Online Appendix for: Demographic Trends and the Transmission of Monetary Policy

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January 2024

Abstract

In this online appendix, I report the description of the data cleaning and preparation process as well as several robustness checks of the empirical analysis of the paper.

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

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All errors are my own.

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. (2020) 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.*[1] 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. (2020) 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

[1]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:

$$X_k^a = \frac{\sum_i fwt_i^a \sum_t c_{i,k,t}^a}{\sum_i fwt_i^a \; MO\_SCOPE_i^a} \times 12 \tag{1}$$

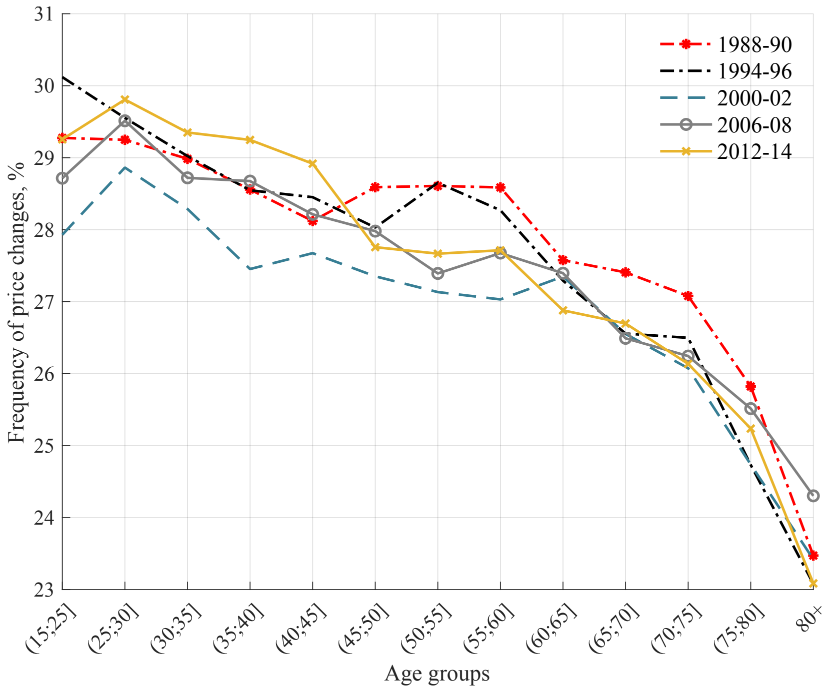
where fwt_i^a is the frequency weight for household i at age group a, $c_{i,k,t}^a$ refers to the annual consumption on UCC category k by household i at age group a and $MO\_SCOPE_i^a$ identifies the number of months per year household i reported its expenditures.

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 Robustness for the microlevel analyis

I first control that the negative relationship between age and frequency of price adjustment is stable over time. Figure 1 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.

Figure 1: Frequency of price adjustment across age groups and time

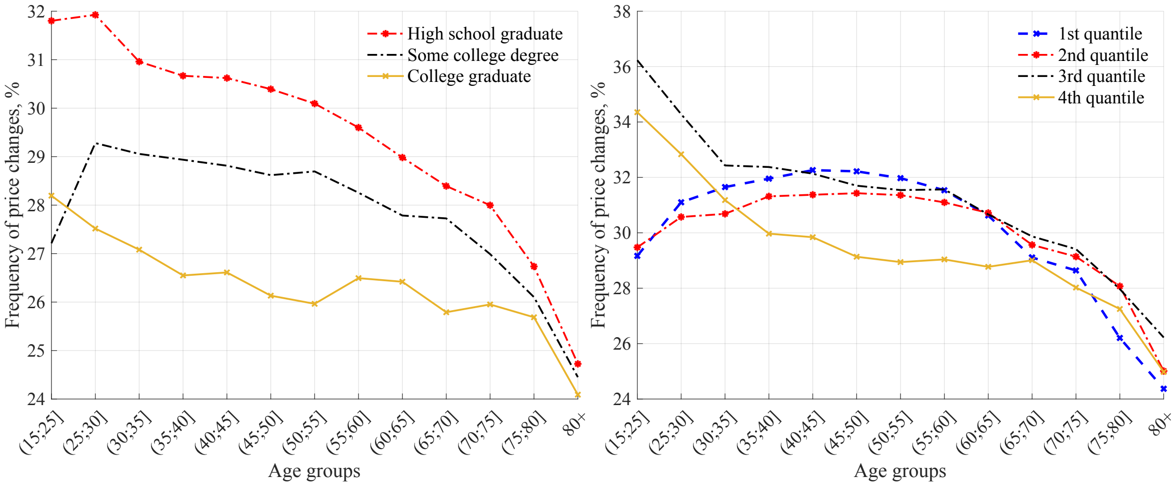


Notes: The figure plots the weighted average frequency of price adjustment at the age group level across five different time periods. The frequency of price adjustment is computed as the fraction of the number of times an item changes its price over the number of times the item is observed and expressed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

A potential source of concern regarding the main findings 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. (2020) demonstrates that price stickiness displays an inverse U-shaped distribution across income groups.

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[2].

Figure 2: Frequency of price adjustment across age groups, education levels, and consumption quantiles



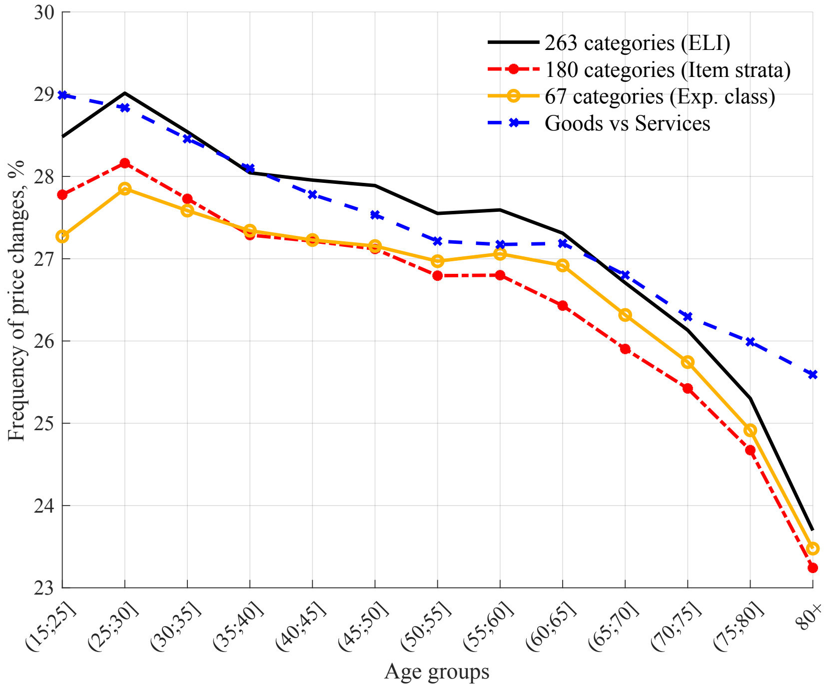
Notes: The left panel plots the weighted average frequency of price adjustment at the age groups level for three different education levels. The right panel reports the weighted average frequency of price adjustment at the age group level for different consumption quantiles. The frequency of price adjustment 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.

The left panel of Figure 2 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. (2020), the right panel of Figure 2 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 negative relationship between the frequency of price adjustment and age.

Finally, I check that no outlier in the expenditure categories is responsible for the pattern observed. Figure 3 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

[2]Cravino et al. (2020) 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 3: 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.

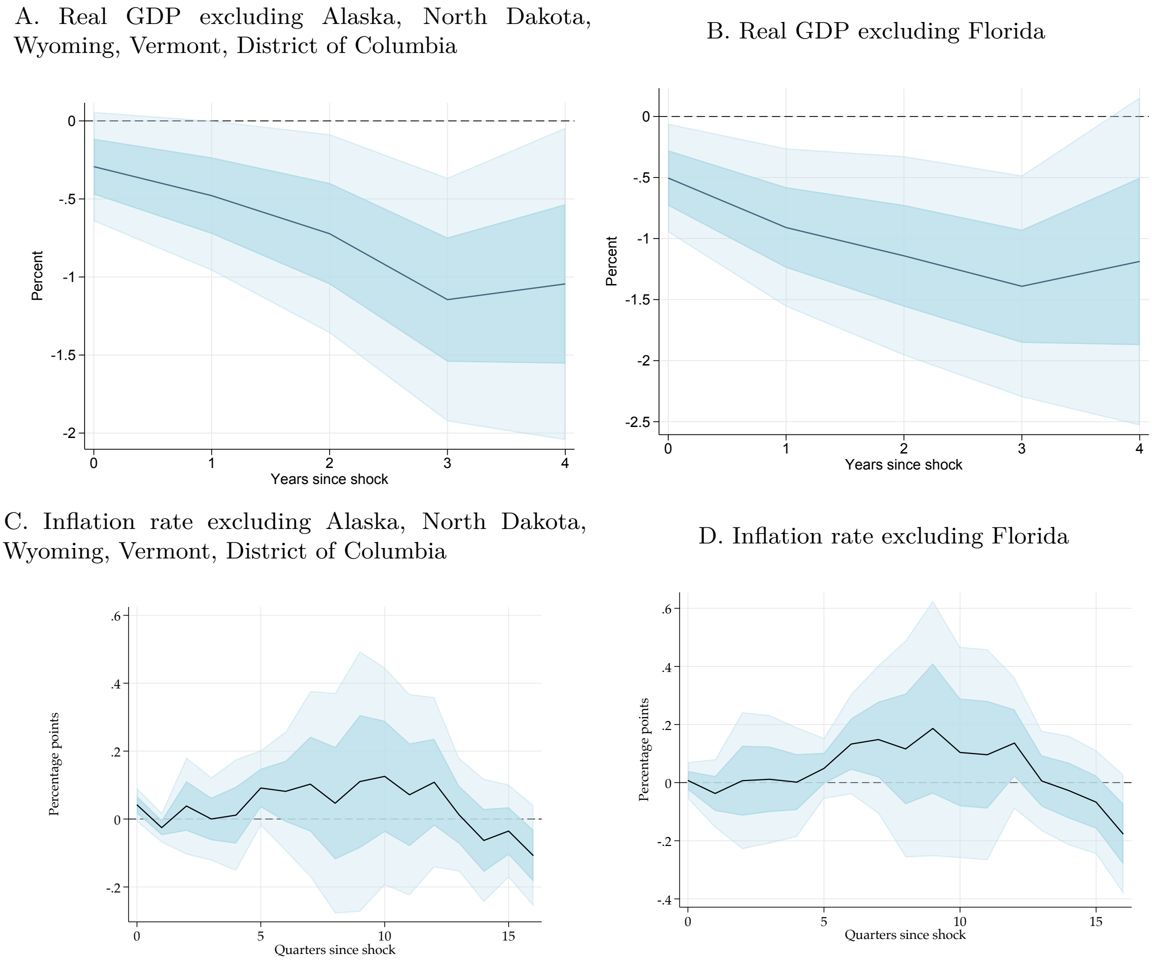
C Robustness for the regional responses

In this section, I consider a number of robustness checks to the baseline specification. First, I repeat the same empirical analysis excluding the five smallest states by population, i.e., Alaska, North Dakota, Vermont, Washington D.C., and Wyoming as well as Florida. As can be seen in Figure 4, this has basically no effect on the interaction coefficients both for real GDP (top row) and inflation (bottom row).

Second, I investigate whether our results are sensitive to altering the beginning and the end of the sample. Coibion (2012) shows how few episodes in the early 80s can be the main drivers of the impulse responses computed using local projection with Romer and Romer (2004) shocks. Therefore, I perform the same analysis starting our sample in 1985 as well as truncating all data in 2006 to exclude the financial crisis period. The results are reported in Figure 5. In this case, the results are also robust.

Third, I evaluate whether including different lags of the dependent variable y and the shock might alter the results. I then compute the responses of real GDP and inflation controlling for one lag of y and one lag of the shock, four lags of y and one lag of the shock, one lag of y

Figure 4: Impact of monetary policy on regional variables, dropping states



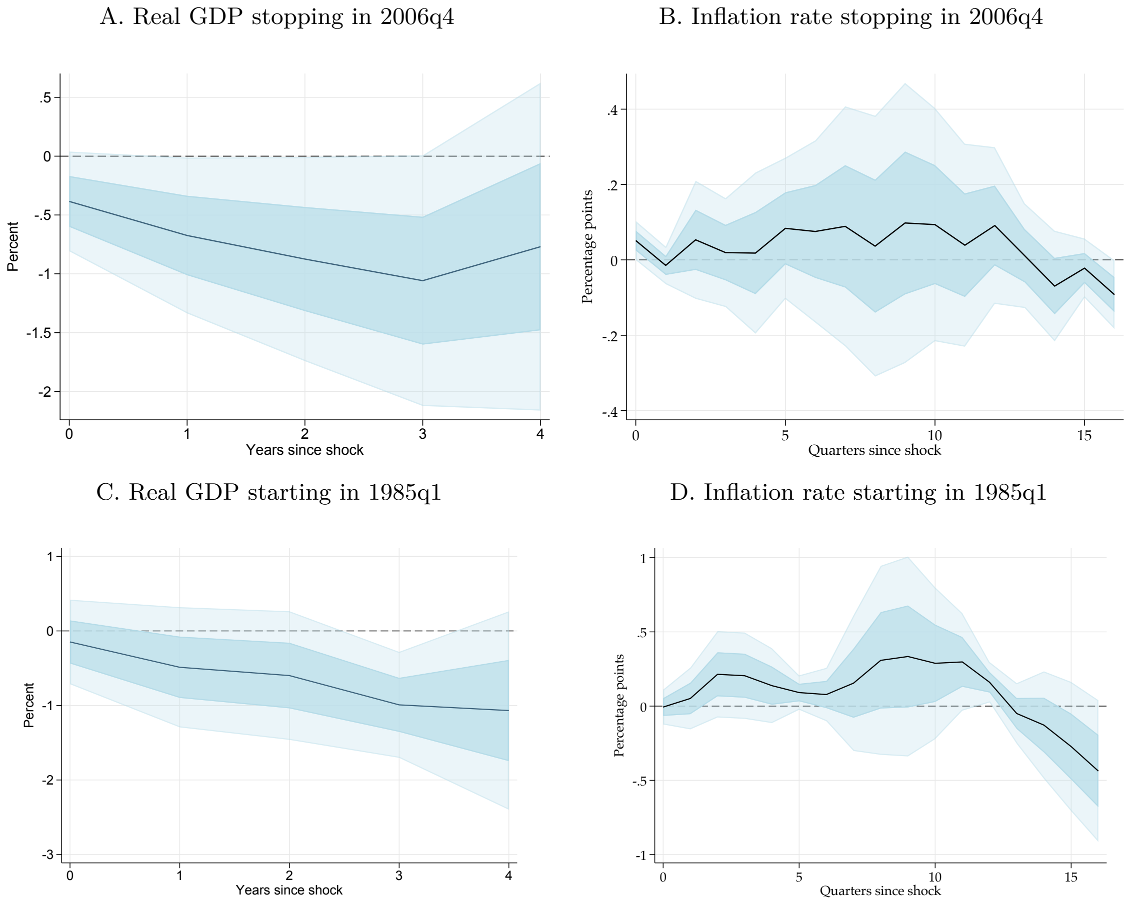
Notes: Each panel reports the interaction coefficients between the monetary policy shock and the dummy identifying the top 20% of the old-age dependency ratio distribution using as dependent variable either the state-level real GDP or the inflation rate. The dark shaded area and the light shaded area represent the 68% and the 95% confidence intervals respectively.

and four lags of the shock, four lags of y and four lags of the shock. Figure 6 and Figure 7 show the responses. The results are basically unaffected by the alternative lag specifications.

Fourth, I consider different thresholds of the old-age dependency ratio distribution which I interact with the monetary shock. I consider a state old if its ratio belongs to the top quartile, one-third, and half of the distribution. I also interact the monetary policy shocks directly with the level of the old-age dependency ratio. The impulse response functions are reported in Figure 8. These alternative thresholds reinforce the conclusion that the effectiveness of monetary policy is influenced by the demographic profile in the economy.

Fifth, another source of concern might be that state characteristics other than the population distribution may confound the results. To control for these state characteristics, I

Figure 5: Impact of monetary policy on regional variables, different subperiods

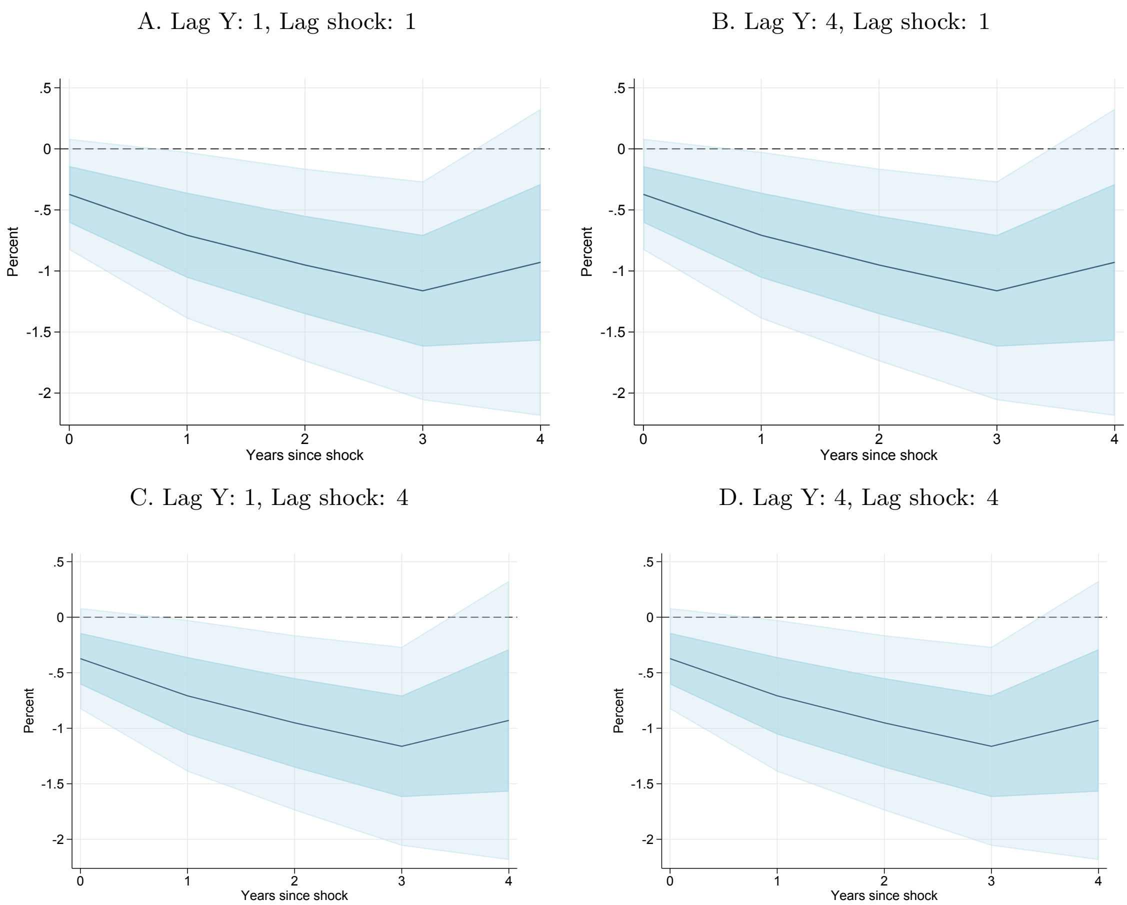


Notes: Each panel reports the interaction coefficients between the monetary policy shock and the dummy identifying the top 20% of the old-age dependency ratio distribution using as dependent variable either the state-level real GDP or the inflation rate. The dark shaded area and the light shaded area represent the 68% and the 95% confidence intervals respectively.

extend the baseline specification by interacting different control variables with the monetary policy shock[3]. For example, Wong (2021) document that the consumption of young homeowners reacts more strongly to monetary policy shocks. Therefore, I consider different measures of the housing market like house prices and the fraction of mortgages that are adjustable-rate mortgages (ARMs) both retrieved from the FHFA. I also control for the share of white workers, college-educated workers, small firms (below 249 employees), and young firms (younger than 5 years old) using data from the LEHD. As suggested by Leahy and Thapar (2022), to take into account that the entrepreneurial activities of the middle-aged might lead to different responsiveness across states, I include the log of establishment deaths and births from the BLS. Finally, Cravino et al. (2020) argues that higher-income households tend to purchase

[3]The results are not affected if the controls are not interacted with the shocks.

Figure 6: Impact of monetary policy on the regional real GDP, different lags

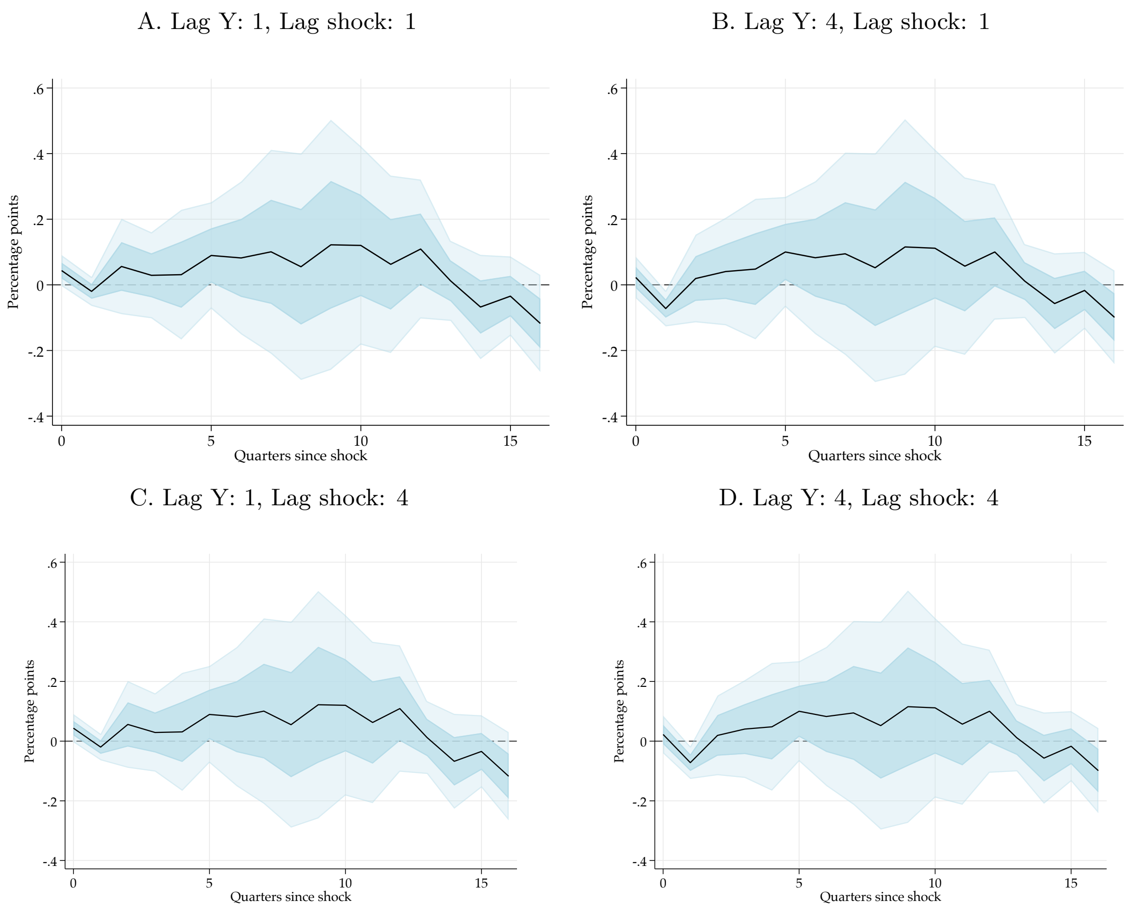


Notes: Each panel reports the interaction coefficients between the monetary policy shock and the dummy identifying the top 20% of the old-age dependency ratio distribution using as dependent variable the state-level real GDP. The dark shaded area and the light shaded area represent the 68% and the 95% confidence intervals respectively. The horizontal axis is in years.

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 add the interaction between state GDP per capita and the monetary shocks as an additional regressor. I report all these extra robustness checks in Figures 9 to and Figure 13.

Sixth, one obvious question is whether the results are driven by the choice of monetary policy shocks. Therefore, as additional estimation techniques, I present the results using the high-frequency identification from Nakamura and Steinsson (2018) as well as the shocks from Miranda-Agrippino and Ricco (2021) cleaned from the informational rigidities of the monetary announcements. The key idea of the approach in Nakamura and Steinsson (2018) is to use changes the change in the 3-month ahead Fed Funds futures within a 30-minute window surrounding scheduled Federal Reserve announcements. Since the time window is

Figure 7: Impact of monetary policy on the regional inflation rate, different lags



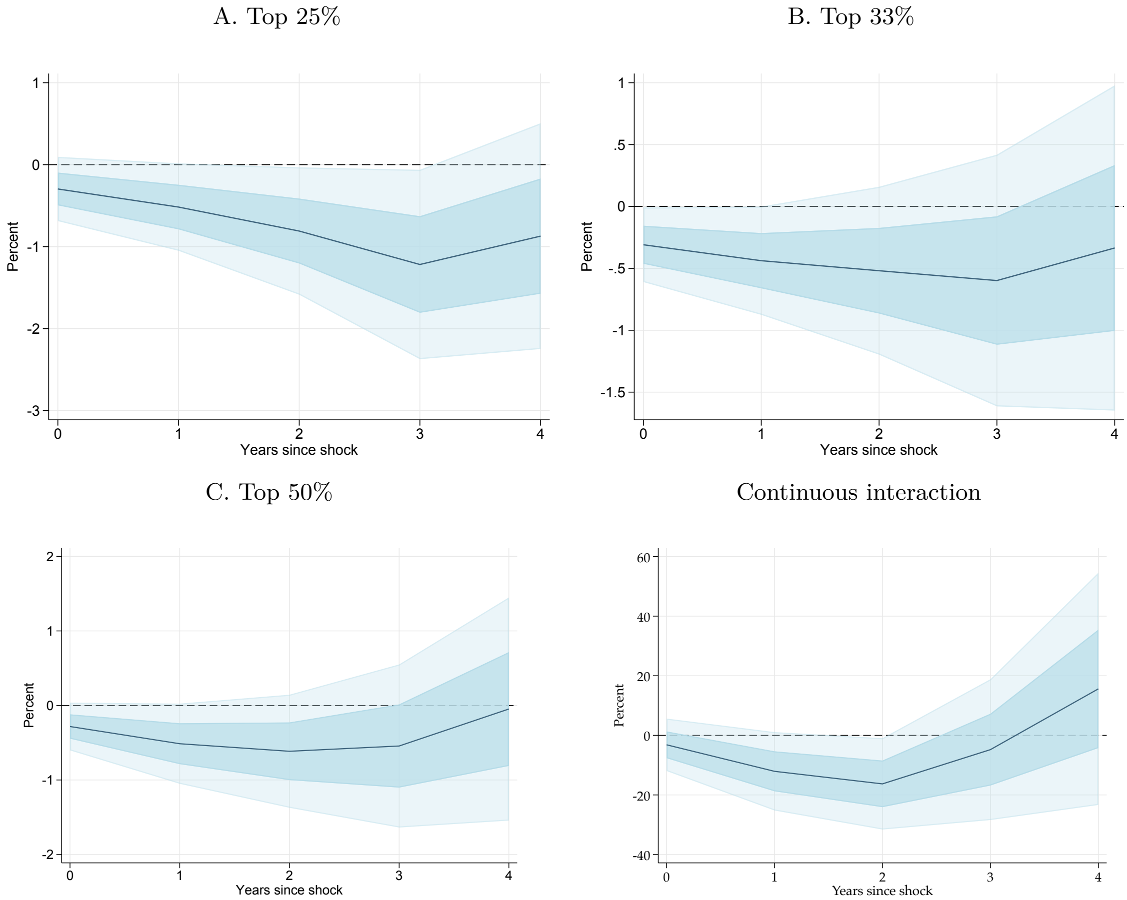
Notes: Each panel reports the interaction coefficients between the monetary policy shock and the dummy identifying the top 20% of the old-age dependency ratio distribution using as dependent variable the state-level inflation rate. The dark shaded area and the light shaded area represent the 68% and the 95% confidence intervals respectively.

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.

The results are presented in Figure 14 using as dependent variables the real GDP and annual inflation rate. All the regressions include the same controls as in the baseline specification. The responses of the interaction coefficients are comparable in shape and magnitude to the baseline specification being significantly stronger for older states.

Seventh, spillover effects from other states might bias the results. It could be the case that the stronger response of GDP observed in older states is actually due to an increase in the demand for tradable goods from the surrounding 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-

Figure 8: Impact of monetary policy on the regional real GDP, different thresholds

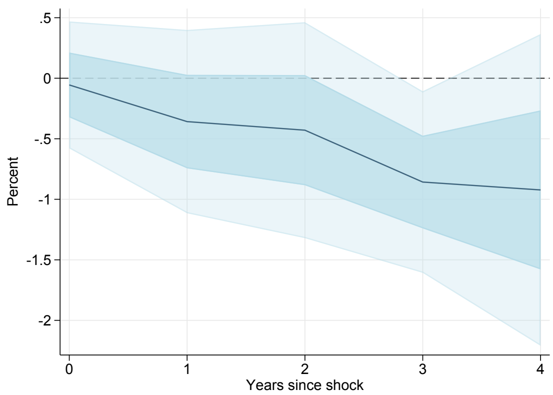


Notes: Each panel reports the interaction coefficients between the monetary policy shock and the dummy identifying the top 20% of the old-age dependency ratio distribution using as dependent variable the state-level real GDP. The dark shaded area and the light shaded area represent the 68% and the 95% confidence intervals respectively. The horizontal axis is in years.

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 15. The response of services in states with a higher old-age dependency ratio is significantly stronger suggesting that the main results are not driven by spillover effects.

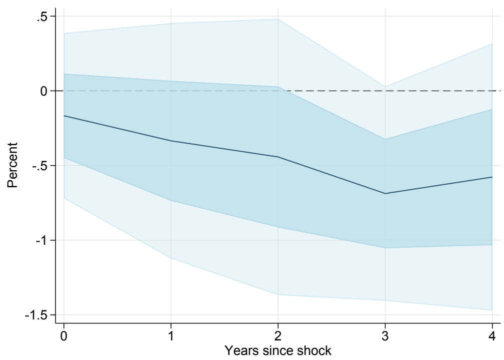
Figure 9: Impact of monetary policy on regional variables, extra controls

A. Real GDP controlling for house prices

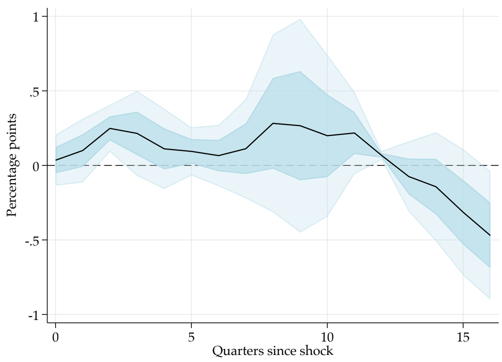


B. Inflation rate controlling for house prices

C. Real GDP controlling for fraction of ARMs



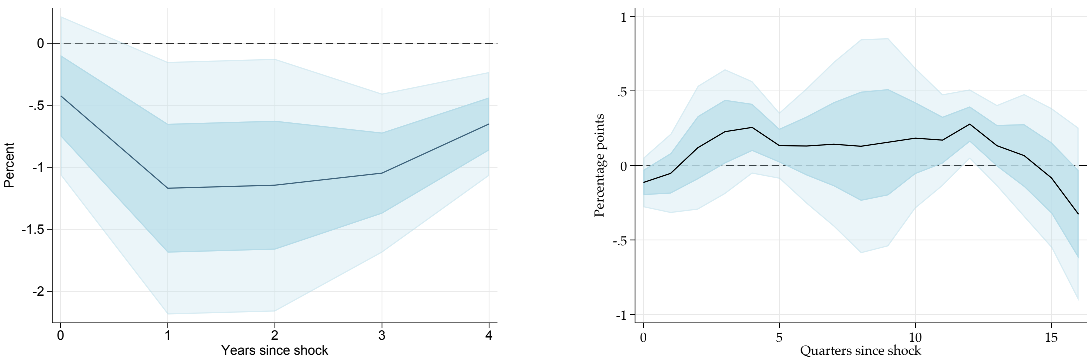
D. Inflation rate controlling for fraction of ARMs



Notes: Each panel reports the interaction coefficients between the monetary policy shock and the dummy identifying the top 20% of the old-age dependency ratio distribution using as dependent variable either the state-level real GDP or the inflation rate. The dark shaded area and the light shaded area represent the 68% and the 95% confidence intervals respectively.

Figure 10: Impact of monetary policy on regional variables, extra controls

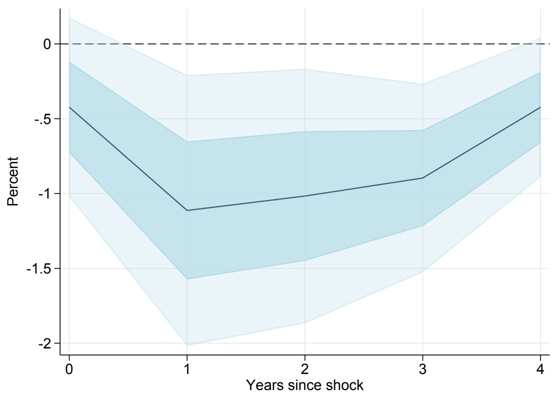
A. Real GDP controlling for workers' race   B. Inflation rate controlling for workers' race



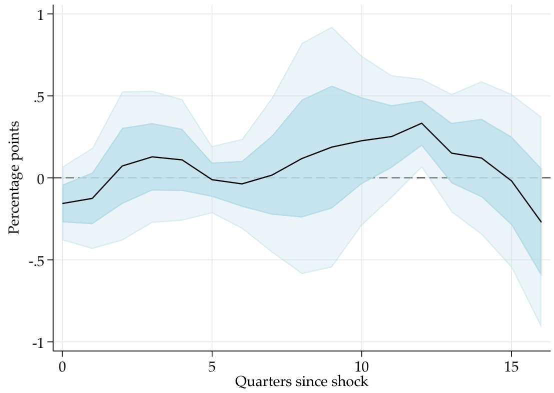
Notes: Each panel reports the interaction coefficients between the monetary policy shock and the dummy identifying the top 20% of the old-age dependency ratio distribution using as dependent variable either the state-level real GDP or the inflation rate. The dark shaded area and the light shaded area represent the 68% and the 95% confidence intervals respectively.

Figure 11: Impact of monetary policy on regional variables, extra controls

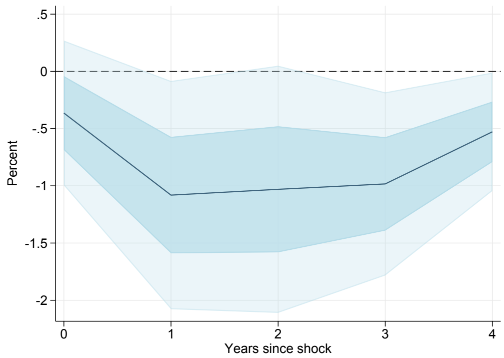
A. Real GDP controlling for workers' education



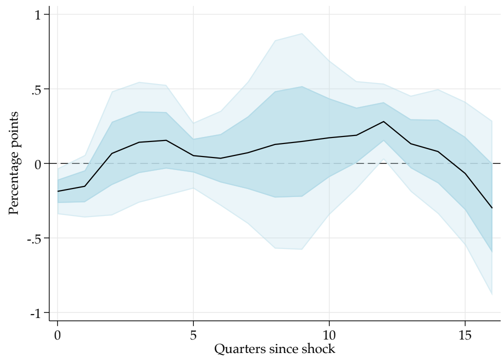
B. Inflation rate controlling for workers' education



C. Real GDP controlling for firms' size



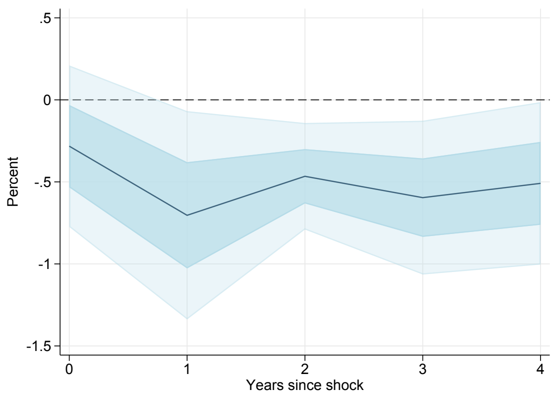
D. Inflation rate controlling for firms' size



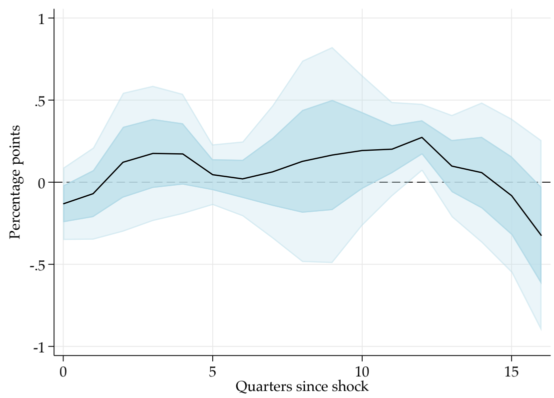
Notes: Each panel reports the interaction coefficients between the monetary policy shock and the dummy identifying the top 20% of the old-age dependency ratio distribution using as dependent variable either the state-level real GDP or the inflation rate. The dark shaded area and the light shaded area represent the 68% and the 95% confidence intervals respectively.

Figure 12: Impact of monetary policy on regional variables, extra controls

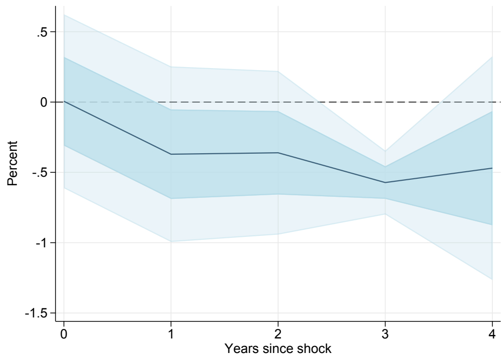
A. Real GDP controlling for firms' age



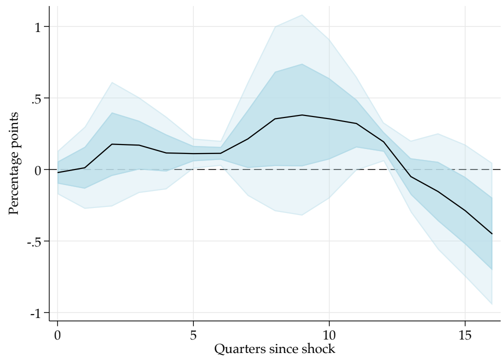
B. Inflation rate controlling for firms' age



C. Real GDP controlling for establishment births

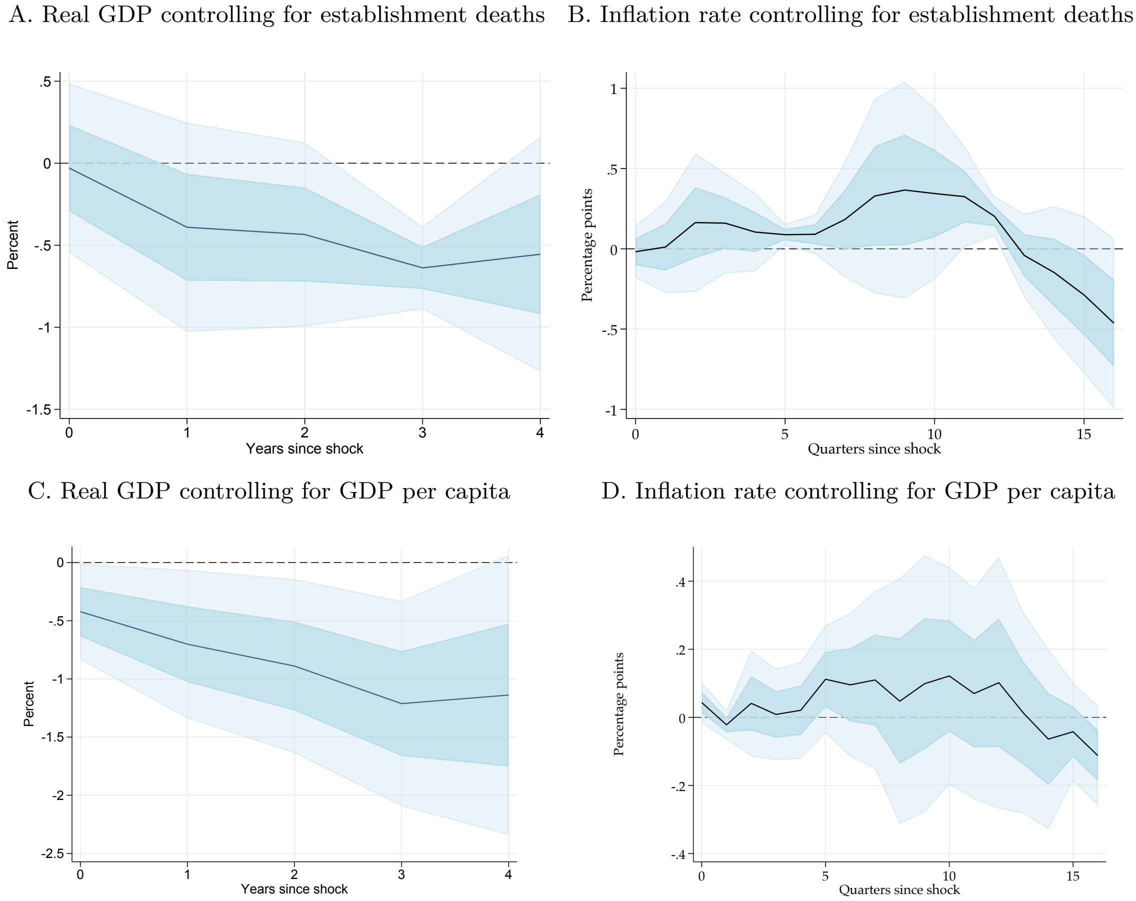


D. Inflation rate controlling for establishment births



Notes: Each panel reports the interaction coefficients between the monetary policy shock and the dummy identifying the top 20% of the old-age dependency ratio distribution using as dependent variable either the state-level real GDP or the inflation rate.

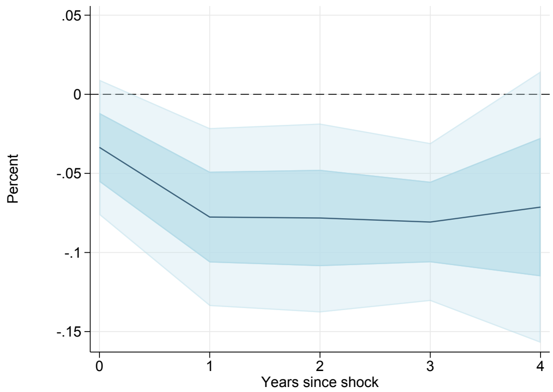
Figure 13: Impact of monetary policy on regional variables, extra controls



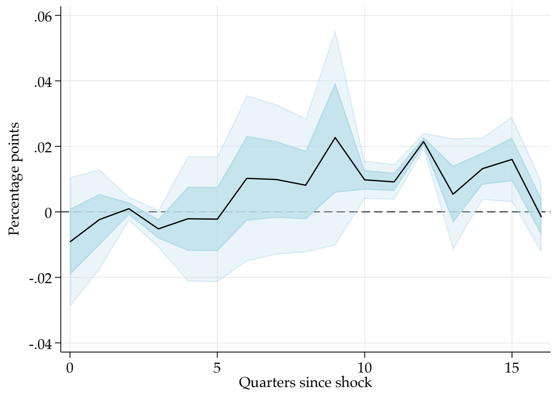
Notes: Each panel reports the interaction coefficients between the monetary policy shock and the dummy identifying the top 20% of the old-age dependency ratio distribution using as dependent variable either the state-level real GDP or the inflation rate. The dark shaded area and the light shaded area represent the 68% and the 95% confidence intervals respectively.

Figure 14: Impact of monetary policy on regional variables, different monetary shocks

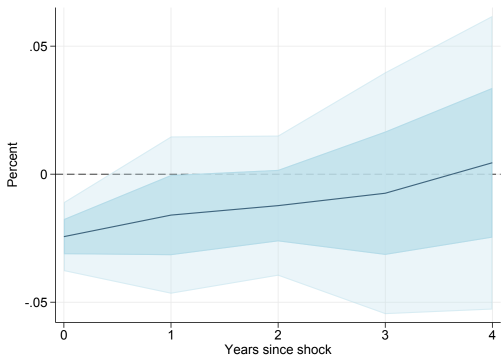
A. Real GDP with shocks from Nakamura and Steinsson (2018)



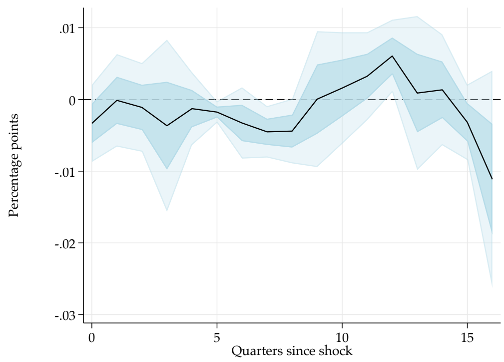
B. Inflation rate with shocks from Nakamura and Steinsson (2018)



C. Real GDP with shocks from Miranda-Agrippino and Ricco (2021)

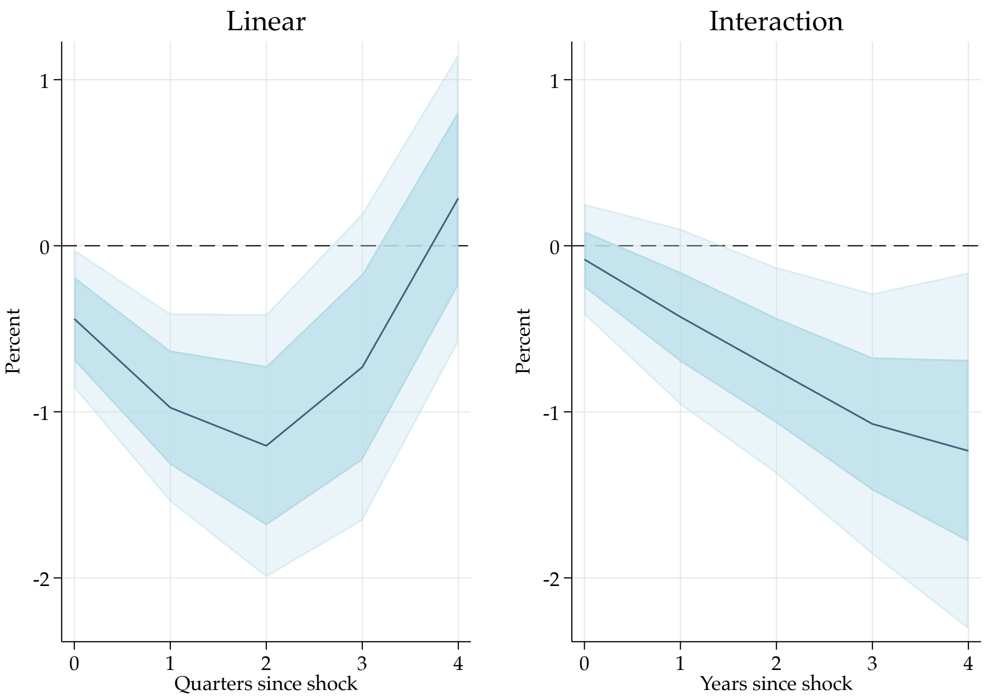


D. Inflation rate with shocks from Miranda-Agrippino and Ricco (2021)



Notes: Each panel reports the interaction coefficients between the monetary policy shock and the dummy identifying the top 20% of the old-age dependency ratio distribution using as dependent variable either the state-level real GDP or the inflation rate. The dark shaded area and the light shaded area represent the 68% and the 95% confidence intervals respectively.

Figure 15: Impact of monetary policy on the production of the regional services



Notes: The left panel of the figure plots the response of the state-level log of the real services production to a percentage point contractionary monetary policy shock, as well as the 68% (dark shaded area) and 95% (light shaded area) confidence intervals. The horizontal axis is in years. The right panel reports the interaction coefficients between the monetary policy shock and the dummy identifying the top 20% of the old-age dependency ratio distribution.

D List of model equations

This appendix presents the full set of equations of the model. Each period t there is a distribution of households of different ages j with $j \in \{1, ..., J\}$. On the supply side, there are two sectors s, services and goods, so that $s \in \{S, G\}$. Variables are expressed in real terms as $x_t = \frac{X_t}{P_t}$, the sectoral MC_t^s are deflated by the relative P_t^s.

To derive a measure ω of aggregate expenditure weights for the service sector I proceed as follow. The demand functions for services and goods relative to the households maximization problem are given by:

$$c_{t,j}^S = \alpha_j \Big(\frac{P_t^S}{P_{t,j}}\Big)^{-\eta} c_{t,j}, \qquad c_{t,j}^G = (1-\alpha_j)\Big(\frac{P_t^G}{P_{t,j}}\Big)^{-\eta} c_{t,j}, \tag{2}$$

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:

$$C_t^S = \omega_t \Big(\frac{P_t^S}{P_t}\Big)^{-\eta} C_t, \qquad C_t^G = (1-\omega_t)\Big(\frac{P_t^G}{P_t}\Big)^{-\eta} C_t, \tag{3}$$

where, following Cravino et al. (2020), 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, ω_t is assumed to be constant and equal to its steady state value.

Households:

$$P_{t,j}^* c_{t,j} + a_{t+1,j+1} = \frac{R_t^a}{\pi_t} a_{t,j} + (1-\tau_t) w_t l_{t,j} h_j \mathbf{I}_{j \le jw} + pen_t \mathbf{I}_{j > jw} + beq_t \tag{4}$$

$$a_{t,0} = 0 \qquad a_{t+J+1,J+1} = 0 \tag{5}$$

$$\nu l_{t,j}^{\eta} = \frac{(1-\tau_t) w_t h_j \mathbf{I}_{j \le jw}}{Z_t^{\omega-\alpha_j}} c_{t,j}^{-\sigma} \tag{6}$$

$$\frac{c_{t,j}^{-\sigma}}{P_{t,j}^*} = \beta s_j \frac{c_{t+1,j+1}^{-\sigma}}{P_{t+1,j+1}^*} \frac{R_{t+1}^a}{\pi_{t+1}} \tag{7}$$

Firms:

$$P_t^{S,*} mc_{i,t}^S = \Big(\frac{w_t}{(1-\psi)}\Big)^{1-\psi} \Big(\frac{r_t^k}{\psi}\Big)^{\psi} \tag{8}$$

$$P_t^{G,*} mc_{i,t}^G = \Big(\frac{w_t}{(1-\psi)}\Big)^{1-\psi} \Big(\frac{r_t^k}{\psi}\Big)^{\psi} \tag{9}$$

$$K_{i,t}^s = \frac{\psi w_t}{(1-\psi) r_t^k} L_{i,t}^s \tag{10}$$

$$f_t = Y - w_t L_t - r_t^k K_t \tag{11}$$

$$v_t^s = (1-\theta^s)\left(\pi_t^{s,\#}\right)^{-\epsilon} (\pi_t^s)^{\epsilon} + \theta^s (\pi_t^s)^{\epsilon} v_{t-1}^s \tag{12}$$

$$(\pi_t^s)^{1-\epsilon} = (1-\theta^s)\left(\pi_t^{s,\#}\right)^{1-\epsilon} + \theta^s \tag{13}$$

$$x_{1,t}^s = \frac{1}{R_t} Y_t^s P_t^{s,*} mc_{i,t}^s + \theta^s \beta \mathbb{E}_t \left(\pi_{t+1}^s\right)^{\epsilon} x_{1,t+1}^s \tag{14}$$

$$x_{2,t}^s = \frac{1}{R_t} Y_t^s P_t^{s,*} + \theta^s \beta \mathbb{E}_t \left(\pi_{t+1}^s\right)^{\epsilon-1} x_{2,t+1}^s \tag{15}$$

$$\pi_t^{s,\#} = \frac{\epsilon}{\epsilon-1} \pi_t^s \frac{x_{1,t}^s}{x_{2,t}^s} \tag{16}$$

Representative investment fund:

$$K_{t+1} = (1-\delta)K_t + \Big[1 - \frac{S}{2}\Big(\frac{I_t}{I_{t-1}} - 1\Big)^2\Big] I_t \tag{17}$$

$$A_{t+1} = q_t(1-\delta)K_t + I_t + p_t^d \tag{18}$$

$$\frac{R_t^a}{\pi_t} A_t = \Big[r_t^k + q_t(1-\delta)\Big] K_t + f_t + p_t^d \tag{19}$$

$$R_t q_t = \mathbb{E}_t\Big[\Big(r_{t+1}^k + q_{t+1}(1-\delta)\Big)\pi_{t+1}\Big] \tag{20}$$

$$R_t p_t^d = \mathbb{E}_t\Big[\Big(p_{t+1}^d + f_{t+1}\Big)\pi_{t+1}\Big] \tag{21}$$

$$1 = q_t\Big[1 - \frac{S}{2}\Big(\frac{I_t}{I_{t-1}} - 1\Big)^2 - S\Big(\frac{I_t}{I_{t-1}} - 1\Big)\frac{I_t}{I_{t-1}}\Big] + \mathbb{E}_t\Big[\frac{\pi_{t+1}}{R_t} q_{t+1} S\Big(\frac{I_{t+1}}{I_t} - 1\Big)\Big(\frac{I_{t+1}}{I_t}\Big)^2\Big] \tag{22}$$

Government:

$$pen_t = \bar{d}(1-\tau_t) w_t \sum_{j=0}^{jw} N_j h_j \tag{23}$$

$$\tau_t w_t \sum_{j=0}^{jw} N_j h_j = pen_t \sum_{j=jw+1}^{J} N_j \tag{24}$$

Monetary authority:

$$\frac{R_t}{R} = \Big(\frac{\pi_t}{\pi}\Big)^{\phi_\pi} \Big(\frac{Y_t}{Y}\Big)^{\phi_y} e^{\nu_t^r} \tag{25}$$

$$\nu_t^r = \rho^\nu \nu_{t-1}^r + \epsilon_t^\nu \tag{26}$$

Market clearing:

$$L_t = L_t^S + L_t^G = \sum_{j=1}^{jw} N_j h_j n_{t,j}, \quad A_t = \sum_{j=1}^{J} N_{j-1} a_{t,j}, \quad K_t = K_t^S + K_t^G \tag{27}$$

$$beq_t = \sum_{j=1}^{J} (N_{j-1} - N_j) a_{t,j} \frac{R_t^a}{\pi_t} \tag{28}$$

$$Y_t^S = (K_t^S)^{\alpha} (L_t^S)^{1-\alpha} / v_t^S = C_t^S \tag{29}$$

$$Y_t^G = (K_t^G)^{\alpha} (L_t^G)^{1-\alpha} / v_t^G = C_t^G + I_t \tag{30}$$

$$C_t = P_t^{S,*} C_t^S + P_t^{G,*} C_t^G \tag{31}$$

$$Y_t = P_t^{S,*} Y_t^S + P_t^{G,*} Y_t^G \tag{32}$$

$$C_t^S = \sum_{j=1}^{J} \alpha_j \left(P_{t,j}^{S,*}\right)^{\eta} N_j c_{t,j}, \qquad C_t^G = \sum_{j=1}^{J} \left(1 - \alpha_j\right) \left(P_{t,j}^{G,*}\right)^{\eta} N_j c_{t,j} \tag{33}$$

Price dynamics

$$\frac{\pi_t^G}{\pi_t^S} = \frac{Z_t}{Z_{t-1}} \tag{34}$$

$$\pi_t = \pi_t^S \frac{\omega + (1-\omega) Z_t^{1-\eta}}{\omega + (1-\omega) Z_{t-1}^{1-\eta}} \tag{35}$$

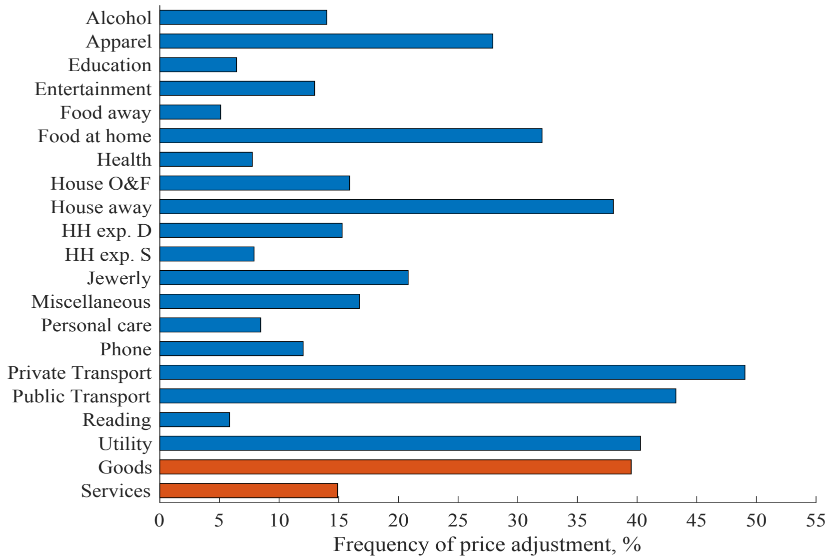
$$P_t^{S,*} = \frac{P_t^S}{P_t} = \left[\omega + (1-\omega) Z_t^{1-\eta}\right]^{\frac{1}{\eta-1}}, \quad P_t^{G,*} = \frac{P_t^G}{P_t} = \left[\omega Z_t^{\eta-1} + (1-\omega)\right]^{\frac{1}{\eta-1}} \tag{36}$$

$$P_{t,j}^{*} = \frac{P_{t,j}}{P_t} = \left[\frac{\alpha_j + (1-\alpha_j) Z_t^{1-\eta}}{\omega + (1-\omega) Z_t^{1-\eta}}\right]^{\frac{1}{1-\eta}} \tag{37}$$

$$P_{t,j}^{S,*} = \frac{P_{t,j}}{P_t^S} = \left[\alpha_j + (1-\alpha_j) Z_t^{1-\eta}\right]^{\frac{1}{1-\eta}}, \quad P_{t,j}^{G,*} = \frac{P_{t,j}}{P_t^G} = \left[\alpha_j Z_t^{\eta-1} + (1-\alpha_j)\right]^{\frac{1}{1-\eta}} \tag{38}$$

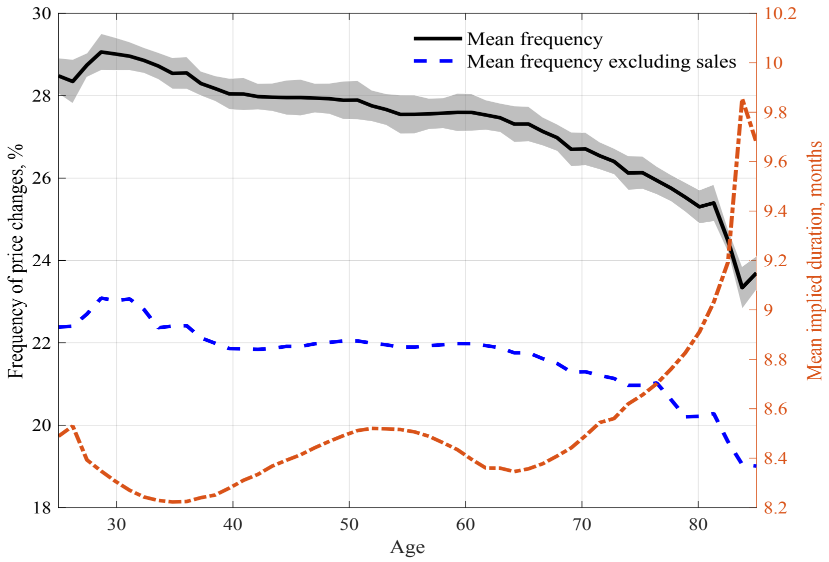
E Additional figures and tables

Figure 16: Average price rigidities across expenditure categories



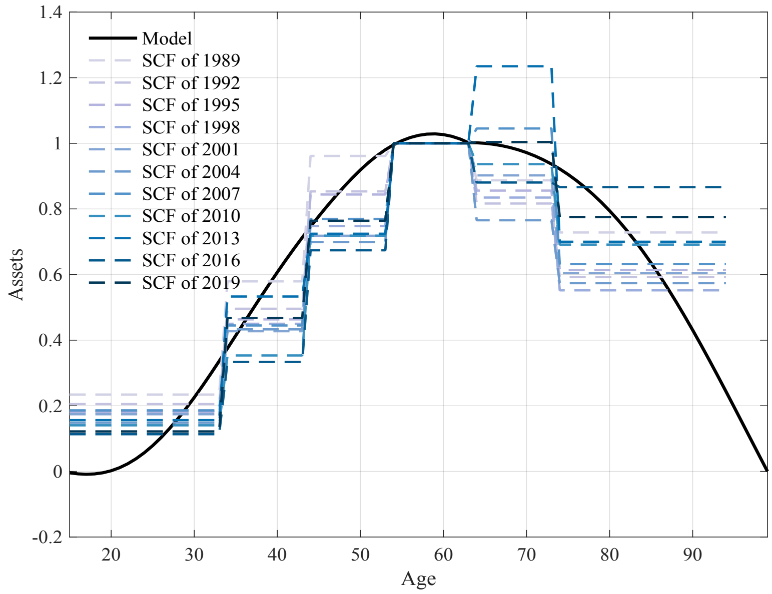
Notes: The bar plot shows the weighted average frequency of price adjustment across different expenditure categories as well as for the aggregation of the categories into Goods and Services.

Figure 17: Frequency of price adjustment and mean implied duration across age groups



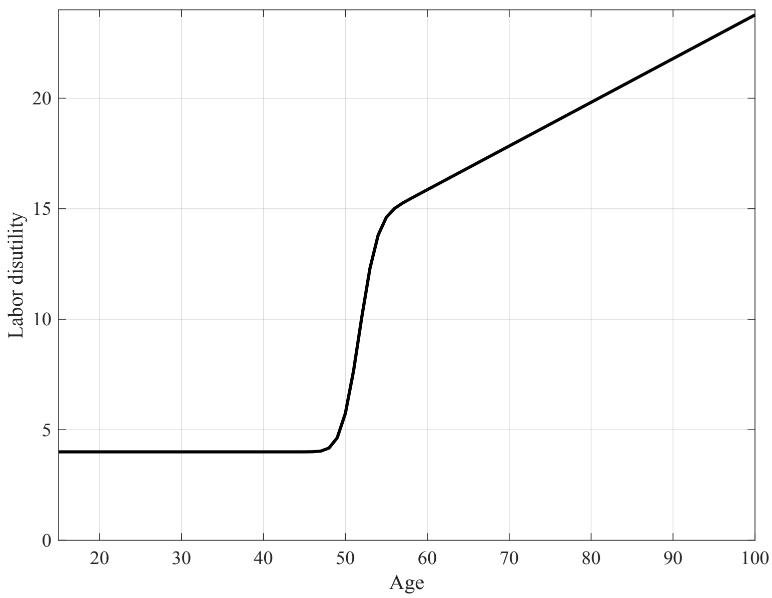
Notes: The figure plots the weighted average frequency of price adjustment with and without temporary sales (left axis) alongside the mean implied duration (right axis) across age groups. The shaded area is the 95% confidence band. The expenditure shares are computed using data from the CEX whereas the sectoral price stickiness parameters are retrieved from Nakamura and Steinsson (2008).

Figure 18: Model vs Data



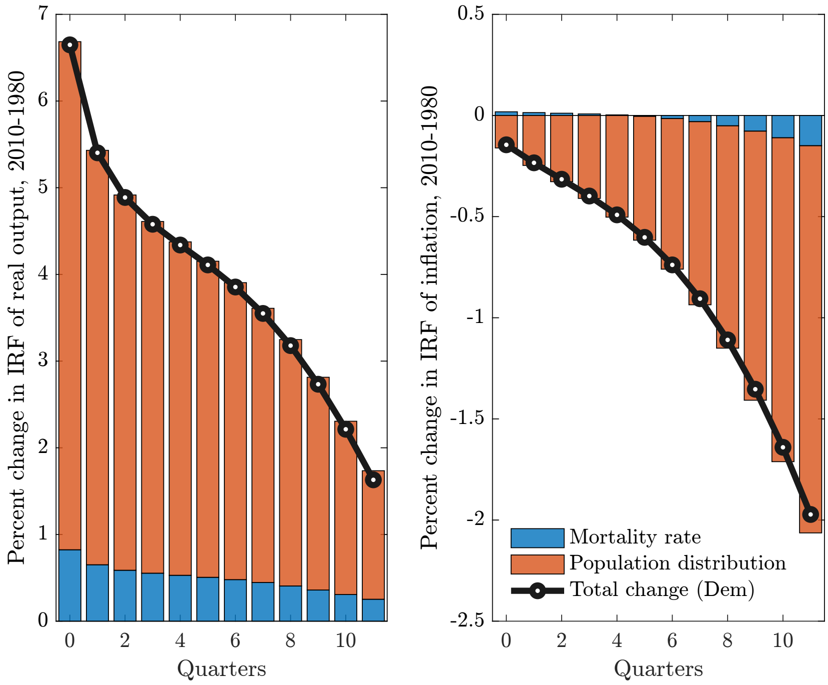
Notes: The plot compares the steady state assets profile from the model (Age 65 = 1) with the asset profile taken from the Survey of Consumer Finances for different years (Age group 55-64 = 1). *Source*: Survey of Consumer Finances.

Figure 19: Age dependent disutility of labor supply, ν_j



Notes: Following Jones (2021), 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 $b_3(J + 1)$.

Figure 20: 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 of 1980 and 2010 but mortality rates kept fixed at the 1980 values (blue bars), using the mortality rates of 1980 and 2010 but the population distribution of 1980 (red bars) and finally using both the population distribution and mortality rates of the two steady states (black line). The services preferences are kept fixed at the 1980 values. The right panel shows the same percent change but for inflation.

Table 1: 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

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