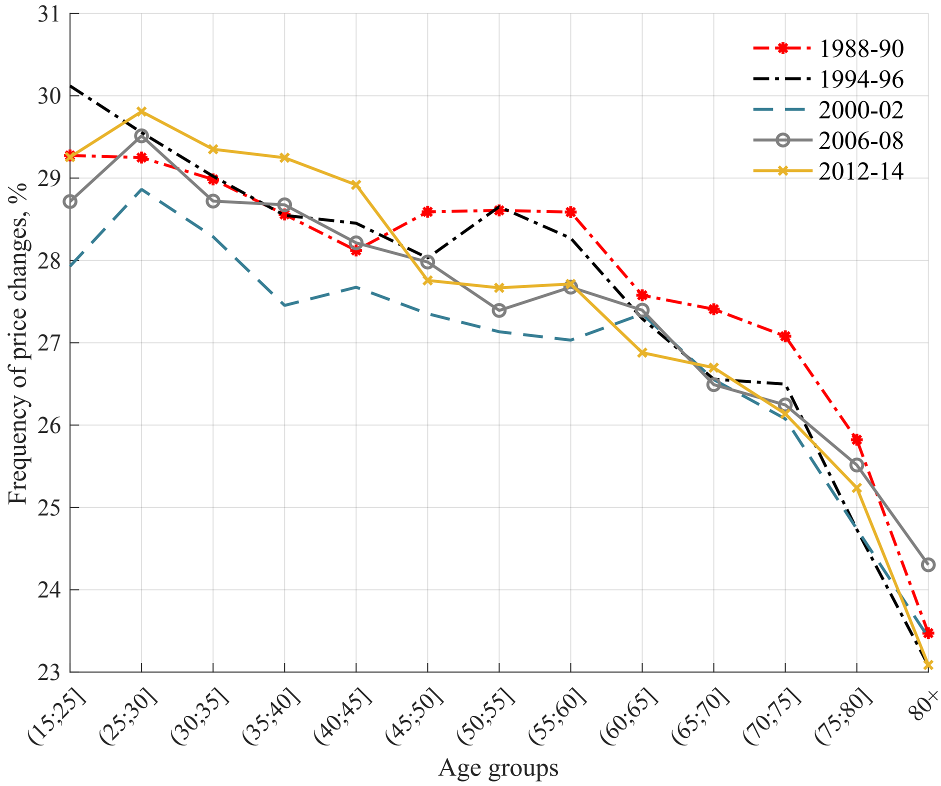
In terms of contribution to the change in price stickiness observed in Figure 2, between 1982 and 2018 the mean implied duration increased by 1.8 months, from 7.7 months to 9.5 months (third column); an increase of approximately 23%. Of this, the between age group changes in expenditures alone account for 0.36 months.

2.3 Robustness

First, I control that the negative relationship between age and frequency of price adjustment is stable over time. Figure 6 shows the same pattern for different periods. There is some marginal variation across time periods, partly due to the fact that some consumption categories are dropped and some are added, and partly due to actual changes in expenditure weights. However, the main conclusion still holds: the frequency of price adjustment decreases with age.

A potential source of concern regarding the findings in Figure 3 is that these patterns might be explained by demographic characteristics other than age. Indeed, Clayton et al. (2018) show that prices are more rigid in sectors selling to college-educated households whereas Cravino et al. (2020a) demonstrates that price stickiness displays an inverse U-shaped distribution across income groups.

Figure 6: Frequency of price adjustment across age groups and time



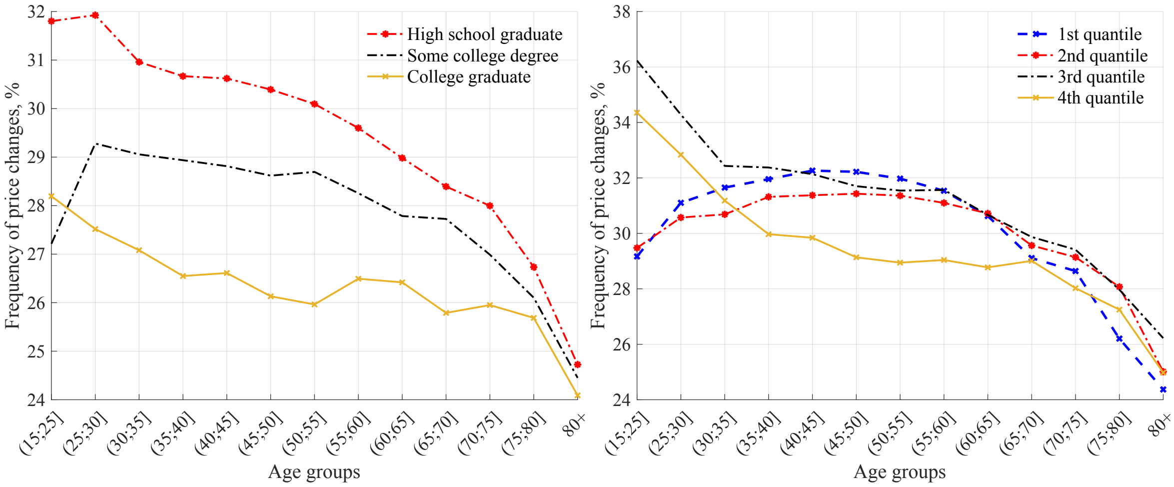
Notes: The figure plots the weighted average frequency of price adjustment at the age groups level across five different time periods. The frequency of price adjustment is computed as the fraction of the number of times an item changes its price over the number of times the item is observed and expressed in percent per month. The source of the data is the CEX.

To control that these demographic characteristics do not drive the results, I compute the frequency of price adjustment across age groups conditioning on the education level of the respondents as well as on the consumption quantile to which they belong[8].

The left panel of Figure 7 confirms that the consumption bundles of college-educated households have a lower frequency of price adjustment as in Clayton et al. (2018). In line with the findings of Cravino et al. (2020a), the right panel of Figure 7 shows that the average frequency of price adjustment tends to decrease along the consumption distribution. However, conditioning on education level as well as on consumption does not weaken the relationship of interest: the frequency of price adjustment significantly decreases with age.

[8] Cravino et al. (2020a) use the imputed income level which is available only from 2004 onward. For this reason, I use consumption level as a proxy for income. Moreover, since the households interviewed in the Interview survey are not the same ones interviewed in the Diary survey, for this robustness check I focus only on the Interview survey.

Figure 7: Frequency of price adjustment across age groups, education levels, and consumption quantiles



Notes: The left panel plots the weighted average frequency of price adjustment at age groups level for three different education levels. The right panel reports the weighted average frequency of price adjustment at the age group level for different consumption quantiles. The frequency of price adjustment is computed as the fraction of the number of times an item changes its price over the number of times the item is observed and expressed in percent per month.

3 The 3-Equation New Keynesian model

In the previous section, I document that the frequency of price adjustment has decreased over time. One of the main reasons is that the share of services has significantly increased in the last 40 years and the firms in these sectors tend to adjust their prices less often. Part of this structural transformation can be explained by demographic trends: old households consume a larger share of services relative to young households so the share of expenditure devoted to services increases as the population ages.

A higher level of price rigidity should result in a stronger response of output to monetary policy shocks and a more muted response of inflation. Before empirically testing these hypotheses, it is important to evaluate how the price stickiness affects the propagation of monetary shocks through the lens of a standard 3-equation New Keynesian model[9].

The three equations of the model are the IS curve (3), the Philips curve (4), and the interest rate rule (5). These equations relate the output gap $\hat{x}_t$ (defined as the deviation of output from its flexible price counterpart), the inflation rate $\hat{\pi}_t$ and the real interest rate $\hat{r}_t$:

$$\hat{x}_t = -\frac{1}{\sigma}\left(\hat{r}_t - E_t\hat{\pi}_{t+1}\right) + E_t\hat{x}_{t+1} \tag{3}$$

[9] The derivation of the model is rather standard in the literature so I refer the interested reader to Galí (2015).

$$\hat{\pi}_t = \beta E_t \hat{\pi}_{t+1} + \kappa(\sigma + \eta)\hat{x}_t \tag{4}$$

$$\hat{r}_t = \phi_\pi \hat{\pi}_t + \phi_x \hat{x}_t + \nu_t \tag{5}$$

where $\kappa \equiv \frac{(1-\theta)(1-\beta\theta)}{\theta}$ is the slope of the Phillips curve. All variables are expressed in log-deviation from a zero inflation steady state. σ is the intertemporal elasticity of substitution, β is the discount factor, η is the Frisch elasticity of labor supply and θ is the fraction of firms that cannot reset their prices each period. The interest rate rule coefficients, ϕ_π and ϕ_x, capture the response of the central bank to changes in inflation and output gap respectively. We assume that the monetary policy shock ν_t follows an AR(1) process with persistence ρ:

$$\nu_t = \rho \nu_{t-1} + \varepsilon_t^\nu \tag{6}$$

It is possible to express the output gap and the inflation as a function of only the monetary policy shock and the model parameters using the method of undetermined coefficients[10]. It can be shown that:

$$\hat{x}_t = -\left(1 - \beta\rho\right)\Lambda_\nu \nu_t \tag{7}$$

$$\hat{\pi}_t = -\kappa \Lambda_\nu \nu_t \tag{8}$$

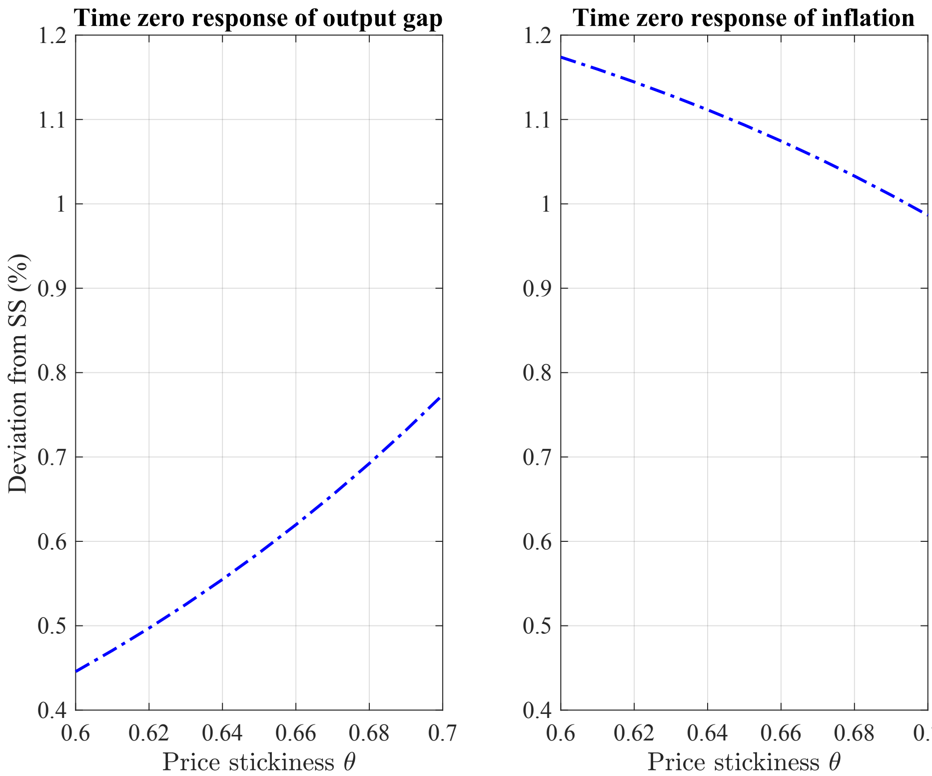
where $\Lambda_\nu \equiv \frac{1}{(1-\beta\rho)[\sigma(1-\rho)+\phi_y]+\kappa(\phi_\pi-\rho)}$. If the conditions for a unique stationary equilibrium are satisfied, Λ_ν is greater than zero so both the coefficients $\left(1-\beta\rho\right)\Lambda_\nu$ and $\kappa\Lambda_\nu$ are positive. Therefore, an expansionary monetary policy shock, i.e., a decrease in ν_t, leads to a persistent increase in the output gap and inflation.

However, the two coefficients differ in magnitude as well as in terms of their sensitivity to changes in the frequency of price adjustment. To see this, I set the model parameters to their standard value in the literature[11], and I compute the contemporaneous response of the output gap and inflation to a 100 basis point expansionary shocks, i.e., $\nu_t = -1$, as a function of the price stickiness parameter θ. From 1980 to 2020 the mean implied duration has increased from 7.5 months to almost 10 months as one can see from Figure 2, which would suggest that the price stickiness parameter has changed from 0.6 to 0.7 so I consider this interval.

[10] See Chapter 3 of Galí (2015).

[11] $\sigma = 1$ such that the utility function is in log-form, $\beta = 0.995$, $\eta = 1$, $\phi_\pi = 1.5$, $\phi_x = 0.2$ and $\rho = 0.8$.

Figure 8: Contemporaneous response of output gap and inflation as a function of price stickiness

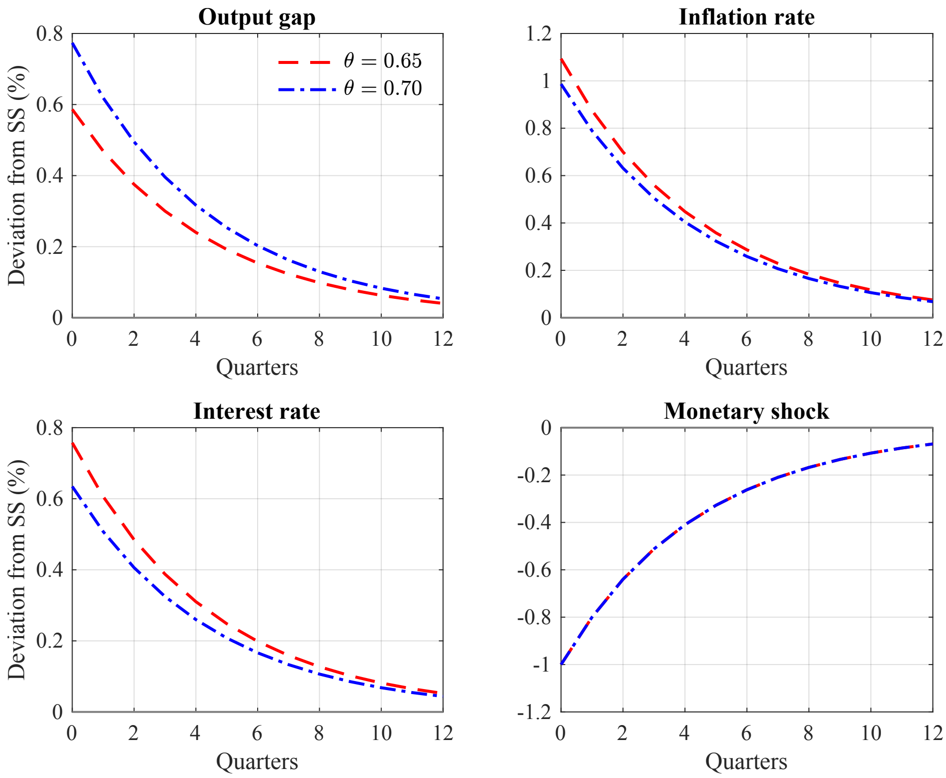


Notes: The figure plots the contemporaneous response of output gap (left panel) and inflation (right panel) to a 100 basis point decrease in interest rate as a function of the price stickiness parameter θ.

The relationships between the contemporaneous responses and price rigidity are reported in Figure 8. First, the size of the inflation coefficient is significantly larger than the output one resulting in a stronger response of inflation to the monetary shock. Second, the relationship is upward-sloping for output gap but downward-sloping for inflation confirming that an increase in price stickiness results in a more muted response of inflation to shocks (fewer firms can adjust their price) but stronger for output (firms need to adjust their production since they cannot adjust their prices). Third, the response of inflation is remarkably less sensitive to changes in price rigidities. Increasing the price stickiness parameter from 0.6 to 0.7 increases the time zero response of output by 75% (from 0.44% to 0.77%) whereas it decreases the response of inflation only by 20% (from 1.17% to 0.98%).

The different sensitivities of inflation and output to changes in price stickiness is due to the fact a lower frequency of price adjustment implies that fewer firms can adjust their price every period. Therefore, following a monetary shock the response of inflation is more muted and inflation also becomes less sensitive to changes in the other macroeconomic variables, i.e., $\kappa(\sigma + \eta)$ from the Philips curve (4) is decreasing when *theta* increases. The firms that

Figure 9: Impulse response functions from the 3-equation NK model



Notes: The figure plots the impulse responses of output gap, inflation, interest rate, and the monetary policy shock from the 3-equation NK model. The red lines are relative to the model with the price stickiness parameter θ sets to 0.6 and the blue line to 0.65.

cannot adjust their price respond by adjusting their production more. On top of that, firms anticipate that on average they might not be able to adjust their price for a longer time period. The expectations channel increases the responsiveness of output even more. Due to the lower sensitivity of inflation to changes in the economy, the increase in output responsiveness has only a marginal impact on the responsiveness of inflation.

Figure 3 shows that the mean implied duration across age groups varies from 8.5 months to almost 10 months. So if everyone had the same consumption bundle of young households the price stickiness parameter would be 0.65 while if everyone had the same consumption bundle of old households it would be 0.7. Therefore, to get a sense of the magnitude we could expect to find empirically, I compute the impulse response functions of output, inflation, and interest rate following a decrease of 100 basis points in ε_t^{ν} when θ is set to 0.65 and 0.7. The responses are reported in Figure 9.

Following the expansionary monetary policy shock both the output gap and inflation increase. As expected from the previous analysis, the response of output is smaller in magnitude than the response of inflation. Moreover, increasing the price stickiness parameter from 0.65 to 0.7 results in a stronger response of output and in a more muted response of inflation. Finally, it is important to notice how the response of output is also much more sensitive to the change in the frequency of price adjustment relative to the response of inflation. Indeed, under these two extreme scenarios the former increases by approximately 30% whereas the latter decreases by less than 10%.

Overall the results from the standard 3-equation NK model suggest that the impact of demographic trends on the transmission of monetary shocks is asymmetric between output and inflation. The decrease in the frequency of price adjustment due to the heterogeneity in consumption bundle across age groups is expected to significantly increase the responsiveness of output and will have a more negligible effect on inflation. In the next section, I empirically test these hypotheses by exploiting the cross-sectional variation in demographic structures across U.S. states.

4 Macro-level implications: across U.S. states comparison

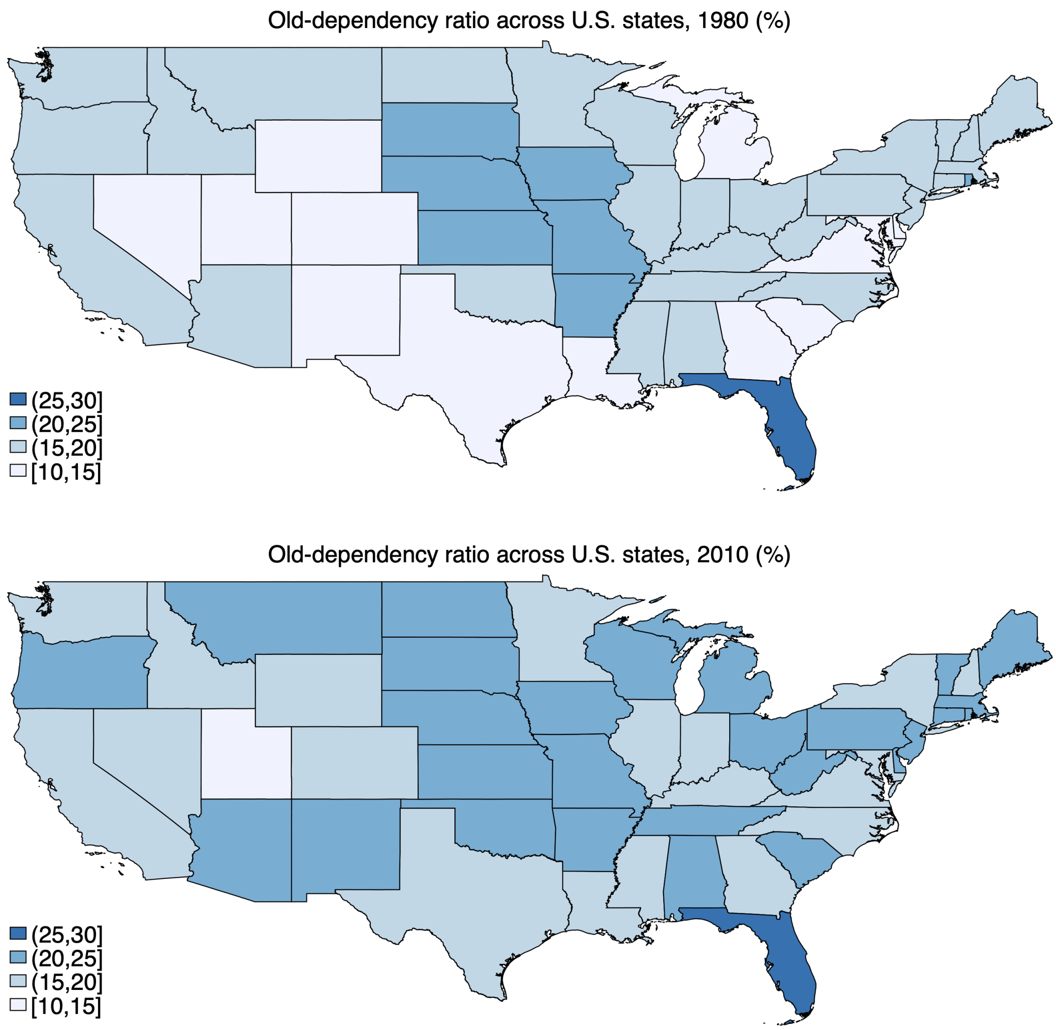
In section 2 I provide evidence of a positive relationship over time between the mean implied duration, the service share, and the old-age dependency ratio which might influence the way monetary policy propagates in the economy. At the aggregate level, a decrease in the frequency of price adjustment leads to a more muted response of inflation (since only a smaller fraction of firms resets their price every period) and to a stronger response of output (since firms that are unable to reset their prices need to respond by adjusting their production). As I document in section 3, these variations are not expected to be symmetrical for output and inflation. In particular, the response of output should be much more sensitive to changes in price stickiness than that of inflation.

In order to test the macro-level implications of the micro-level results I find, ideally, I would like to compare how economic activity reacts to shocks in periods of a high and low old-age dependency ratio. However, as shown in Figure 1, the demographic structure in the U.S. evolves almost linearly over time so this state-dependent approach is not feasible since there is basically no variation over time. Therefore, I compensate for the lack of time variation by exploiting the cross-sectional variation in the old-age dependency ratio across U.S. states. I find that the economic activity in U.S. states with a higher old-age dependency ratio reacts more to monetary shocks.

4.1 Data

I collect state- and country-level macroeconomic variables from different sources. The main variable of interest at the state level is the real personal income and the GDP from the Bureau of Economic Analysis (BEA) as well as the annual inflation rate from Hazell et al. (2021). Whereas personal income and inflation rate are available at a quarterly frequency, the GDP is available only at an annual frequency. The country-level variables that are used as controls are collected from FRED and include the industrial production (IP), the consumer price index (CPI), the federal funds rate (FFR), the unemployment rate, and the commodity price index computed by Ramey (2016). I also include information on state population size and demographics from the U.S. Census Bureau.

Figure 10: Old-age dependency ratio across U.S. states and over time



Notes: The figure shows the old-age dependency ratio across the U.S. in 1980 (top panel) and 2010 (bottom panel) using data from the Census Bureau.

Figure 10 shows the significant heterogeneity across states in terms of demographic structure for two different periods that I will use in the theoretical exercise, that is in 1980 (top panel) and in 2010 (bottom panel). These maps illustrate the substantial variation across states in both years, with the old-age dependency ratio ranging from 11% to 27% as well as the significant shift in demographics across almost every state in the U.S. over the past 3 decades.

In the next subsection, I describe the empirical approach I adopt to study the impact of demographic trends on the pass-through of monetary policy by exploiting the cross-sectional variation in the demographic structure across states.

4.2 Empirical specification

To investigate how different demographic structures affect the transmission of monetary policy, I adopt panel Local Projection à la Jordà (2005). In particular, I compute the average state-level response to a monetary policy shock by estimating the following regression:

$$y_{i,t+h} = \alpha_{i,h} + \beta_h MP_t + \theta_{i,h} X_{i,t-1} + \gamma_h X_{t-1} + \epsilon_{i,t+h} \tag{9}$$

for different horizons $h = 1, ..., 16$. As dependent variable $y_{i,t}$ I use the state-level log of real personal income, the annual inflation rate, and the log real GDP. As monetary shocks MP_t I use the narrative based Romer and Romer (2004) shocks and include state fixed effects $\alpha_{i,h}$. As state controls $X_{i,t-1}$ I use the lagged dependent variable and the log of the population size whereas as aggregate controls X_{t-1} I follow Ramey (2016) by including IP, CPI, FFR, unemployment rate, and commodity price index. To deal with the potential endogeneity, all control variables, except for the monetary policy shocks, are lagged by one period. Standard errors are clustered at the state level. The main coefficient of interest is β_h which captures the impact of monetary policy shocks on the dependent variable over the horizon h.

To evaluate how different demographic structures across U.S. states influence monetary policy effectiveness, I follow the approach proposed by Cloyne et al. (2018) and define dummy variables for different percentiles P of the old-age dependency ratio distribution which I interact with the monetary shock MP_t:

$$y_{i,t+h} = \alpha_{i,h} + \sum_{p=1}^{P} \gamma_h D_{i,t}^p + \sum_{p=1}^{P} \beta_h^p D_{i,t}^p MP_t + \theta_{i,h} X_{i,t-1} + \gamma_h X_{t-1} + \epsilon_{i,t+h}, \tag{10}$$

where $D_{i,t}^{p}$ is a dummy equal to 1 if the old-age dependency ratio of state i belongs to the p-th percentile at time t and 0 otherwise. The coefficients β_h^p, which are different for each percentile included in the regression, capture how states are heterogeneously affected by monetary policy shocks according to their demographic structure.

4.3 Results

I begin this section by presenting the baseline result that the economic activity of states with a higher old-age dependency ratio responds more to monetary policy shocks. I then assess the robustness of this finding across several dimensions.

I start by focusing on the impact of monetary policy shocks on the log of real personal income. The left panel of Figure 11 plots the estimated β_h coefficient at different horizons h from equation (9). The shaded area is the 1.65 standard deviation confidence interval. Following a contractionary monetary shock, that is an exogenous increase in interest rate, the real personal income decreases by 0.4% after 3 years. The magnitude and the shape of the response are in line with the literature.

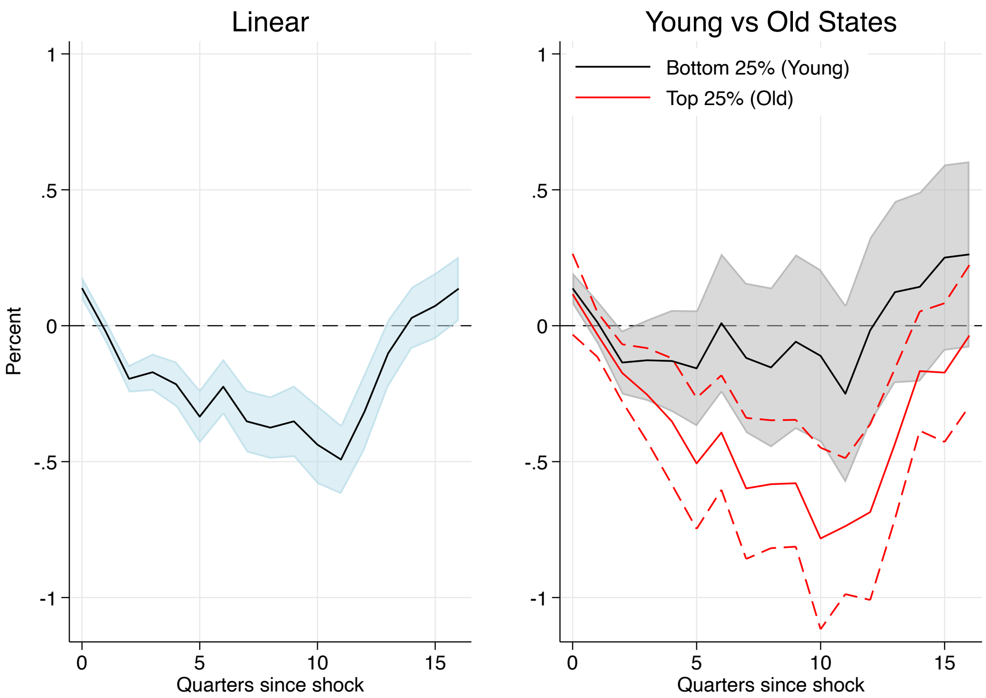
The right panel of Figure 11 plots the estimated β_h^p coefficients from equation (10) for the bottom 25% and top 25% states in terms of old dependency rate. As one can notice, the response of the "old" states (top 25%) is significantly and persistently stronger than the response of the "young" states. This result is in line with the empirical evidence provided by Leahy and Thapar (2020) and suggests that monetary policy becomes more effective when the share of old people in the economy increases.

Figure 12 reports the same responses using the annual inflation rate as the dependent variable. Following a contractionary shock, the annual inflation rate, after an initial increase, decreases by approximately 0.4 percentage points. In line with the theoretical predictions of section 3, I find no significant differences in the responses across states. As I will show in section 5, also the more complex model I develop will be able to replicate this result.

Finally, in Figure 13 I repeat the same analysis but using the log of the real GDP at an annual frequency as the dependent variable. Real GDP decreases by around 1.2% after a monetary shock and even in this case, the states with a higher old-age dependency ratio tend to react much more strongly.

These empirical findings confirm that demographic structure plays an important role in the pass-through of monetary policy. On the one hand, the results are in line with the new channel proposed in this paper, that is, the higher the share of old people in the economy, the

Figure 11: Impact of monetary policy on real personal income in young and old states



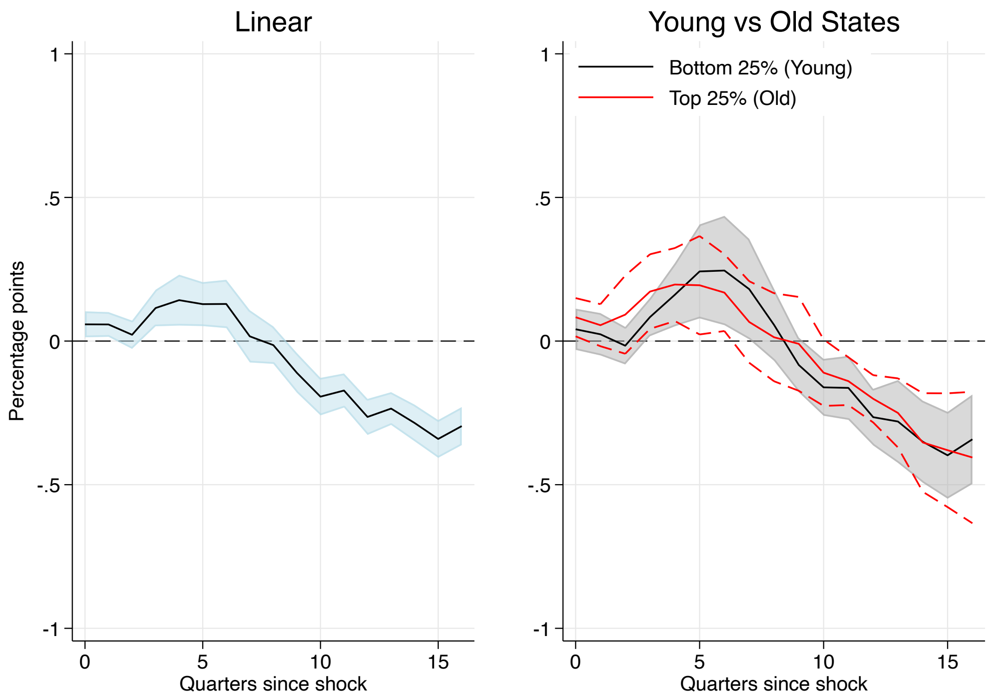
Notes: The left panel of the figure plots the response of the real personal income to a percentage point contractionary monetary policy shock, as well as 1.65 standard deviation confidence intervals for the state level log of real personal income. The horizontal axis is in quarters. The right panel reports the interaction coefficients between the monetary policy shock and the dummies identifying the bottom 25% and top 25% of the old-age dependency ratio distribution.

lower the frequency of price adjustment, and the stronger the response of output to shock. On the other hand, I clearly cannot conclude that the entire effect observed is due to my channel alone. For this reason, in the next section, I develop a two-sector OLG-NK model to evaluate the impact of demographic trends on the transmission of monetary policy shocks and quantify the size of the new channel.

4.4 Robustness

To strengthen the validity of the results, I try a number of alternative specifications whose figures are reported in Appendix C. First, I repeat the same empirical analysis using different thresholds to distinguish between young and old states. As an alternative measure of monetary shocks, I also employ a high-frequency identification in a local projection with instrumental variables (LP-IV). Furthermore, I add state-level GDP as additional control and I exclude the five smallest states from the sample. Finally, for the dependent variable, I use the services

Figure 12: Impact of monetary policy on annual inflation rate in young and old states

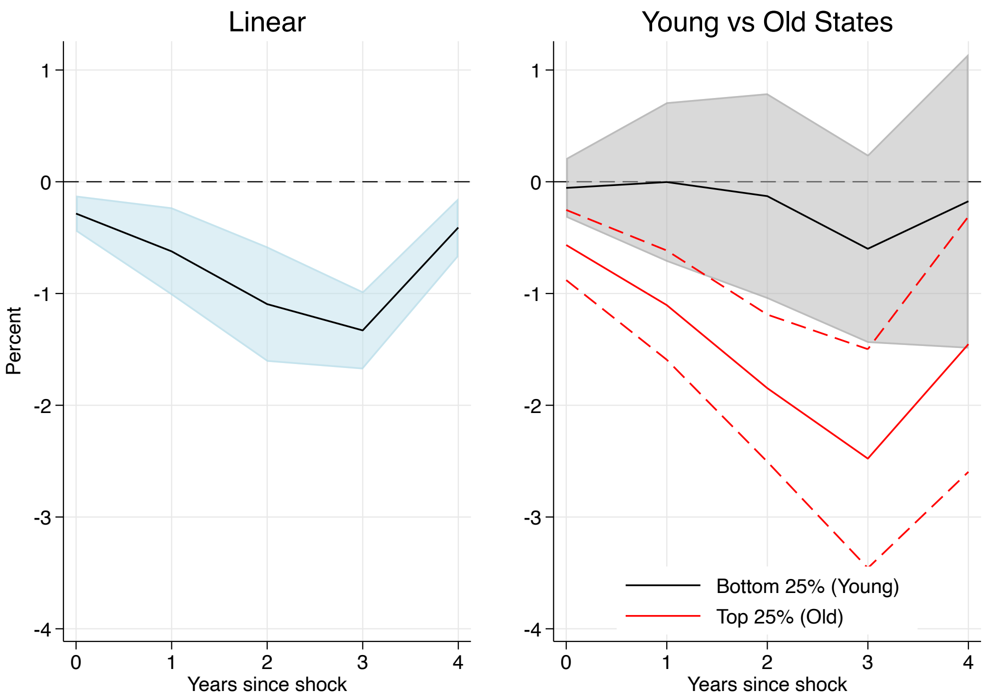


Notes: The left panel of the figure plots the response of the annual inflation rate to a percentage point contractionary monetary policy shock, as well as 1.65 standard deviation confidence intervals for the state-level annual inflation rate. The horizontal axis is in quarters. The right panel reports the interaction coefficients between the monetary policy shock and the dummies identifying the bottom 25% and top 25% of the old-age dependency ratio distribution.

component of the local GDP as a proxy for the non-tradable sector. The bottom line is that the basic pattern presented in the previous section, in which the economic activity of states with a higher old-age dependency ratio responds more to shocks, survives all of these modifications.

For the first robustness check, I consider different percentiles of the old-age dependency ratio distribution which I interact with the monetary shock. I consider a state old if its old-age dependency ratio is above the cross-sectional median and young otherwise. The impulse response functions are reported in Figures 24 to 26. This alternative classification has little to no impact on my baseline results. Similar results are found by using the bottom and top 10% of the old-age dependency ratio distribution as thresholds. Figures 27 to 29 present the results under this alternative classification. The gap between the responses of personal income and GDP across states with different demographic structures is larger under this specification

Figure 13: Impact of monetary policy on the real GDP in young and old states



Notes: The left panel of the figure plots the response of the real GDP to a percentage point contractionary monetary policy shock, as well as 1.65 standard deviation confidence intervals for the state level log of real GDP. The horizontal axis is in years. The right panel reports the interaction coefficients between the monetary policy shock and the dummies identifying the bottom 25% and top 25% of the old-age dependency ratio distribution.

thus reinforcing the conclusion that the effectiveness of monetary policy is influenced by age composition.

One obvious question is whether the results are driven by the choice of monetary policy shocks. Therefore, as an additional estimation technique, I present the results from local projection instrumental variables, LP-IV as in Stock and Watson (2018), using a high-frequency identification for the monetary shocks. The key idea of this approach is to use changes in future prices around policy announcements. Since the time window around the announcements is relatively small, one can consider these changes to be entirely due to the announcement itself and orthogonal to the information set of the financial market.

Despite the fact that these high-frequency shocks have been extensively used in the literature (e.g., Stock and Watson, 2018, Jarociński and Karadi, 2020), they have a big disadvantage in the context of this study: the sample for which we have data on high-frequency future prices is too short, as they are available only from January 1991. For this reason, I try to overcome this problem by extracting the estimated structural shocks directly from the proxy-VAR run by Gertler and Karadi (2015) from July 1980 to June 2012. Since the structural shocks extracted from the VAR are identified up to scaling, I combine them with the LP-IV specification which easily solves this issue, similarly to Cloyne et al. (2018).

The results are presented in Figures 30 to 32 using as dependent variables the real personal income, annual inflation rate, and GDP at the state level respectively. All the regressions include the same controls as in the baseline specification. The instrumented variable is the change in federal funds rate and the instruments are the structural shocks discussed above.

On the one hand, the responses of the state-level real personal income and GDP are comparable in shape and magnitude to the baseline specification being significantly stronger for states with a higher old-age dependency ratio. On the other hand, the weaker response of the annual inflation rate for the "older" states is in line with the consumption heterogeneity channel presented in this paper: the higher the share of older individuals in a state, the higher the consumption of services which have a lower frequency of price adjustment, the more muted the response of inflation to shocks.

Another source of concern might be that state characteristics other than the demographic structure may confound the results. Cravino et al. (2020a) argue that higher-income households tend to purchase goods with stickier prices. Since households' age and income tend to be positively correlated, the results could reflect this mechanism. To control for this, I, therefore, add state GDP as an additional regressor. Regression results are reported in Figure 35 and Figure 36. Again I find no evidence that this mechanism drives the results.

I then repeat the same empirical analysis excluding the five smallest states by population: Alaska, North Dakota, Vermont, Washington D.C., and Wyoming. As can be seen in Figure 33 and Figure 34, this has basically no effect on the results.

Finally, spillover effects might bias the results. It could be the case that the stronger response of personal income and GDP observed in older states is actually due to an increase in the demand for tradable goods from younger states rather than from the different frequencies of price adjustment across age groups. I test this hypothesis by using the services component of GDP as the dependent variable and as a proxy for the consumption of non-tradable goods: since services are usually not traded across states, differences in responses to shocks are mainly caused by local characteristics. The results are reported in Figure 37. The response of services in states with a higher old-age dependency ratio is significantly stronger suggesting that my main results are not driven by spillover effects.

5 A Quantitative Life-Cycle Model

This section presents a two-sector overlapping generations (OLG) model for a closed economy with New Keynesian frictions in price settings that will be used to evaluate the impact of population aging in the U.S. on monetary shock propagation. The model presented here is an extension of the OLG models derived in Heer et al. (2017), Bielecki et al. (2020) and Bielecki et al. (2021) with one crucial modification: households of different ages have heterogeneous preferences over two sectors, services, and goods, which differ in terms of the frequency of price adjustment.

5.1 Demographics

Households are born at age $j = 1$ (equivalent to real life age of 15), live for a maximum of $J = 85$ years (real-life age of 99), and survive each period with an age-specific probability s_j. The parameter $(1 - s_j)$ is then the age-specific mortality rate. The households work until they are $jw = 50$ years old (real-life age of 64) and then retire. I denote with N_j the size of cohort j relative to the overall population and so we have that $\sum_{j=1}^{J} N_j = 1$. As in Jaimovich et al. (2013) and Heer et al. (2017), the size of each age group is constant over time in order to match the empirical age-specific population shares with the model implied ones[12].

5.2 Households

The representative household of age j at time t maximizes its discounted lifetime utility (16) by choosing aggregate consumption $c_{t,j}$, the amount of hours to supply $l_{t,j}$ and the amount of assets to hold the sequent period $a_{t+1,j+1}$ subject to a budget constraint (13). The household receives a lump-sum transfer beq_t as well as an income $y_{t,j}$ composed of the net of tax labor-income $(1 - \tau_t)W_t l_{t,j} h_j$ if younger than jw years old, pension transfer from the government pen_t if older than jw years old. The transfers come from the unintentional bequests left by the households who die every period which are redistributed equally across all living agents. I express a variable in real terms by deflating it by the aggregate price index and define the relative price of the two sectors as:

$$Z_t = \frac{P_t^G}{P_t^S}. \tag{11}$$

[12]Households die every period at a rate $(1 - s_j)$ so the reader might think of an age-specific migration rate that keeps the size of each cohort constant. This assumption has a limited influence on the results since I will focus only on 3/4 years around the steady state and in such a short time span population distribution is basically constant.

The value function of the household of age j at time t can then be summarized as:

$$V_{t,j} = \max_{c_{t,j}, l_{t,j}, a_{t+1,j+1}} u\left(c_{t,j}, l_{t,j}\right) + \beta s_j \mathbb{E}_t V_{t+1,j+1}, \tag{12}$$

subject to the following constraints:

$$P_{t,j} c_{t,j} + P_t a_{t+1,j+1} = R_t^a P_{t-1} a_{t,j} + y_{t,j} \tag{13}$$

$$y_{t,j} = (1-\tau_t) W_t l_{t,j} h_j \mathbf{I}_{j \leq jw} + pen_t \mathbf{I}_{j > jw} + beq_t \tag{14}$$

$$a_{t,0} = 0 \qquad a_{t+J+1,J+1} = 0, \tag{15}$$

where R_t^a is the gross nominal rate on the real stock of assets that are managed by investment funds, W_t is the nominal wage per effective hour, h_j is the age-specific labor productivity rate, $\mathbf{I}$ is an indicator function to distinguish workers from retirees. Households are born and die without assets. Finally, the utility function takes the form:

$$u\left(c_{t,j}, l_{t,j}\right) = \left(\frac{c_{t,j}^{1-\sigma}}{1-\sigma} - \nu \frac{l_{t,j}^{1+\eta}}{1+\eta}\right). \tag{16}$$

The bundle of services and goods consumed by the household is given by:

$$c_{t,j} = \left[\alpha_j^{\frac{1}{\eta}} (c_{t,j}^S)^{\frac{\eta-1}{\eta}} + (1-\alpha_j)^{\frac{1}{\eta}} (c_{t,j}^G)^{\frac{\eta-1}{\eta}}\right]^{\frac{\eta}{\eta-1}}, \tag{17}$$

where the parameters $0 < \alpha_j < 1 \ \forall j$ capture the age-specific preferences over the services sector and will be used to match the expenditure shares observed in the data. η is the elasticity of substitution between services and goods. The price index associated with this bundle is:

$$P_{t,j} = \left[\alpha_j^{\frac{1}{\eta}} (P_t^S)^{\frac{\eta-1}{\eta}} + (1-\alpha_j)^{\frac{1}{\eta}} (P_t^G)^{\frac{\eta-1}{\eta}}\right]^{\frac{\eta}{\eta-1}}. \tag{18}$$

5.3 Firms

On the firms' side, there are two sectors: one that produces services and one goods. The main differences between the two sectors stem from the fact that only the output of the goods sector can be used for capital investment and they differ in their frequency of price adjustment. In line with the empirical evidence, a lower share of firms in the services sector is able to adjust prices each period. As in standard New Keynesian models, the production side in each sector is split into a competitive final goods firm and a continuum of intermediate goods firms.

Final firms. For each sector, $s \in \{S, G\}$ the final good is produced under perfect competition using a continuum of intermediate goods indexed by i with a constant-returns-to-scale technology. The final firms are price-takers and they solve the profit-maximization problem:

$$\max_{Y_{i,t}^s} P_t^s Y_t^s - \int_0^1 P_{i,t}^s Y_{i,t}^s \, dj, \tag{19}$$

subject to the CES production function where the parameter ϵ denotes the elasticity of substitution across different varieties of intermediate goods:

$$Y_t^s = \Big(\int_0^1 (Y_{i,t}^s)^{\frac{\epsilon-1}{\epsilon}} \, di \Big)^{\frac{\epsilon}{\epsilon-1}}. \tag{20}$$

The solution to the maximization problem gives the standard demand function for variety i for the production of final good s:

$$Y_{i,t}^s = \Big(\frac{P_{i,t}^s}{P_t^s} \Big)^{-\epsilon} Y_t^s. \tag{21}$$

Intermediate firms. The optimization problem of the monopolistically competitive intermediate good producer i is divided into two stages. In the first stage, for a given production function $Y_{i,t}^s$, the intermediate firm chooses the amount of inputs $L_{i,t}^s$ and $K_{i,t}^s$, taking nominal prices as given, such that costs are minimized:

$$\min_{L_{i,t}^s, K_{i,t}^s} W_t L_{i,t}^s + R_t^k K_{i,t}^s \tag{22}$$

$$s.t. \;\; Y_{i,t}^s = (K_{i,t}^s)^{\psi} (L_{i,t}^s)^{1-\psi},$$

where ψ is the capital share in the production function and R_t^k is the nominal rental rate on capital.

In the second stage, $Y_{i,t}^s$ and $P_{i,t}^s$ are determined such that the discounted real profits are maximized subject to the demand function of the final output producer. However, firms are not free to adjust their prices as they want since they face a Calvo staggered price setting mechanism: in each period, a fraction θ^S of services intermediate goods producers and a fraction θ^G of manufacturing intermediate goods producers cannot reset their prices and maintain those of the previous period. The Calvo friction parameters are constant over time and differ across sectors to match the empirical estimates on the lower frequency of price adjustment in the services sector relative to the goods sector, that is $\theta^S > \theta^G$.

The fact that a firm in sector s might not be able to adjust its price in period t with probability θ^s makes the pricing problem dynamic equal to solving:

$$\max_{P^s_{i,t}} \mathbb{E}_0 \sum_{t=0}^{\infty} \Big(\prod_{r=0}^{t} R_r^{-1} \Big) (\theta^s)^r \Big[(P^s_{i,t} - MC^s_{t+r}) \Big(\frac{P^s_{i,t}}{P^s_{t+r}} \Big)^{-\epsilon} Y^s_{t+r} \Big], \tag{23}$$

where MC^s_t is the nominal marginal cost in sector s. Since intermediate goods producers are risk-neutral they use the nominal risk-free rate to discount expected future profit flows.

5.4 Investment funds

As in Bielecki et al. (2021), the households' savings are managed by perfectly competitive and risk-neutral investment funds which transfer the earned gross return back to households every period. The portfolio managed by the investment funds consists of physical capital K_t, bonds B_t, and claims on intermediate goods-producing firms (shares) $D_{i,t}$. A representative investment fund maximizes the expected present value of future gross returns:

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \Big(\prod_{r=0}^{t} R_r^{-1} \Big) \Big[[R^k_{t+1} + (1-\delta) Q_{t+1}] K_{t+1} + R_t P_t B_{t+1} + \int_0^1 [P_{t+1} F_{i,t+1} + P^d_{i,t+1}] D_{i,t+1} \, di \Big], \tag{24}$$

where δ is the depreciation rate of capital, R_t denotes the gross nominal risk-free rate, Q_{t+1} is the nominal price of a unit of capital, and $D_{i,t}$ refers to the number of shares issued by intermediate goods producing firm i which are traded at the end of period t at price $P^d_{i,t}$ and yield real dividends $F_{i,t}$. The nominal balance sheet of investment funds at the end of period t can be written as:

$$P_t A_{t+1} = Q_t (1-\delta) K_t + P_t I_t + P_t B_{t+1} + \int_0^1 P^d_{i,t} D_{i,t+1} \, di. \tag{25}$$

I_t denotes investment in physical capital which accumulates according to:

$$K_{t+1} = (1-\delta) K_t + \Big[1 - S_k \Big(\frac{I_t}{I_{t-1}} \Big) \Big] I_t, \tag{26}$$

where $S_k()$ captures investment adjustment costs which have the following functional form:

$$S_k \Big(\frac{I_t}{I_{t-1}} \Big) = \frac{S_1}{2} \Big(1 - \frac{I_t}{I_{t-1}} \Big)^2. \tag{27}$$

Finally, since I assume that all revenues are transferred back to households, the ex-post rate of return on assets R^a_t is implicitly given by:

$$R^a_t P_{t-1} A_t = [R^k_t + (1-\delta)Q_t]K_t + R_{t-1}P_{t-1}B_t + \int_0^1 [P_t F_{i,t} + P^d_{i,t}] D_{i,t}\, di. \tag{28}$$

5.5 Government

The government funds a pay-as-you-go social security system. The amount of pension benefit pen_t received by households with age above jw is given by the replacement rate $\bar{d}$ and the average net labor income $(1-\tau_t)W_t\bar{h}$. The tax rate on labor income τ_t is set such that the budget is balanced in each period:

$$pen_t = \bar{d}(1-\tau_t)W_t\bar{h} \tag{29}$$

$$\tau_t W_t \sum_{j=1}^{jw} N_j l_{t,j} h_j = pen_t \sum_{j=jw+1}^{J} N_{t,j}, \tag{30}$$

where $\bar{h} = \frac{\sum_{j=1}^{jw} h_j}{jw}$ is the average efficiency-hours worked in the working life-periods.

5.6 Monetary authority

The central bank follows the following simple Taylor-type rule:

$$\frac{R_t}{R} = \Big(\frac{\Pi_t}{\Pi}\Big)^{\phi_\pi} \Big(\frac{Y_t}{Y}\Big)^{\phi_y} e^{\nu_t}, \tag{31}$$

where R_t is the gross nominal interest rate, $\Pi_t = \frac{P_t}{P_{t-1}}$ is the gross rate of aggregate inflation, Y_t is the aggregate output and R, Π, and Y are the steady state values of the respective variable. ϕ_π and ϕ_y measure the elasticity at which the monetary authority adjusts the interest rate to changes in the current inflation rate and output and ν_t is a monetary shock following an $AR(1)$ process with persistence ρ.

Aggregate output is defined as:

$$P_t Y_t = P^S_t Y^S_t + P^G_t Y^G_t \tag{32}$$

and aggregate price level as $P_t = \Big[\omega_t^{\frac{1}{\eta}} (P^S_t)^{1-\eta} + (1-\omega_t)^{\frac{1}{\eta}} (P^G_t)^{1-\eta}\Big]^{\frac{1}{1-\eta}}$ where $\omega_t = \sum_j \alpha_j \chi_{t,j} \frac{P^{\eta-1}_{t,j}}{\sum_j \chi_{t,j} P^{\eta-1}_{t,j}}$ and $\chi_{t,j}$ is the share of household j expenditure in aggregate expenditures at time t. See Appendix B for the full derivation.

5.7 Market clearing

The market for final output in both sectors needs to clear. Only the output of the goods sector can be stored into the next period and used for capital investment while the output of the services sector needs to be consumed every period. Hence:

$$Y_t^S = C_t^S \tag{33}$$

$$Y_t^G = C_t^G + K_{t+1} - (1-\delta)K_t. \tag{34}$$

Moreover, both the labor and the capital market also need to clear:

$$L_t^S + L_t^G = \sum_{j=1}^{J} N_{t,j} l_{t,j} h_j \tag{35}$$

$$K_t = K_t^S + K_t^G = \sum_{j=1}^{J} N_{t,j} a_{t+1,j+1}. \tag{36}$$

Since bonds are traded only between (identical) investment funds they are in zero net supply, $B_t = 0$. Finally, the lump-sum transfer beq_t from the unintentional bequests is equal to:

$$beq_t = \sum_{j=1}^{J} (N_{j-1} - N_j) \frac{R_t^a}{\Pi_t} a_{t,j}. \tag{37}$$

5.8 Quantitative analysis

I am interested in studying how demographic trends affect monetary policy shock propagation. Therefore, I use the model to study the transmission of monetary policy shocks around three steady states that differ only in terms of population distribution N_j, mortality rate $(1 - s_j)$, and service preferences α_j. All other parameters are fixed. I choose 1980 as the first steady state and baseline since that is when CEX data, necessary to compute the sectoral preferences across age groups, becomes available. The second steady state is 2010 and the final steady state is set at 2050 using the World Bank population projection for the U.S.

5.8.1 Calibration

The model parameters are set in two ways: externally set with the values in the literature and internally set to target data moments.

Table 2: Externally set parameters

Parameter	Value	Description
J	85	Terminal life-age (99). Death with certainty at age 100
jw	50	Terminal working-age (64)
σ	1	Elasticity of intertemporal substitution
ϕ	4	Disutility of labor supply
ν	2	Inverse of the Frisch elasticity of labor supply
η	0.4	Elasticity of substitution between services and goods from Galesi and Rachedi (2018)
ψ	0.33	Cobb-Douglas capital elasticity of output
S_1	4.39	Investment adjustment cost curvature from Bielecki et al. (2021)
$\bar{d}$	0.33	Pension replacement rate. Source: Bárány et al. (2019)
ϕ_π	1.5	Inflation coefficient in the Taylor rule
ϕ_y	0.2	Output coefficient in the Taylor rule
ρ	0.8	Monetary shock persistence
σ_{ϵ^r}	1	Std. Dev. of Monetary shock

Notes: The table reports the externally set parameters of the model.

The externally set parameters are reported in Table 2. As previously mentioned, households live for a maximum of 85 ($J = 85$) years and then die with certainty. They work until they are $jw = 50$ years old (64 years old in real life) and then they retire. The elasticity of intertemporal substitution σ, the disutility of labor supply ϕ, and the inverse of the Frisch elasticity ν are set to their standard values of 1, 4, and 2 respectively. The elasticity of substitution between the two sectors η, which captures how easy it is for the household to switch goods and services, is from Galesi and Rachedi (2018) and set to 0.4. The investment adjustment cost curvature S_1 equals 4.39 as in Bielecki et al. (2021). The pension replacement rate $\bar{d}$ is taken from Bárány et al. (2019). Finally, the Taylor rule coefficients are set to the standard values in the literature.

The internally calibrated parameters are reported in Table 3. The discount factor β and the depreciation rate δ are set to 0.999 and 0.02 respectively in order to match the annual interest rate and the capital-output ratio estimated in the early 80s. The elasticity of demand for each intermediate good ϵ is set to 6 such that the steady-state markup is equal to 20%. The age-group-specific labor productivity parameters h_j, shown in Panel A of Figure 14, are taken from Fullerton (1999) in order to match the hump-shaped distribution of labor income over the life cycle.

Table 3: Calibrated parameters

Parameter	Value	Description	Target
β	0.999	Discount factor	Annual interest rate between 4 and 5 %
δ	0.02	Depreciation rate	Capital-output ratio between 2 and 2.7
N_j	Panel B of Figure 14	Population shares. *Source*: UN (2017) World Population Prospects	Realised and forecasted population shares
$(1 - s_j)$	Panel C of Figure 14	Survival probability. *Source*: Social Security Administration	Realised and forecasted mortality rates
α_j	Panel D of Figure 14	Share of consumption devoted to services	Age-group service preferences from CEX
h_j	Panel A of Figure 14	Age-group specific labor productivity from Fullerton (1999)	Wage profile
ϵ	6	Elasticity of demand for each intermediate good	Steady state markup of 20%
θ^S	0.75	Calvo Frequency Services. *Source*: Nakamura and Steinsson (2008)	Price adjustment every 13 months
θ^G	0.25	Calvo Frequency Goods. *Source*: Nakamura and Steinsson (2008)	Price adjustment every 3 months

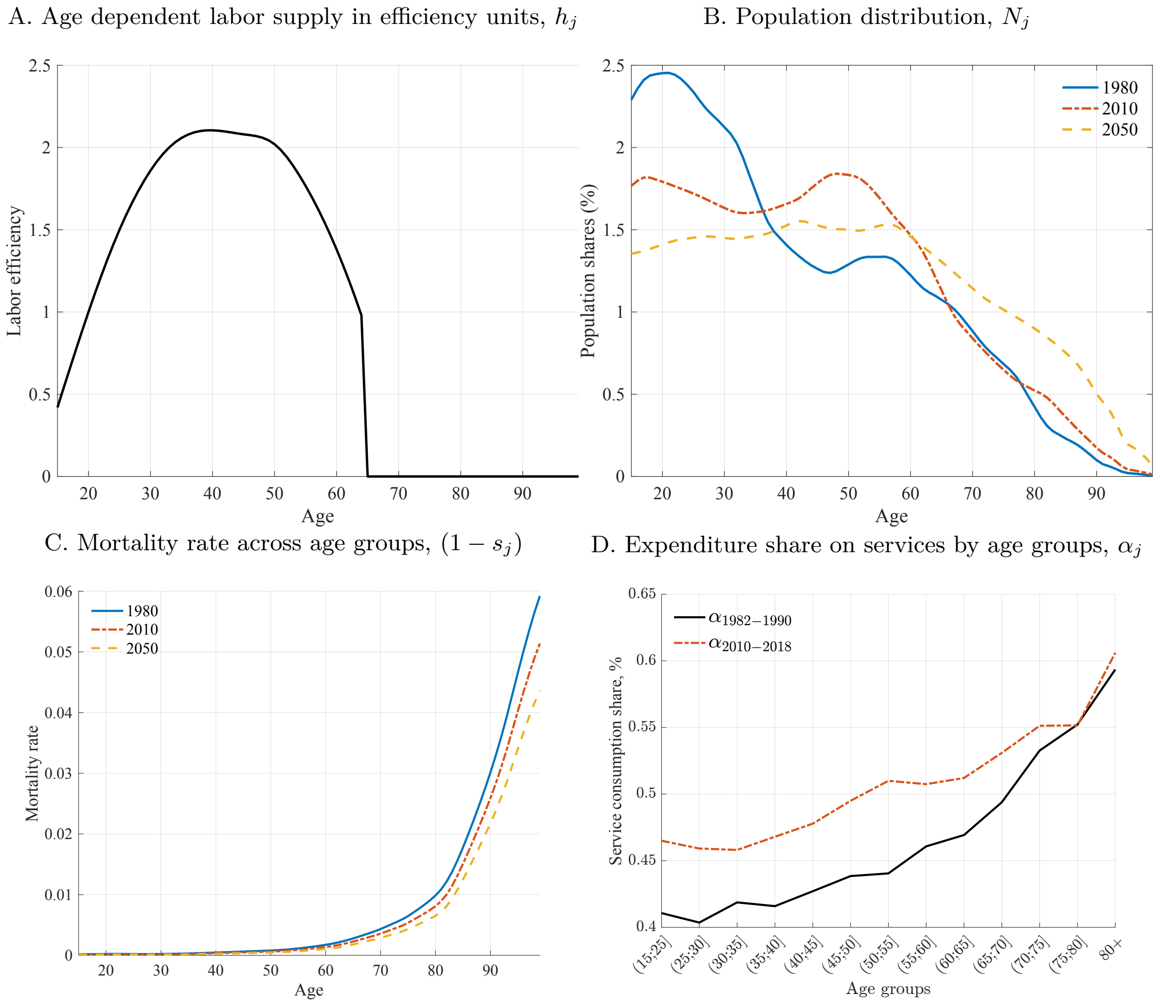
Notes: The table reports the internally calibrated parameters of the model.

The most important parameters for the analysis are the shares of each age group N_j, the mortality rates $(1 - s_j)$, and the shares of consumption devoted to services α_j. The U.S. population distributions for the years 1980, 2010, and 2050, reported in Panel B of Figure 14, are retrieved from the UN (2017) World Population Prospects. As one can notice, demographic trends are a complex phenomenon that cannot be entirely captured by simply considering the effects on workers and retirees. On the one hand, the share of people below 35 years old is decreasing over time whereas the share of people above 65 years old is increasing. On the other hand, the share of highly productive workers (households between 35 and 65 years old) has actually increased relative to 1980. These shifts in labor force participation might have conflicting predictions regarding the effectiveness of monetary policy if not properly included in the model.

Much more straightforward is the analysis of the changes in the U.S. mortality rates $(1 - s_j)$ reported in Panel C of Figure 14. For all the age groups considered, the survival probability has increased from 1980 to 2010 and it is expected to increase even further in 2050.

Panel D of Figure 14 shows the share of consumption α_j that each age group devotes to services. The services shares are computed from the CEX data which is available since the early 80s. Since there are no predictions regarding the state of these shares in 2050 when I evaluate how changes in preferences influence the pass-through of monetary policy I focus only on the 1980 and 2010 steady states. The share of services almost linearly increases over the life cycle in line with previous findings. Since the early 80s, each age group has increased its consumption of services mainly because of income and price effects as shown in Cravino et al. (2020b).

Figure 14: Age specific parameters



Notes: Panel A: The profile of the age-specific labor productivity is obtained by interpolating the estimates from Fullerton (1999). Panel B: The plot shows the population share distribution across age groups for 1980, 2010, and the forecasted values for 2050. *Source*: UN (2017) World Population Prospects. Panel C: The plot displays the age-group quarterly mortality rates in 1980, 2010, and the forecasted values for 2050. *Source*: Table 7 from the Cohort Life Tables for the Social Security Area. Panel D: The plot displays the average age group level expenditure shares on services across age groups over two different periods. *Source*: CEX.

Finally, the Calvo parameters for the services sector θ^S and the goods sector θ^G are set to 0.75 and 0.25 respectively as in Galesi and Rachedi (2018) in order to match the mean implied duration in months estimated by Nakamura and Steinsson (2008).

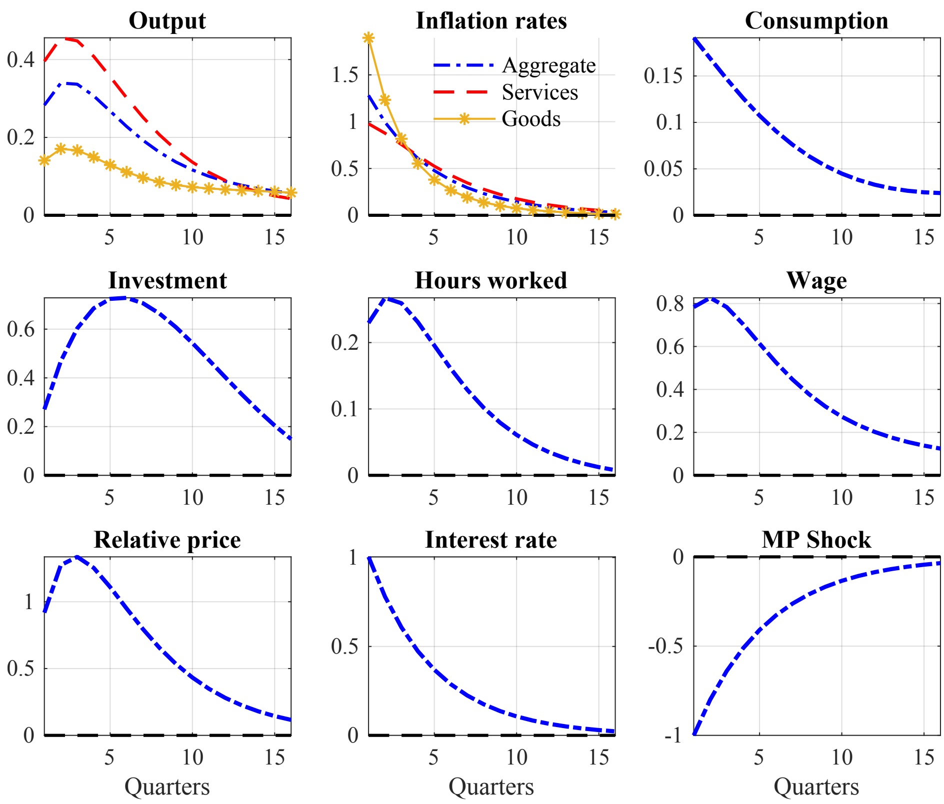
I assess the quality of the calibration of the lifecycle parameters by comparing some untargeted moments with the data. In particular, Figure 38 plots the age profile of assets implied by the model (normalized to asset holdings at age 65) with the age profile observed over different years in the Survey of Consumer Finances (normalized for the group 65-54). The model performs quite well in replicating the hump-shaped lifecycle asset profile which peaks around 60 years old. In line with the data, individuals borrow when young and dissave after they retire.

5.8.2 Demographic trends and the effectiveness of monetary policy

In this section, I use the theoretical model to evaluate how demographic trends influence the way monetary policy shocks propagate in the U.S., to what extent consumption heterogeneity across age groups contributes to this, and finally whether population aging had any effect on the flattening of the Phillips curve.

Figure 15 reports the IRFs to an expansionary monetary shock of the main variables in the model computed using the demographic structure in 1980. The shapes and the magnitudes are in line with the literature. Following a 100 basis points expansionary monetary policy shock, i.e., an exogenous decrease in the interest rate, output, inflation, consumption, and investment increase. The central bank then responds by increasing the real interest rate to slow down economic growth until the economy returns to the initial steady state.

Figure 15: Model impulse response functions



Notes: The plot reports the IRFs of several variables of interest computed using 1980 as steady states.

Of particular interest are the responses in the two top left panels. On the one hand, given the different price stickiness parameters between the two sectors, the price response in the services sector is more muted relative to the response in the goods sector. On the other hand, since firms in the services sector cannot adjust their prices as frequently, they respond to the shock by adjusting their production more vigorously leading to a stronger and less persistent response of the output in the services sector relative to the response in the goods sector.

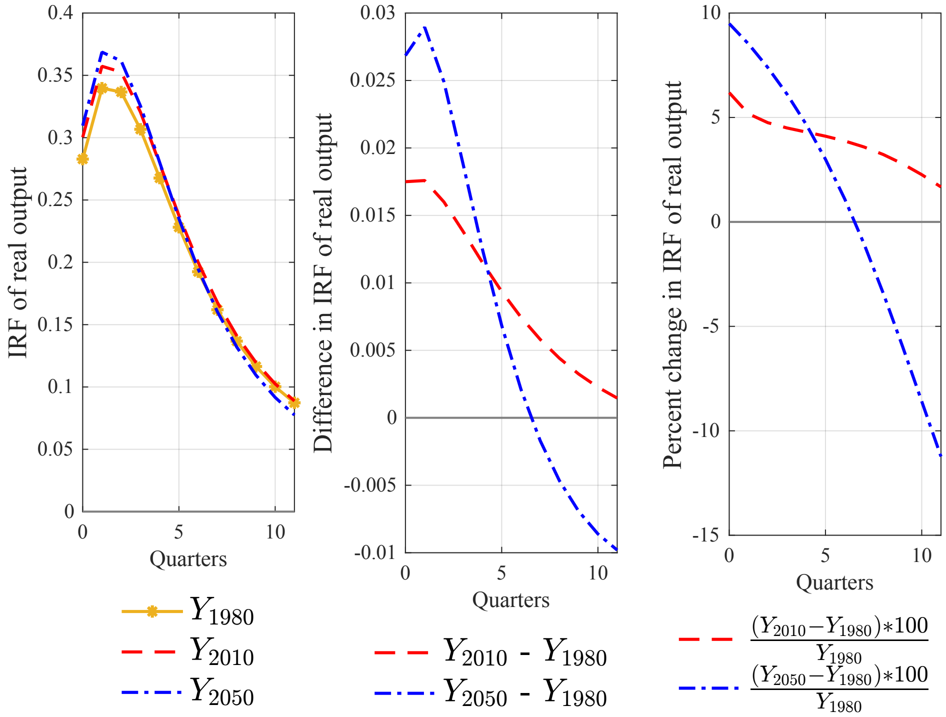
Since older households tend to have a higher preference for the services sector, an increase in their population share will increase the aggregate demand for this sector. This will shift the aggregate output response, which can be considered a weighted average of the sectoral responses, more towards the response of the services sector which is relatively stronger and less persistent over time.

I now focus on the influence that demographic trends have had on monetary shock propagation in the U.S. over the last decades and the influence that they will have in the next 30 years. To evaluate this relationship, I compute the response of output to an expansionary monetary shock using the population distribution N_j and the mortality rates $(1 - s_j)$ in 1980, 2010, and 2050. All the other parameters are kept fixed including the services shares α_j which are set to their 1980 values.

The responses are plotted in the left panel of Figure 16. Moving from 1980 to 2010 and then to 2050 results in a stronger response of output to the shock and the increase is economically sizable. On top of that, the responses have become less persistent over time. In the middle panel, I report the differences in output responses with respect to the baseline of 1980. By increasing the share of old people who have a higher preference for the services sector, the demographic structures of 2010 and 2050 increase the response of output by 0.018 and 0.026 percentage points respectively relative to that of 1980. The right panel shows the same results in percent deviation: simply changing the population distribution and the mortality rate over time makes the response of output 6% stronger in 2010 relative to 1980 and 10% stronger in 2050.

Figure 17 reports the same analysis for the responses of the aggregate inflation rate. In line with the empirical evidence found in Section 4, demographic trends have a negligible impact on the IRFs of inflation: the demographic structures of 2010 and 2050 relative to that in 1980 result in more muted responses of inflation (so the differences $\pi_{2010} - \pi_{1980}$ and $\pi_{2050} - \pi_{1980}$ are negative) but the overall decrease is less than 1% for both steady states.

Figure 16: Model IRFs of output for different demographic structures

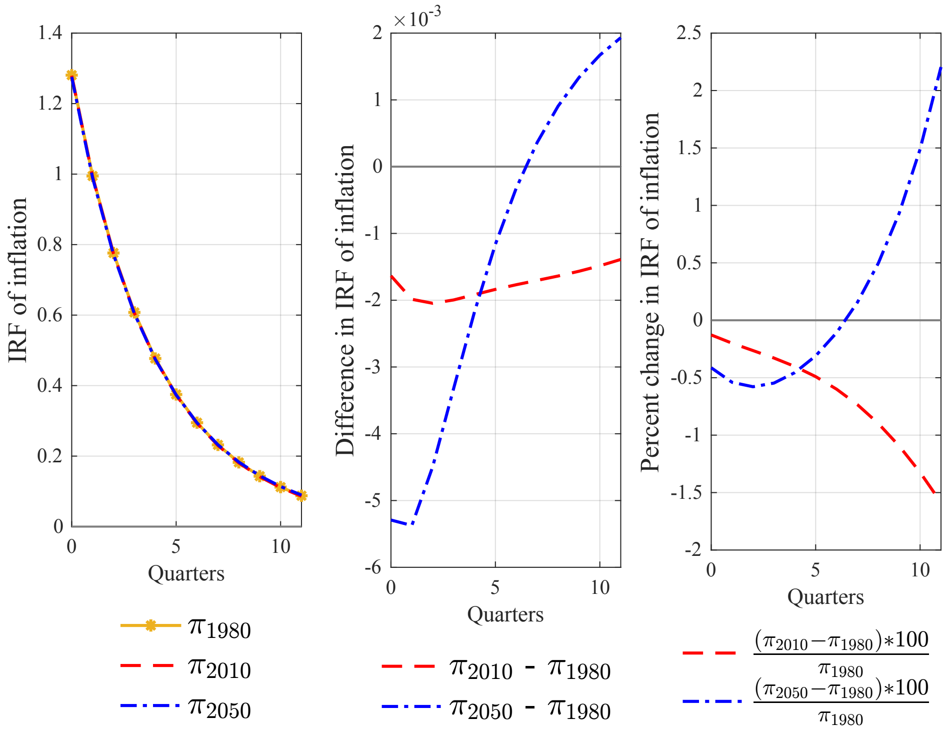


Notes: The left panel of the plot reports the IRFs of output across the three different steady states changing only the population distribution and mortality rate and keeping service preferences at the 1980 values. The middle panel shows the first differences of these IRFs, i.e., the difference between the IRF of output in 2050 and 2020 with the respect to the baseline IRF in 1980, whereas the right panel reports the percentage change in IRFs across the different steady states.

The results so far presented document that demographic trends alone are able to influence monetary policy effectiveness by making output more responsive to interest rate shocks. keeping the U.S. is only partially explained by changes in age-group distribution. As demonstrated in Cravino et al. (2020b), population aging accounts for around a fifth of the overall rise in the share of services and the real income growth, and changes in relative prices explain another three fifth.

To quantify the importance for monetary policy propagation of demographic trends relative to other channels, I compare the variation in output and inflation responsiveness under three different scenarios. In the first scenario, I isolate the demographic component by computing the percent change in the IRFs of output and inflation from 1980 to 2010 by adjusting the population distribution and mortality rates but keeping the service preferences constant as in Figures 16 and 17. The results are reported in the blue bars of Figure 18. The responses of output are shown on the left panel and the responses of inflation are on the right panel. In the second scenario, I use the service preferences of 1980 and 2010 but the demographic

Figure 17: Model IRFs of inflation for different demographic structures



Notes: The left panel of the plot reports the IRFs of inflation across the three different steady states changing only the population distribution and mortality rate and keeping service preferences at the 1980 values. The middle panel shows the first differences of these IRFs, i.e., the difference between the IRF of inflation in 2050 and 2020 with the respect to the baseline IRF in 1980, whereas the right panel reports the percentage change in IRFs across the different steady states.

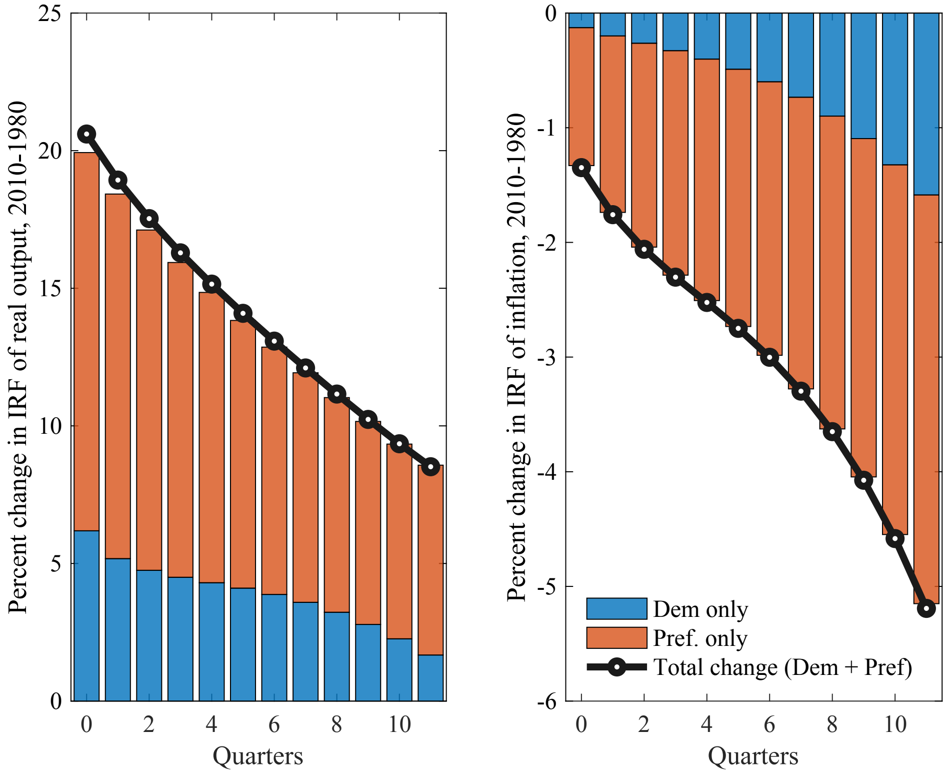
structure of 1980 (red bars). In the third scenario, I use both the demographic structures and service preferences of the two steady states (black line).

The response of output in 2010 is 20% stronger than in 1980 when both the demographic structure and the service preferences are changed and a significant share of this increase is explained by population aging alone. The ratio between the blue bars and the black line in the left panel is approximately 30% suggesting that, even though other structural changes like income and price effects are important drivers of the change in service share, demographic trends account for a sizable extent of the overall effect.

The right panel of Figure 18 delivers a similar story for inflation. The overall percent change in IRFs is between 1.5% and 4.5% more muted in 2010 relative to 1980 and the share explained by demographic trends is between 10% and 25%

Finally, I evaluate to which extent the new proposed channel of consumption heterogeneity across age groups contributes to the observed variation in monetary policy effectiveness. To do so, I compare the results from Figure 16 and Figure 17 in which I compute the responses

Figure 18: Model IRFs under different scenarios



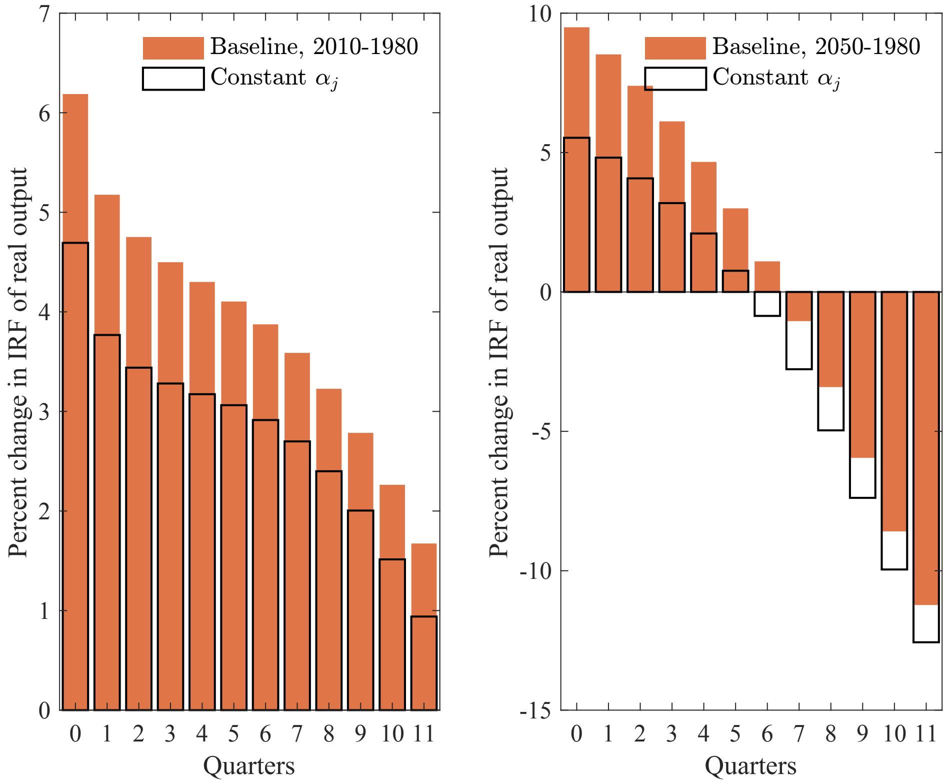
Notes: The left panel of the plot shows the percent change in impulse responses for output from 1980 to 2010 under three different scenarios: using the population distribution and mortality rates of 1980 and 2010 but services preferences kept fixed at the 1980 values (blue bars, same plot as before), using the service's preferences of 1980 and 2010 but the demographic structure of 1980 (red bars) and finally using both the demographic structures and services preferences of the two steady states (black line). The right panel shows the same percent change but for inflation.

using three different steady-state values for the demographic structure and keeping everything else fixed with a contrafactual scenario where the share of consumption devoted to services α_j is constant across age groups and equal to the weighted mean value.

Figure 19 compares the percent changes of output under the baseline and the contrafactual scenario for 2010 relative to 1980 (left panel) and for 2050 relative to 1980 (right panel). Neglecting preference heterogeneity across age groups leads to a clear underestimation of the effect of demographic trends on monetary policy: the percent change of the response of output on impact drops from 6% to 4.5% in 2010 and from 9% to 4.8% in 2050.

It is important to notice that demographic trends still lead to an increase in the overall effectiveness of monetary policy. This is mainly due to changes in the labor market: the share of workers decreases over time so the firms need to adjust the wage level more vigorously to shocks in order to increase the supply of hours of labor.

Figure 19: Model IRFs of output between the baseline and the contrafactual scenario



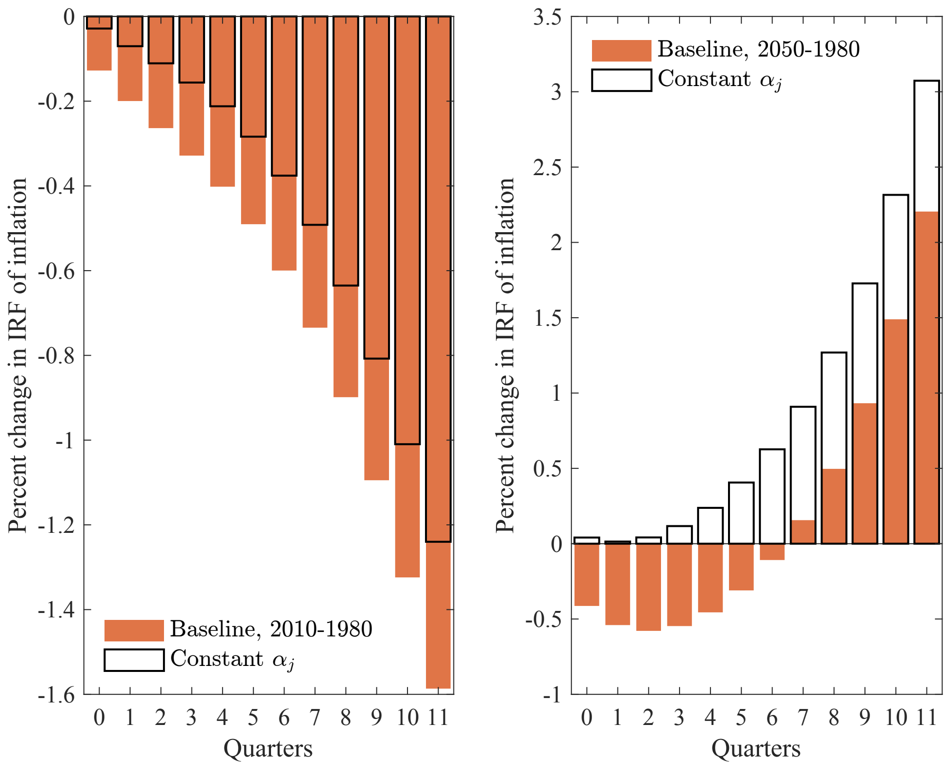
Notes: The plot compares the percent changes of output for 2010 relative to 1980 (left panel) and for 2050 relative to 1980 (right panel) for the baseline and a contrafactual scenario in which all age groups have the same sectoral preferences.

The same exercise is repeated for inflation and reported in Figure 20. A symmetrical effect is found here: neglecting preference heterogeneity results in an overestimation of the impact of population aging on the response of inflation. The effect is such that the percent change is smaller from 1980 to 2010 than in the baseline and becomes even positive for 2050.

Overall the results suggest that the demographic trends that the U.S. has experienced in the last decades and that are expected to happen in the next 30 years will significantly influence the way monetary policy shocks propagate. Moreover, I demonstrate that population aging accounts for a sizable share of the overall change in monetary policy effectiveness. Finally, I quantify the size of the new channel proposed in this paper, i.e., that demographic trends shift aggregate demand towards the stickier expenditure category.

However, the effects of demographic trends are unlikely to be homogeneous across age groups. As I show in the next subsection, young households are the most exposed to the changes in monetary shock propagation.

Figure 20: Model IRFs of inflation between the baseline and the contrafactual scenario



Notes: The plot compares the percent changes of inflation for 2010 relative to 1980 (left panel) and for 2050 relative to 1980 (right panel) for the baseline and a contrafactual scenario in which all age groups have the same sectoral preferences.

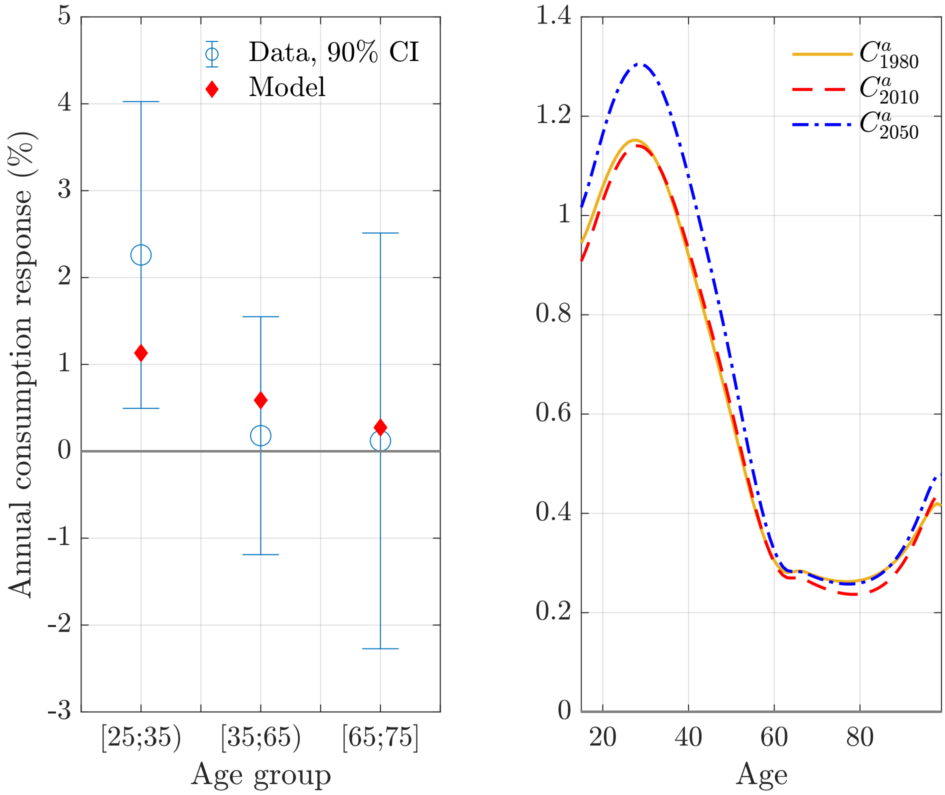
5.8.3 Heterogeneous consumption responses by age

The shift in aggregate demand towards services caused by demographic trends leads to a stronger response of output following an expansionary monetary shock. However, these changes are unlikely to be homogeneous across age groups. I now evaluate which age groups are more exposed to the structural transformation induced by population aging.

I start by comparing the model-implied consumption responses with the empirical estimates from the literature. The left panel of Figure 21 reports the annual percent change of consumption, i.e., the sum of the responses of the first four quarters, from the model with those estimated by Wong (2021) for three age groups. The model is able to capture quite well the negative relationship between age and consumption responsiveness and the predicted responses fall within the 90% confidence bands of the empirical estimates.

The left panel of Figure 21 shows the model-implied annual percent change of consumption for each age group C^a following an expansionary monetary shock using the demographic structure of 1980, 2010, and 2050. The relationship between age and consumption responsiveness

Figure 21: Heterogeneous consumption responses to expansionary monetary policy shocks, by age



Notes: The left panel compares the annual percent change of consumption following a contractionary shock from the model (red diamond) with the empirical estimates from Wong (2021) (blue error plot with 90% confidence bands) for three age groups. The right panel reports the model-implied annual percent change of consumption across age groups following an expansionary shock using the demographic structure of 1980, 2010, and 2050.

is not linear. In particular, it increases until households are 30 years old and then drastically decreases. After they turn 60 years old the relationship becomes rather stable with a slight increase towards the end. The nonlinearity in the relationship is due to the hump-shaped distribution of assets and labor productivity reported in Figure 38 and Panel A of Figure 14 respectively.

The change in population distribution from 1980 to 2010 has a negligible and rather homogeneous effect on consumption responsiveness across age groups. However, in 2050 demographic trends will have an extremely heterogeneous impact across age groups and the consumption of younger households will be the one most affected by demographic trends. For the age group between 25 and 35 years, old consumption will respond 15% more in 2050 than in 1980. The consumption responses of older people are basically unaffected.

The results suggest that population aging will significantly influence the propagation of monetary policy shocks and that the consumption of younger households is the most exposed to these trends. In the next subsection, I evaluate whether changes in population distribution have contributed to the flattening of the Phillips curve.

5.8.4 Phillips curve

The slope of the Phillips curve, which captures the strength of the relationship between inflation and economic activity, has been found to decrease over time. This so-called "flattening" of the Phillips curve has crucial implications for policymakers and central bankers. A lower sensitivity of inflation to real activity implies that to stabilize inflation, larger movements in economic activity are needed, which in turn require larger shifts in the interest rate. This is of particular importance in times when the interest rate is close to zero.

Several explanations have been proposed to justify this phenomenon and including the success of monetary policy in anchoring expectations (Bernanke, 2010), the increase in central bank credibility and transparency (McLeay and Tenreyro, 2019), or global forces (Jorda et al., 2019).

In this paper, I argue that part of the flattening of the Phillips curve is due to the increase in the consumption share devoted to services and, therefore, to demographic trends that shift demand towards this stickier category.

The New Keynesian Phillips curve for sector s can be derived by linearizing equation (23) around a steady state with zero inflation in both sectors. Applying the canonical derivations leads to the following sectoral Phillips curves:

$$\hat{\pi}_t^S = \beta \mathbb{E}_t \hat{\pi}_{t+1}^S + \kappa^S \hat{mc}_t^S \tag{38}$$

$$\hat{\pi}_t^G = \beta \mathbb{E}_t \hat{\pi}_{t+1}^G + \kappa^G \hat{mc}_t^G, \tag{39}$$

with

$$\kappa^S = \frac{(1-\theta^S)(1-\theta^S\beta)}{\theta^S}, \qquad \kappa^G = \frac{(1-\theta^G)(1-\theta^G\beta)}{\theta^G}. \tag{40}$$

Inflation in sector $s \in \{S, G\}$ is a function of the next period expected sectoral inflation discounted by β and the sectoral marginal cost $\hat{mc}_t^s$ times the slope of the Phillips curve κ^s. Notice that since $\theta^S > \theta^G$, that is, the share of firms that cannot reset their price every period is higher in the services sector, it follows that $\kappa^S < \kappa^G$ so the inflation in the services sector has a lower sensitivity to changes in marginal cost.

Table 4: Effect of population aging on the slope of the Phillips curve

	Baseline 1980	Dem+Pref 2010	Only Dem 2010
Service weight ω	0.4498	0.4953 (+10.11 %)	0.4542 (+0.97 %)
PC slope	1.2759	1.1773 (-7.72 %)	1.2665 (-0.74 %)

Notes: The table compares the weight given to the services sector and the slope of the Phillips curve under different contrafactuals.

As shown in Appendix B, I can derive a general formula for the aggregate Phillips curve as a weighted average of the sectoral ones:

$$\hat{\pi}_t = \omega\hat{\pi}_t^S + (1-\omega)\hat{\pi}_t^G = \beta\mathbb{E}_t\hat{\pi}_{t+1} + \Big[\omega\kappa^S + (1-\omega)\kappa^G\Big](\hat{w}_t - \psi(\hat{k}_t - \hat{l}_t)) - \lambda\hat{z}_t, \tag{41}$$

with $\omega = \sum_j \alpha_j \chi_j \frac{P_j^{\eta-1}}{\sum_j \chi_j P_j^{\eta-1}}$, $\chi_j = \frac{N_j P_j C_j}{\sum_j N_j P_j C_j}$ and $\hat{z}_t = logP_t^G - logP_t^S$.

Aggregate inflation is then a function of the discounted next period expected inflation, the ratio between the prices of the two sectors $\hat{z}_t$ and the price mark-up $(\hat{w}_t - \alpha(\hat{k}_t - \hat{l}_t))$. The slope of the aggregate Phillips curve is $\Big[\omega\kappa^S + (1-\omega)\kappa^G\Big]$. The weight ω used to combine the sectoral slopes can be considered as a weighted average of the age-group service preferences α_j using the share of nominal consumption of age group j as weight.

Therefore, whereas the slopes of the sectoral Phillips curves are constant over time, changes in service preferences and population distribution might affect the slope of the aggregate Phillips curve through the weight ω. The first row of Table 4 examines this relationship: the service weight ω increased by approximately 10% from 1980 to 2010 when both changes in preferences and demographic trends are taken into account (from 45% to around 50%, in line with the empirical evidence of section 2.1) and population aging alone (third column) accounts for around 10% of the overall effect.

In terms of the slope of the aggregate Phillips curve (second row), the coefficient decreased overall by around 8% (from 1.28 to 1.18) moving from 1980 to 2010 and again demographic trends explain approximately 10% of the decrease. Therefore, these results suggest that changes in service preferences and population distribution played a non-negligible role in the flattening of the Phillips curve observed in the last decades.

Table 5: Response of Output and Inflation - Robustness Checks

	Output response (%)			Inflation response (%)		
	Time 0	After 1 year	After 2 years	Time 0	After 1 year	After 2 years
Baseline	6.18	4.30	3.22	-0.12	-0.40	-0.89
Different ψ	5.63	4.01	2.93	-0.07	-0.26	-0.64
Different ϵ	5.07	3.72	2.83	-0.15	-0.34	-0.63
Different ϕ	6.97	4.58	2.95	-0.12	-0.36	-0.82
Constant τ	5.79	4.03	3.02	-0.09	-0.31	-0.71
$\theta^G = \theta^S$	2.78	3.85	2.79	-0.02	-0.21	-1.09

Notes: The table reports the percent change in IRFs of output and inflation between 1980 to 2010 under alternative assumptions of the model.

5.8.5 Sensitivity analyis

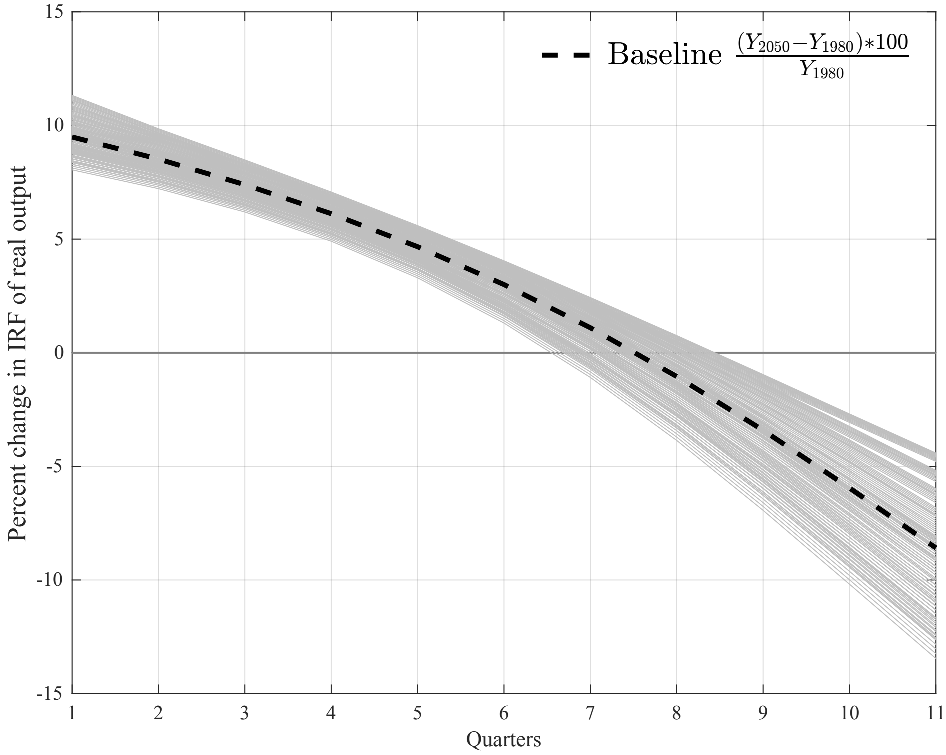
I evaluate the robustness of the theoretical results in a number of variations of the benchmark model. For each alternative specification, I compute the percent change in the IRFs of output and inflation under the different population distribution and mortality rates for 1980 and 2010. Table 5 reports the results.

First of all, I relax the assumption that the production function of the services and the goods sectors have the same labor share. As in Galesi and Rachedi (2018), the labor share of services is set equal to 0.5283 whereas the labor share of goods is set equal to 0.2927. Second, I allow the two sectors to differ in their elasticity of substitution across varieties within sectors. In particular, the elasticities are calibrated to match the estimates of Rebekka and Vermeulen (2012) on the markups of services and manufacturing in the United States. I target a markup equal to 38% in the services sector and to 28% in the goods sector.

Third, following Jones (2018) and Papetti (2019), instead of imposing a constant disutility of labor ϕ across age groups, I assume it to be equal to the cumulative density function of a normal distribution. Figure 39 shows the shape and details of the functional form and parameter values. Fourth, for the PAYGO pension system instead of the constant replacement rate $\bar{d}$ used in the baseline, I fix the contribution rate at the steady state level $\tau = 0.0653$ while the replacement rate $\bar{d}$ is adjusted such that the government budget is balanced in each period.

All these cases deliver quantitatively similar results to the baseline specification (which is reported in the first row of Table 5). This holds on impact as well as after one and two years after the monetary shocks. Overall the robustness exercise confirms that the main conclusions of the previous section are insensitive to several of the assumptions made: demographic trends from 1980 to 2010 significantly increased the responsiveness of output to shocks whereas they had a minor effect on the responsiveness of inflation.

Figure 22: Model IRFs of output for different demographic structures, alternative price stickiness parameters



Notes: The figure reports the percentage change in IRFs changing the population distribution and mortality rate from 1980 to 2050. The black dashed line is the baseline response obtained with $\theta^S = 0.75$ and $\theta^G = 0.25$. The gray lines are the responses from all the possible combinations of θ^S and θ^G increasing and decreasing their values by 20%.

The implicit assumption I have made throughout the paper is that sectoral price stickiness will not change in the future. However, several ongoing trends, e.g., automation, are likely to affect the frequency at which prices are adjusted. Therefore, in Figure 22 I test how sensitive are the results to difference price stickiness parameters. The black dashed line reports the percentage change in output due to demographic trends from 1980 to 2050. This is the baseline response obtained by setting $\theta^S = 0.75$ and $\theta^G = 0.25$ as for the main analysis. I compare this response with the responses from all the possible combinations of θ^S and θ^G increasing and decreasing their values by 20% (gray lines). The range of percentage changes of the contemporaneous responses to an expansionary monetary shock is between 8 and 11.5%. Therefore, the specific values chosen for the price stickiness parameters do not affect the main conclusion that demographic trends will increase the responsiveness of output to monetary shocks.

Finally, one might be concerned that the different responses of output and inflation between the two sectors stem from their structural differences (e.g., the fact that only the output from the goods sector can be stored and invested) rather than from the different frequencies of price adjustments. To isolate the role played by price stickiness, the last row of Table 5 reports the percent change in the IRFs assuming that the share of firms unable to adjust their prices is the same between the two sectors, i.e., $\theta^G = \theta^S = 0.75$. The contemporaneous effect of demographic trends on the responsiveness of output and inflation is reduced by approximately one-third and one-fourth respectively. This suggests that the structural differences between the two sectors only marginally contribute to the overall change in monetary policy effectiveness caused by population aging.

6 Conclusion

For almost every country in the world, the share of old people is projected to significantly increase and the share of the working population to decrease over the next decades. However, given the extremely slow-moving pace of this transition, limited attention has been given to the way these demographic trends might influence the effectiveness of monetary policy.

I propose and quantify a new channel through which the transmission of monetary policy shocks is affected by the demographic structure of the economy. Using household-level data for the U.S., I show that older people tend to purchase more from product categories that on average adjust their prices less often. Therefore, changes in the population distribution shift the aggregate demand towards categories with a higher level of price stickiness.

To confirm the macro implications of these micro-level findings, I empirically evaluate whether the response of U.S. states to monetary shocks is heterogeneous in their demographic structure. I find that the real personal income and the real GDP of states with a higher old-age dependency ratio respond significantly more to shocks. No significant differences are found for inflation.

Finally, to assess the overall effects of population aging on the pass-through of monetary policy, I develop a two-sector OLG NK model. I find that demographic trends have a non-negligible impact on the response of output, that the new channel I proposed significantly contributes to this, that younger households are the most exposed to these trends, and that the flattening of the Phillips curve is partially explained by the fact that the U.S. society is aging.

In conclusion, my research provides substantial evidence that demographic trends, despite their long-term nature, should not be overlooked by policymakers and central bankers even when it comes to short-term policy decisions like the level of the interest rate.

In future work, I intend to further develop the theoretical framework to provide additional insights into my empirical findings. Age groups differ in several dimensions which were not included in the model. A richer model which incorporates housing decisions, access to credit, and investment preferences would allow us to assess more precisely how population aging affects monetary policy transmission and would better support policymakers' decisions.

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A Data sources

A.1 CEX

The expenditure data necessary to compute age-group level weights are obtained from the Consumer Expenditure Survey (CEX). The survey is run by the Bureau of Labor Statistics and covers expenditures, income, and demographic characteristics of households in the United States since the beginning of the 80s and it is the main source of data for the construction of the U.S. Consumer Price Index.

The CEX contains two modules: the Interview and the Diary. The first covers the entire household consumption bundle and the respondents are interviewed for a maximum of four consecutive quarters regarding the purchases over the previous three months. The second focuses more on daily expenditures such as groceries and personal products for two consecutive survey reference weeks.

Household expenditures are collected at Universal Classification Code (UCC) level for about 600 categories. Moreover, demographic characteristics such as age, education, gender, race, etc. are included as well. Since the Diary and Interview surveys contact different households each year, to obtain the full consumption profiles the households are aggregated into age groups based on the age of the respondent.

The UCC level is the most disaggregated expenditure level available in the survey. These categories can be aggregated into less granular categories as, in increasing order, the Entry Level Items (ELI), the Item Strata, and the Expenditure Class. As an example, the UCC categories *White bread (020110)* and *Bread other than white (020210)* can be aggregated into the ELI *Bread (FB011)* and then into the Item Strata *Bread (FB01)* which is one of the components of the Expenditure Class *Bakery products (FB)*. The concordance across levels is provided by the BLS in the document "CPI requirements for CE" Appendix B.

Since the data on the frequency of adjustment provided by Nakamura and Steinsson (2008) are provided at the ELI level, the expenditure data at the UCC level from CEX are aggregated at the ELI level as well. Out of the 272 categories in Nakamura and Steinsson (2008), I have a match for 263 ELIs which can be further aggregated into 180 Item Strata or 67 Expenditure Classes.

To compute the expenditure shares for each product category at the age-group level, I proceed in the following way. First, I compile the consumption data from the two surveys of the CEX. From the Interview survey, I obtain information about each household interviewed month and year, monthly expenditures at the UCC level for the previous three months as well as its demographic characteristics. Similarly, from the Diary survey, I gather data on household weekly expenditure (at the UCC level as well) and its demographic characteristics. The Interview data file is then appended to the Diary to get the whole sample of UCCs.

Then, in line with the BLS procedure and following the instructions in the document "CPI Requirements of CE", several adjustments are performed on the expenditure data.

Homeowner insurance/maintenance/major appliance. The housing expenses on insurance, maintenance, and major appliances need to be corrected to take into account that these expenditures include an investment component for homeowners. Therefore, in line with BLS, the homeowner's total expenditure on the corresponding UCC categories is multiplied by a factor of 0.43 to isolate the consumption portion. The factor is based on the likelihood that renters will purchase these types of appliances and perform these types of home maintenance and improvement.

Medical care. The BLS redistributes the weights from private health insurance and the Medicare premium to the other medical care services using the National Health Expenditure (NHE) tables produced by the Center for Medicare and Medicaid Services (CMS). Since this information is not publicly available, I follow Cravino et al. (2020a) by taking the redistributing factors from the NHE *Table 20 Private Health Insurance Benefits and Net Cost; Levels, Annual Percent Change and Percent Distribution, Selected Calendar Years 1960-2015.*[13] The factors from this table allow us to redistribute the expenditures from private health insurance and Medicare premiums to health care service categories, such as nursing homes and adult day services.

Used cars and trucks. Expenditures on used cars and trucks should only reflect dealer value added. However, the data on trade-in values of cars and trucks are not provided by the CEX. Therefore, as in Cravino et al. (2020a) which found that the ratio of trade-in values and other sales of vehicles to spending on used cars and trucks is around 1/2, I reduce the spending on used cars and trucks to half to isolate only the dealer value added.

Gasoline. In the CEX data total gasoline expenditures are available only for one UCC category (470111). However, Nakamura and Steinsson (2008) computes the frequency of price adjustment for three different ELIs: *Regular Unleaded Gasoline (TB011)*, *Midgrade Unleased Gasoline (TB012)* and *Premium Unleased Gasoline (TB013).* Since the price stickiness parameters are similar among the three categories (88.6, 87.6, and 86.9 respectively), the

[13]See the link `https://www.cms.gov/research-statistics-data-and-systems/statistics-trends-and-reports/nationalhealthexpenddata/nhe-fact-sheet.html`

expenditure weight of total gasoline is matched with the average frequency of price adjustment for the three ELIs.

Finally, I aggregate households into age groups and calculate the relative expenditure shares. The Interview and the Diary survey different households but both modules provide data on the age of the respondent so the grouping is rather straightforward. I then compute the average expenditure for each UCC category at age group in the calendar year. The fact that a respondent interviewed in February will report personal consumption not only for January but also for November and December of the previous year needs to be taken into account. Similar to what the Bureau of Labor Statistics (BLS) does for the computation of the official Consumer Price Index (CPI), I create a variable called MO_SCOPE to control for the number of months a household reports expenditures during a calendar year. Therefore, this variable takes value 1 if the household is interviewed in February and value 3 if it is interviewed from April onwards. In the Diary survey, there is no distinction between the survey period and the expenditure reference period. Hence, the variable MO_SCOPE is always equal to 3 for the households in the Diary survey since all their purchases refer to the same calendar year in which they are interviewed. The weekly expenditures are multiplied by 13 to convert them into quarterly expenditures.

Following the BLS procedure, I can then use the formula below to compute the average expenditure for each UCC category k at each age group level a. First, for household i at age group a, I aggregate over all the expenditures on good k during the calendar year. Second, the household total expenditures are weighted by the sampling weights, fwt, provided by BLS to make the survey sample representative of the U.S. population. Third, the weighted household expenditures are summed up at the age group level. Fourth, to obtain the monthly average income spent on good k by decile d, we divide the annual weighted household expenditures for category k by the sum of the weighted number of months household at age group a reported expenditures during the calendar year. Then, to annualize the average UCC category expenditure at the age group level it is sufficient to multiply the monthly average expenditure by twelve:

$$X_k^a = \frac{\sum_i fwt_i^a \sum_t c_{i,k,t}^a}{\sum_i fwt_i^a \ MO\_SCOPE_i^a} \times 12 \tag{42}$$

where fwt_i^a is the frequency weight for household i at age group a, $c_{i,k,t}^a$ refers to the annual consumption on UCC category k by household i at age group a and $MO\_SCOPE_i^a$ identifies the number of months per year household i reported its expenditures.

In the final step, I compute the age group level average expenditure for each UCC category. I then aggregate the UCC categories according to the constructed concordance between UCC categories and ELIs to get the age group level average expenditure X_j^a for each of the 259 ELIs and the corresponding expenditure share $\omega_j^a = \frac{X_j^a}{\sum_k X_j^a}$.

B Model derivation

In this section, I derive the optimal conditions of the model presented in section 5.

The demand functions for services and goods associated with the bundle (13) are given by:

$$c_{t,j}^S = \alpha_j \Big(\frac{P_t^S}{P_{t,j}}\Big)^{-\eta} c_{t,j}, \qquad c_{t,j}^G = (1-\alpha_j)\Big(\frac{P_t^G}{P_{t,j}}\Big)^{-\eta} c_{t,j} \tag{43}$$

where $c_{t,j}$ is the aggregate consumption of household j and $P_{t,j}$ is the price index associated with its bundle.

Adding across households, one can obtain the following expression of the sectoral aggregate demand:

$$C_t^S = \omega_t \Big(\frac{P_t^S}{P_t}\Big)^{-\eta} C_t, \qquad C_t^G = (1-\omega_t)\Big(\frac{P_t^G}{P_t}\Big)^{-\eta} C_t \tag{44}$$

where, following Cravino et al. (2020a), the expenditure share is defined as $\omega_t \equiv \sum_j \alpha_j \chi_{t,j} \frac{P_{t,j}^{\eta-1}}{\sum_j \chi_{t,j} P_{t,j}^{\eta-1}}$ and $\chi_{t,j}$ is the share of household j in aggregate expenditures at time t. One can then define the aggregate price index as $P_t \equiv \Big[\omega_t^{\frac{1}{\eta}} (P_t^S)^{1-\eta} + (1-\omega_t)^{\frac{1}{\eta}} (P_t^G)^{1-\eta}\Big]^{\frac{1}{1-\eta}}$.

To simplify the log-linearization process, I assume that ω_t is constant and equal to its steady state value. By log-linearizing the aggregate price index I obtain:

$$\hat{p}_t = \omega \hat{p}_t^S + (1-\omega)\hat{p}_t^G \tag{45}$$

which allows obtaining an expression for the aggregate inflation rate:

$$\hat{\pi}_t = \hat{p}_t - \hat{p}_{t-1} = \omega(\hat{p}_t^S - \hat{p}_{t-1}^S) + (1-\omega)(\hat{p}_t^G - \hat{p}_{t-1}^G) = \omega\hat{\pi}_t^S + (1-\omega)\hat{\pi}_t^G \tag{46}$$

By solving the cost minimization problem of the intermediate firm i, I find the following expression for the sectoral marginal costs in real terms:

$$Z^{\omega-1}mc^S_{i,t} = \Big(\frac{w_t}{(1-\psi)}\Big)^{1-\psi}\Big(\frac{r^k_t}{\psi}\Big)^{\psi} \tag{47}$$

$$Z^{\omega}mc^G_{i,t} = \Big(\frac{w_t}{(1-\psi)}\Big)^{1-\psi}\Big(\frac{r^k_t}{\psi}\Big)^{\psi} \tag{48}$$

as well as the standard relationship between capital and labor for both sectors s:

$$K^s_{i,t} = \frac{\psi w_t}{(1-\psi)r^k_t}L^s_{i,t} \tag{49}$$

Notice that since all firms use the same capital-output ratio I can drop the subindex i. I then log-linearize the marginal cost equations for both sectors:

$$\hat{mc}^S_t = -(1-\omega)\hat{z}_t + (1-\psi)\hat{w}_t + \psi\hat{r}^k_t \tag{50}$$

$$\hat{mc}^G_t = -\omega\hat{z}_t + (1-\psi)\hat{w}_t + \psi\hat{r}^k_t \tag{51}$$

and by combining the two log-linearized expression of the capital-output ratios $\hat{k}^s_t - \hat{l}^s_t = \hat{w}_t - \hat{r}^k_t$, I obtain that $\hat{k}_t - \hat{l}_t = \hat{w}_t - \hat{r}^k_t$.

I can now replace the expressions of the log-linearized real marginal costs in the sectoral Phillips curve, obtained by linearizing equation (23) around a steady state with zero inflation in both sectors:

$$\hat{\pi}^S_t = \beta\mathbb{E}_t\hat{\pi}^S_{t+1} + \kappa^S\hat{mc}^S_t \tag{52}$$

$$\hat{\pi}^G_t = \beta\mathbb{E}_t\hat{\pi}^G_{t+1} + \kappa^G\hat{mc}^G_t \tag{53}$$

with

$$\kappa^S = \frac{(1-\theta^S)(1-\theta^S\beta)}{\theta^S}, \qquad \kappa^G = \frac{(1-\theta^G)(1-\theta^G\beta)}{\theta^G} \tag{54}$$

i.e.,

$$\hat{\pi}^S_t = \beta\mathbb{E}_t\hat{\pi}^S_{t+1} + \kappa^S[-(1-\omega)\hat{z}_t + (1-\psi)\hat{w}_t + \psi\hat{r}^k_t] \tag{55}$$

$$\hat{\pi}^G_t = \beta\mathbb{E}_t\hat{\pi}^G_{t+1} + \kappa^G[-\omega\hat{z}_t + (1-\psi)\hat{w}_t + \psi\hat{r}^k_t] \tag{56}$$

i.e.,

$$\hat{\pi}^S_t = \beta\mathbb{E}_t\hat{\pi}^S_{t+1} + \kappa^S[-(1-\omega)\hat{z}_t + \hat{w}_t - \psi(\hat{w}_t - \hat{r}^k_t)] \tag{57}$$

$$\hat{\pi}_t^G = \beta \mathbb{E}_t \hat{\pi}_{t+1}^G + \kappa^G[-\omega \hat{z}_t + \hat{w}_t - \psi(\hat{w}_t - \hat{r}_t^k)] \tag{58}$$

Using the fact that $\hat{w}_t - \hat{r}_t^k = \hat{k}_t - \hat{l}_t$, I find:

$$\hat{\pi}_t^S = \beta \mathbb{E}_t \hat{\pi}_{t+1}^S + \kappa^S[-(1-\omega)\hat{z}_t + \hat{w}_t - \psi(\hat{k}_t - \hat{l}_t)] \tag{59}$$

$$\hat{\pi}_t^G = \beta \mathbb{E}_t \hat{\pi}_{t+1}^G + \kappa^G[-\omega \hat{z}_t + \hat{w}_t - \psi(\hat{k}_t - \hat{l}_t)] \tag{60}$$

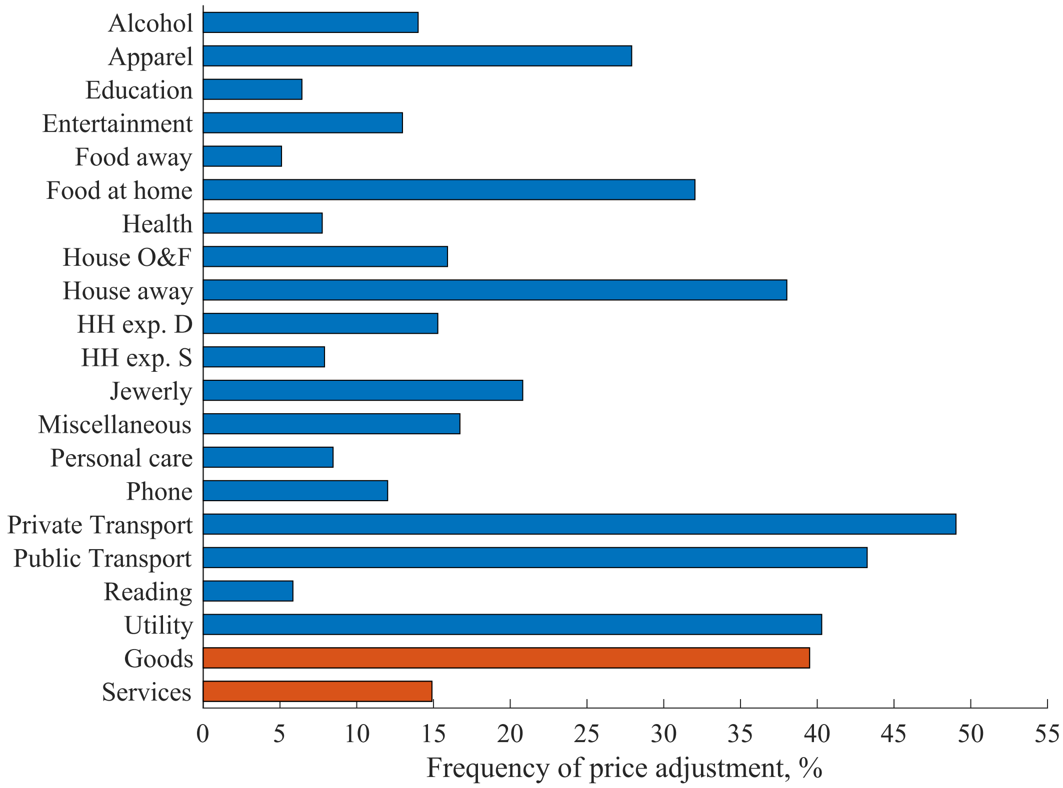
The sectoral Phillips curves can be replaced in equation (46):

$$\hat{\pi}_t = \omega \hat{\pi}_t^S + (1-\omega)\hat{\pi}_t^G = \beta \mathbb{E}_t \hat{\pi}_{t+1} + \Big[\omega \kappa^S + (1-\omega)\kappa^G\Big](\hat{w}_t - \psi(\hat{k}_t - \hat{l}_t)) - \lambda \hat{z}_t \tag{61}$$

with $\lambda = \omega \kappa^S (1-\omega) + (1-\omega)\kappa^G \omega$.

C Additional figures and tables

Figure 23: Average price rigidities across expenditure categories

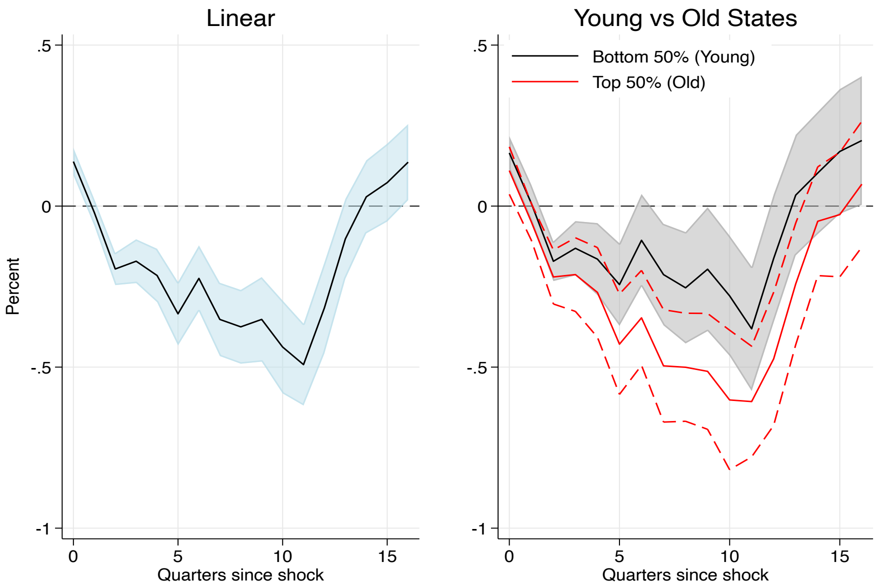


Notes: The bar plot shows the weighted average frequency of price adjustment across different expenditure categories as well as for the aggregation of the categories into Goods and Services.

Table 6: The table reports the expenditure shares across the major consumption categories for different age groups

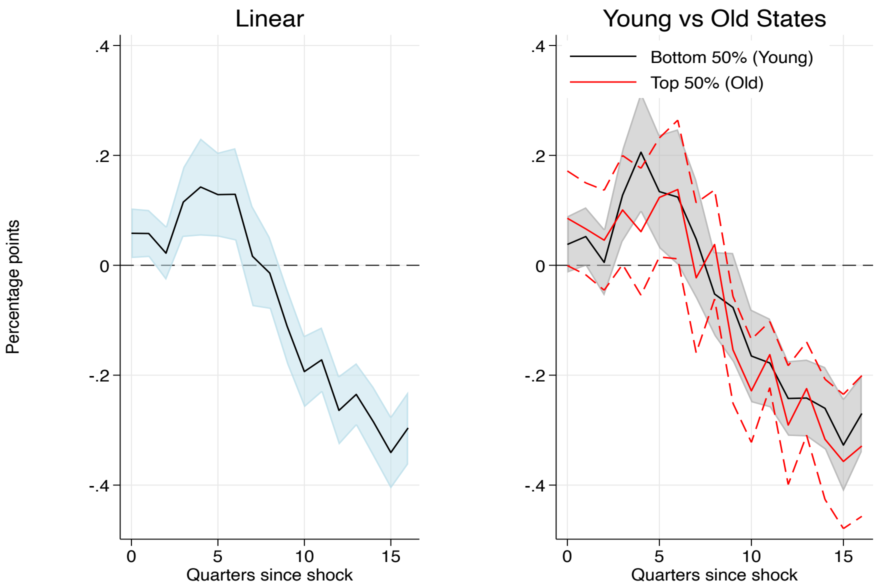
	Age groups						
	25-	(30,35]	(40,45]	(50,55]	(60,65]	(70,75]	80+
Alcohol	2.1	1.4	1.2	1.2	1.2	1.1	0.6
Apparel	5.1	4.8	4.7	4.2	3.8	3.1	2.3
Education	6.7	1.5	2.4	3.9	1.0	0.6	0.4
Energy	3.8	5.0	5.4	5.5	6.0	6.7	7.9
Entertainment	5.9	7.0	7.5	6.9	6.8	6.0	4.4
Food Away	6.1	5.6	5.8	5.8	5.6	5.1	4.1
Food at Home	11.4	12.5	13.0	12.1	12.3	12.9	13.5
Medical	3.4	5.4	6.4	7.6	10.7	15.1	19.0
Household F&O	6.4	9.9	9.1	9.0	9.8	10.1	11.1
Other Lodging	1.2	1.0	1.4	2.0	1.8	2.0	0.9
Owned Dwellings	1.8	6.5	7.5	7.7	8.1	7.6	5.9
Other Expenses	0.9	1.1	1.3	1.4	1.6	1.8	2.4
Personal Care	1.9	1.9	2.0	1.9	1.9	2.0	2.1
Private Transportation	20.5	21.8	21.7	21.6	20.8	17.5	11.3
Public Transportation	1.2	1.3	1.4	1.5	1.8	1.7	1.1
Reading	0.3	0.4	0.4	0.5	0.6	0.7	0.7
Rented Dwellings	19.4	10.8	6.4	4.4	3.7	3.9	10.2
Tobacco	1.3	1.0	1.1	1.2	1.1	0.8	0.4
Water	0.6	1.1	1.2	1.2	1.3	1.5	1.7

Figure 24: Impact of monetary policy on real personal income in young and old states, above/below the median



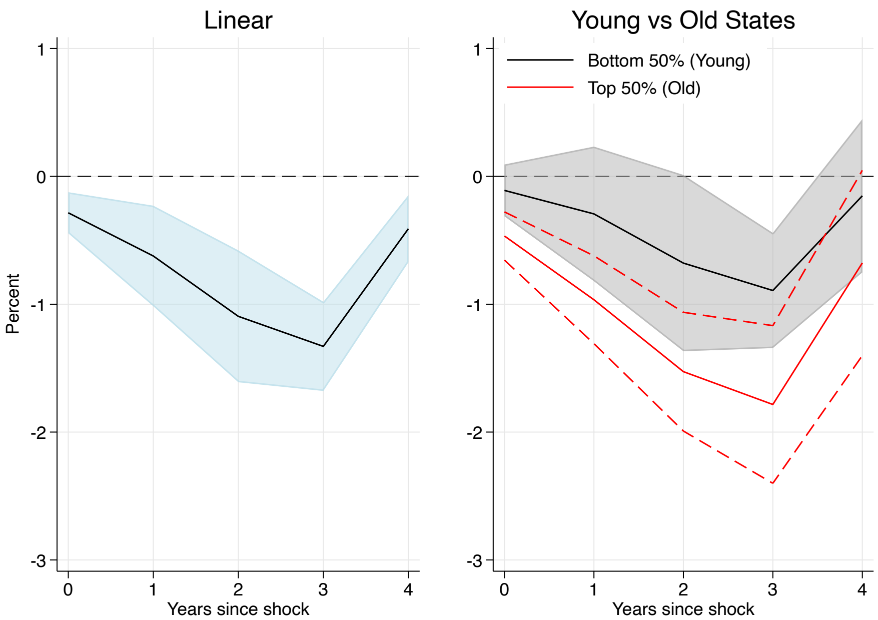
Notes: The left panel of the figure plots the response of the real personal income to a percentage point contractionary monetary policy shock, as well as 1.65 standard deviation confidence intervals for the state level log of real personal income. The horizontal axis is in quarters. The right panel reports the interaction coefficients between the monetary policy shock and the dummies identifying the bottom 50% and top 50% of the old-age dependency ratio distribution.

Figure 25: Impact of monetary policy on annual inflation rate in young and old states, above/below the median



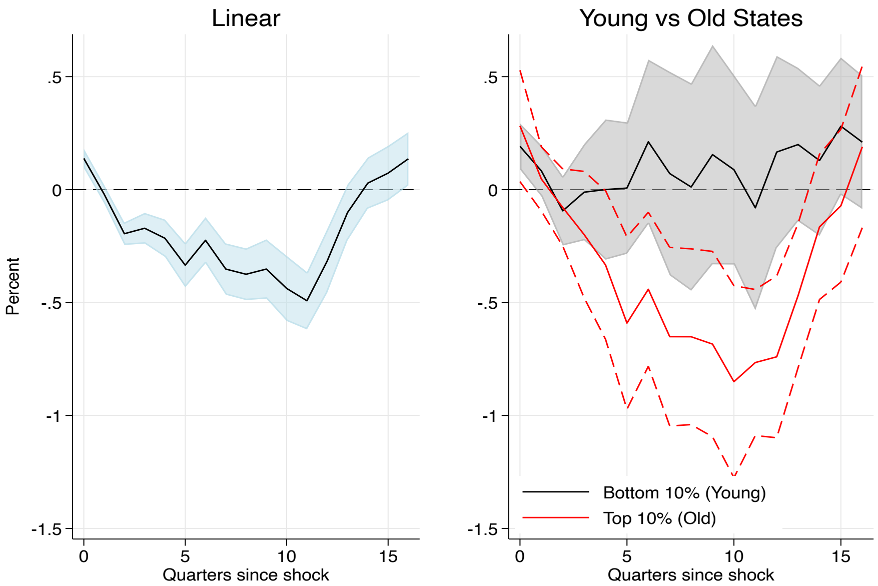
Notes: The left panel of the figure plots the response of the annual inflation rate to a percentage point contractionary monetary policy shock, as well as 1.65 standard deviation confidence intervals for the state level annual inflation rate. The horizontal axis is in quarters. The right panel reports the interaction coefficients between the monetary policy shock and the dummies identifying the bottom 50% and top 50% of the old-age dependency ratio distribution.

Figure 26: Impact of monetary policy on real GDP in young and old states, above/below the median



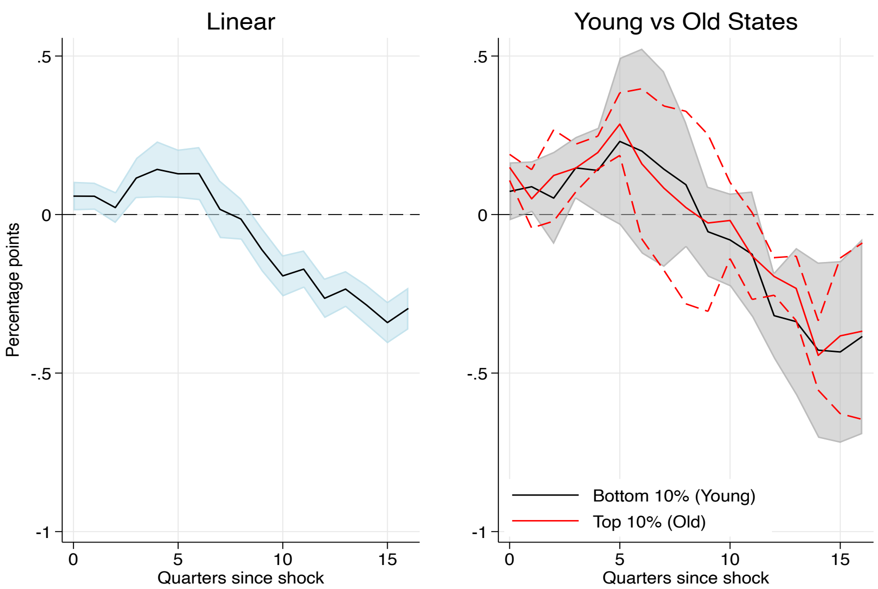
Notes: The left panel of the figure plots the response of real GDP to a percentage point contractionary monetary policy shock, as well as 1.65 standard deviation confidence intervals for the state level log of real GDP. The horizontal axis is in years. The right panel reports the interaction coefficients between the monetary policy shock and the dummies identifying the bottom 50% and top 50% of the old-age dependency ratio distribution.

Figure 27: Impact of monetary policy on real personal income in young and old states, top/bottom 10%



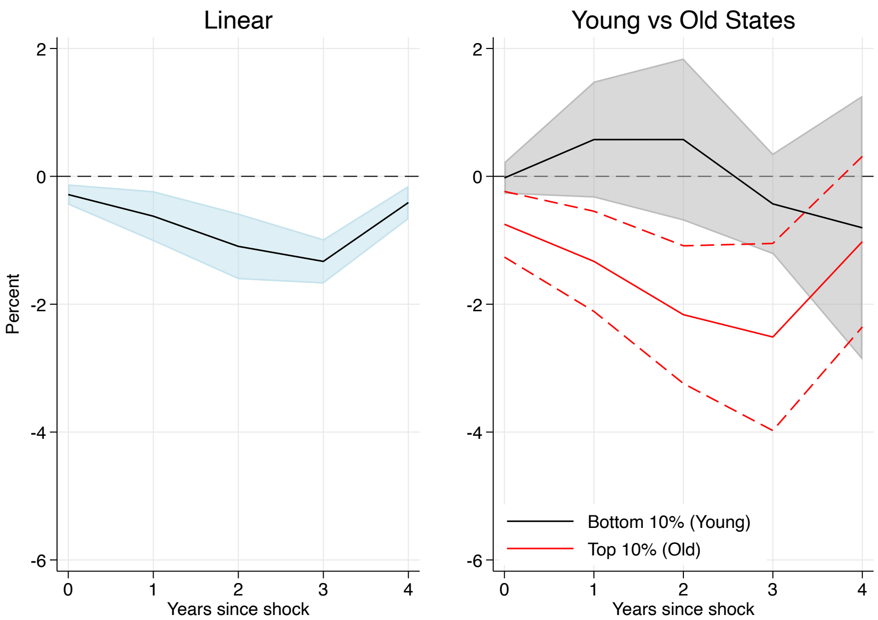
Notes: The left panel of the figure plots the response of the real personal income to a percentage point contractionary monetary policy shock, as well as 1.65 standard deviation confidence intervals for the state level log of real personal income. The horizontal axis is in quarters. The right panel reports the interaction coefficients between the monetary policy shock and the dummies identifying the bottom 10% and top 10% of the old-age dependency ratio distribution.

Figure 28: Impact of monetary policy on annual inflation rate in young and old states, top/bottom 10%



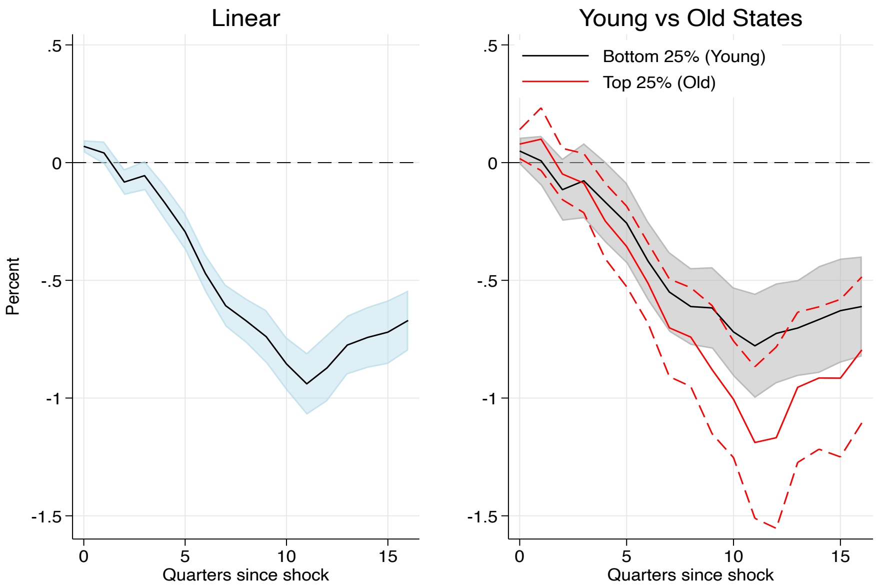
Notes: The left panel of the figure plots the response of the annual inflation rate to a percentage point contractionary monetary policy shock, as well as 1.65 standard deviation confidence intervals for the state level annual inflation rate. The horizontal axis is in quarters. The right panel reports the interaction coefficients between the monetary policy shock and the dummies identifying the bottom 10% and top 10% of the old-age dependency ratio distribution.

Figure 29: Impact of monetary policy on real GDP in young and old states, top/bottom 10%



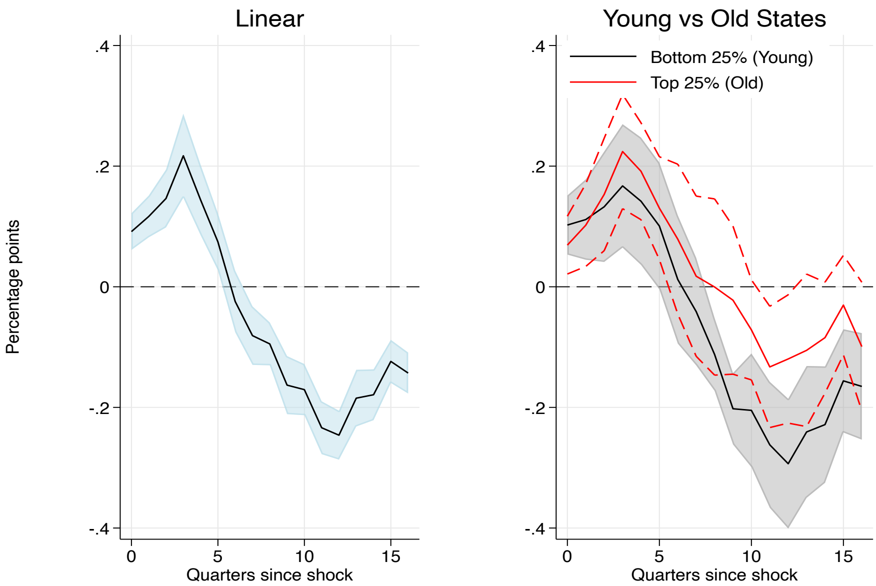
Notes: The left panel of the figure plots the response of real GDP to a percentage point contractionary monetary policy shock, as well as 1.65 standard deviation confidence intervals for the state level log of real GDP. The horizontal axis is in years. The right panel reports the interaction coefficients between the monetary policy shock and the dummies identifying the bottom 10% and top 10% of the old-age dependency ratio distribution.

Figure 30: Impact of monetary policy on real personal income in young and old states, LP-IV



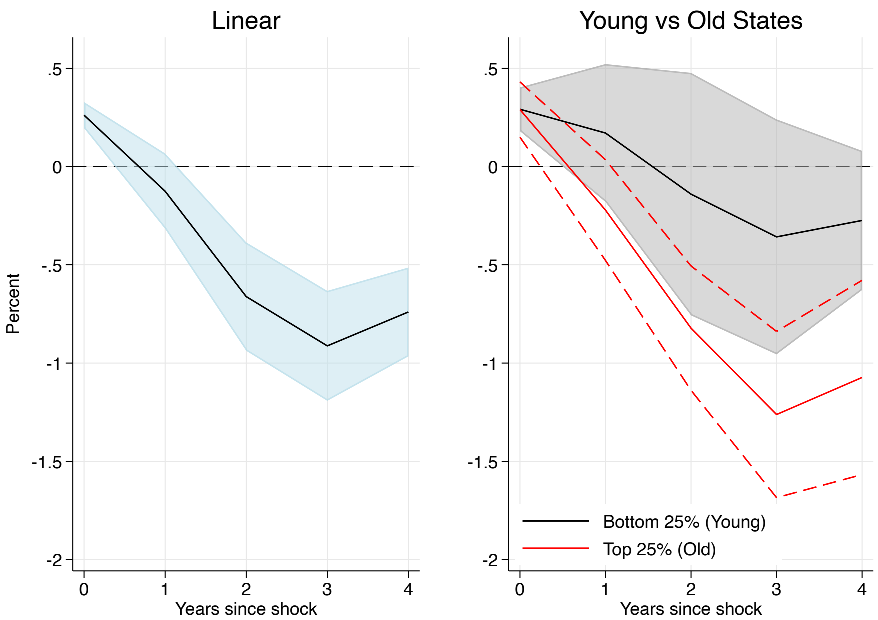
Notes: The left panel of the figure plots the response of the real personal income to a percentage point contractionary monetary policy shock, as well as 1.65 standard deviation confidence intervals for the state level log of real personal income computed using the local projection instrumental variable approach. The horizontal axis is in quarters. The right panel reports the interaction coefficients between the monetary policy shock and the dummies identifying the bottom 25% and top 25% of the old-age dependency ratio distribution.

Figure 31: Impact of monetary policy on annual inflation rate in young and old states, LP-IV



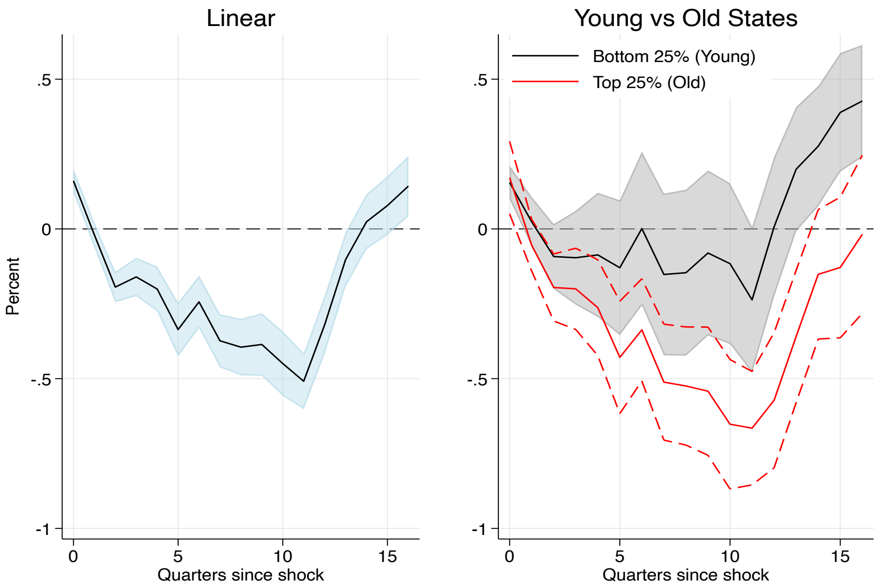
Notes: The left panel of the figure plots the response of the annual inflation rate to a percentage point contractionary monetary policy shock, as well as 1.65 standard deviation confidence intervals for the state level annual inflation rate computed using the local projection instrumental variable approach. The horizontal axis is in quarters. The right panel reports the interaction coefficients between the monetary policy shock and the dummies identifying the bottom 25% and top 25% of the old-age dependency ratio distribution.

Figure 32: Impact of monetary policy on real GDP in young and old states, LP-IV



Notes: The left panel of the figure plots the response of real GDP to a percentage point contractionary monetary policy shock, as well as 1.65 standard deviation confidence intervals for the state level log of real GDP computed using the local projection instrumental variable approach. The horizontal axis is in years. The right panel reports the interaction coefficients between the monetary policy shock and the dummies identifying the bottom 25% and top 25% of the old-age dependency ratio distribution.

Figure 33: Impact of monetary policy on real personal income in young and old states, no small states

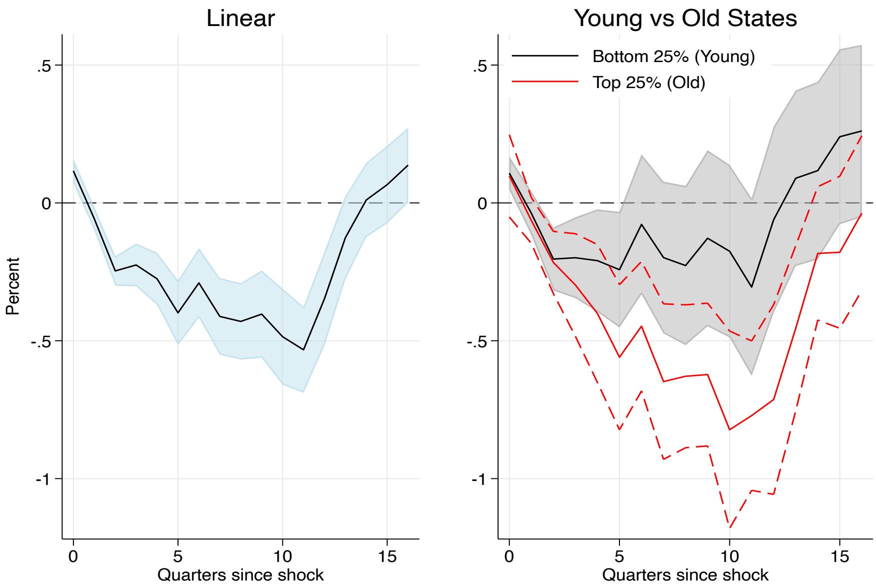


Notes: The left panel of the figure plots the response of the real personal income to a percentage point contractionary monetary policy shock, as well as 1.65 standard deviation confidence intervals for the state level log of real personal income. The horizontal axis is in quarters and the five smallest states (i.e., Alaska, North Dakota, Vermont, Washington D.C., and Wyoming) are excluded from the sample. The right panel reports the interaction coefficients between the monetary policy shock and the dummies identifying the bottom 25% and top 25% of the old-age dependency ratio distribution.

Figure 34: Impact of monetary policy on annual inflation rate in young and old states, no small states

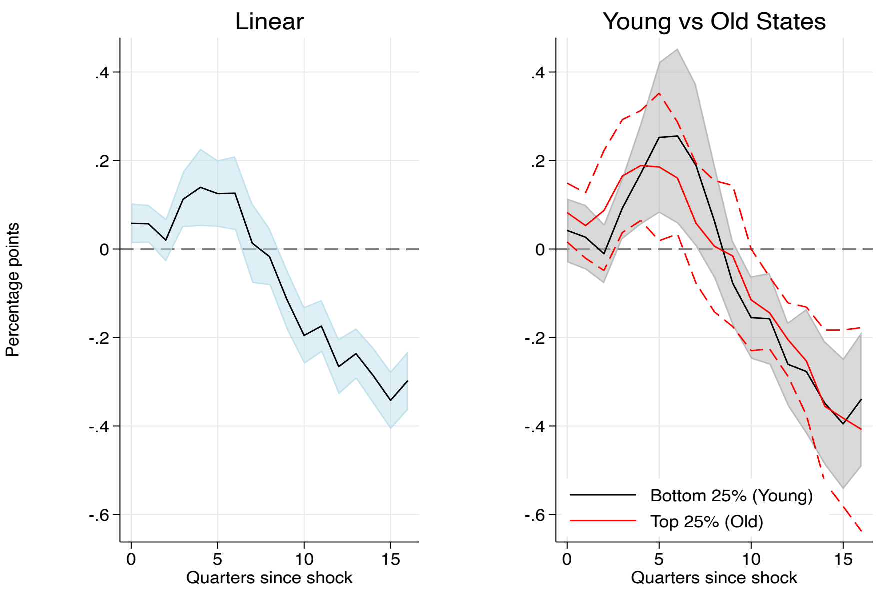
Notes: The left panel of the figure plots the response of the annual inflation rate to a percentage point contractionary monetary policy shock, as well as 1.65 standard deviation confidence intervals for the state-level annual inflation rate. The horizontal axis is in quarters and the five smallest states (i.e., Alaska, North Dakota, Vermont, Washington D.C., and Wyoming) are excluded from the sample. The right panel reports the interaction coefficients between the monetary policy shock and the dummies identifying the bottom 25% and top 25% of the old-age dependency ratio distribution.

Figure 35: Impact of monetary policy on real personal income in young and old states, controlling for income



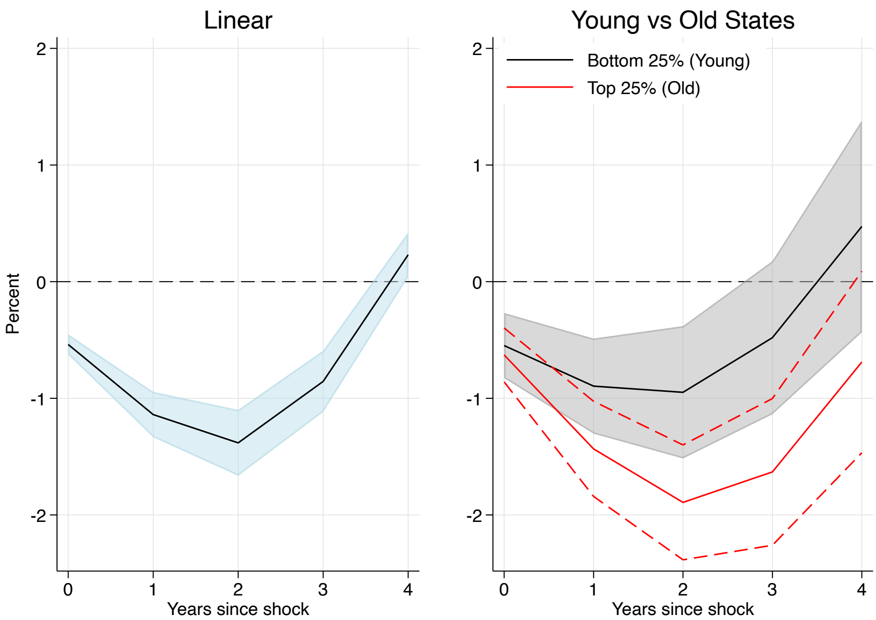
Notes: The left panel of the figure plots the response of the real personal income to a percentage point contractionary monetary policy shock, as well as 1.65 standard deviation confidence intervals for the state level log of real personal income. The log of the state level GDP is included as an additional regressor. The horizontal axis is in quarters. The right panel reports the interaction coefficients between the monetary policy shock and the dummies identifying the bottom 25% and top 25% of the old-age dependency ratio distribution.

Figure 36: Impact of monetary policy on annual inflation rate in young and old states, controlling for income



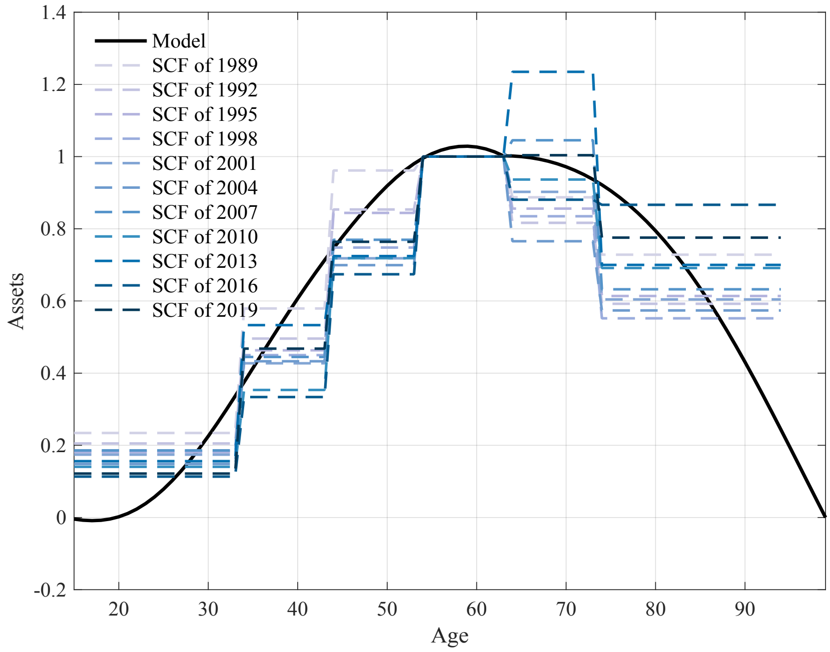
Notes: The left panel of the figure plots the response of the annual inflation rate to a percentage point contractionary monetary policy shock, as well as 1.65 standard deviation confidence intervals for the state-level annual inflation rate. The log of the state-level GDP is included as an additional regressor. The horizontal axis is in quarters. The right panel reports the interaction coefficients between the monetary policy shock and the dummies identifying the bottom 25% and top 25% of the old-age dependency ratio distribution.

Figure 37: Impact of monetary policy on services in young and old states, services



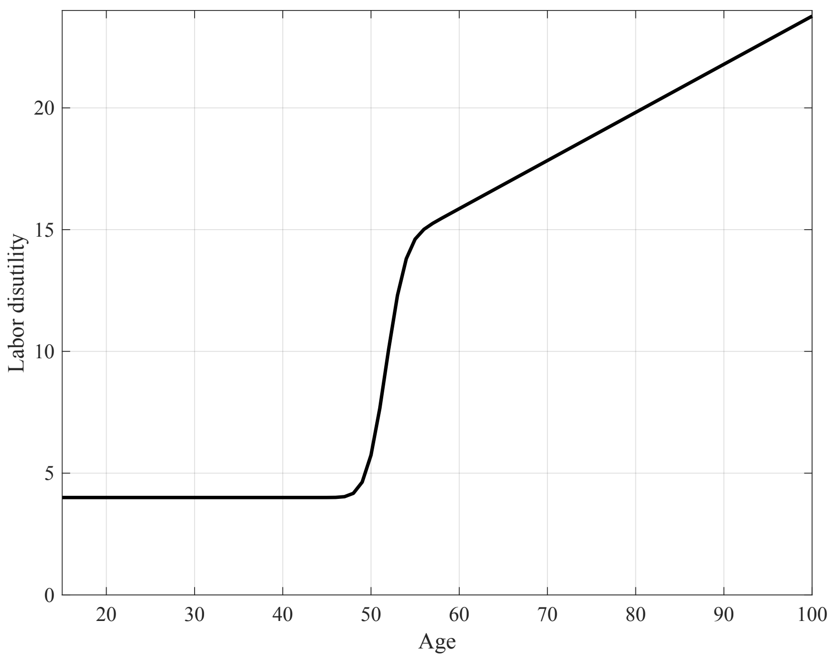
Notes: The left panel of the figure plots the response of services to a percentage point contractionary monetary policy shock, as well as 1.65 standard deviation confidence intervals for the state level log of real services production. The horizontal axis is in years. The right panel reports the interaction coefficients between the monetary policy shock and the dummies identifying the bottom 25% and top 25% of the old-age dependency ratio distribution.

Figure 38: Model vs Data



Notes: The plot compares the steady state assets profile from the model (Age 65 = 1) with the asset profile taken from the Survey of Consumer Finances for different years (Age group 55-64 = 1). *Source*: Survey of Consumer Finances.

Figure 39: Age dependent disutility of labor supply, ν_j



Notes: Following Jones (2018), the time-invariant disutility of labor supply is given by the following expression: $\nu_j = b_0 + (b_1 \frac{j}{J+1}) \int_{-\infty}^{J} \frac{1}{(J+1)b_3\sqrt{2\pi}} exp\left\{ \frac{1}{2} \left(\frac{j-(J+1)b_2}{(J+1)b_3} \right)^2 dj \right\}$ where the parameter values chosen are: $b_0 = 4$, $b_1 = 17$, $b_2 = 0.65$, $b_3 = 0.02$ as in Papetti (2019). $J + 1 = 86$ is the number of periods the individual can be alive since the household enters the world at age 15 and remains alive up to the maximum age of 100. Finally, the integral expression is the normal cumulative distribution function over age j with mean $b_2(J+1)$ and standard deviation $b_3(J+1)$.