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

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Link to most recent version

October 2023

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:

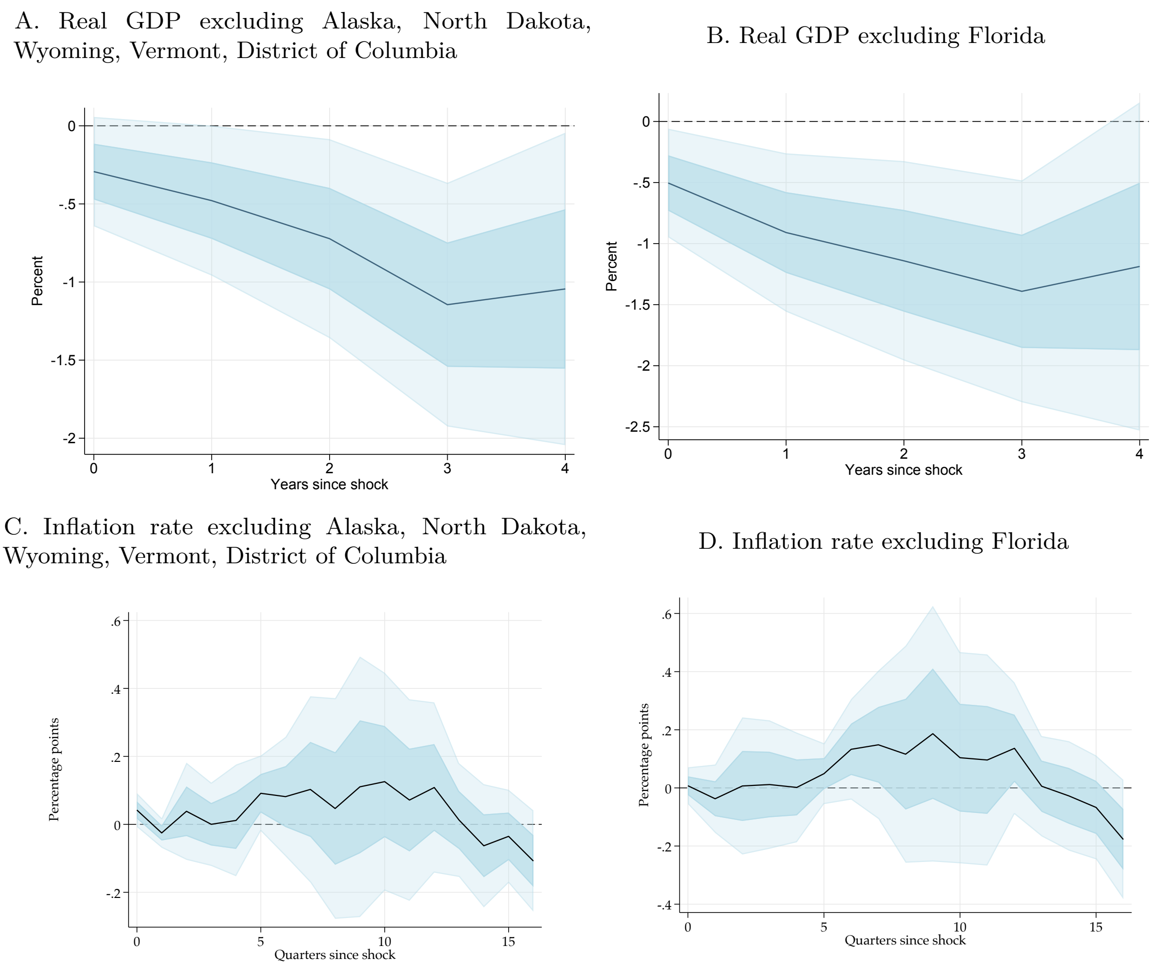
$$X_k^a = \frac{\sum_i fwt_i^a \sum_t c_{i,k,t}^a}{\sum_i fwt_i^a \ MO\_SCOPE_i^a} \times 12 \tag{1}$$

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 regional responses

Figure 1: Impact of monetary policy on regional variables, dropping states

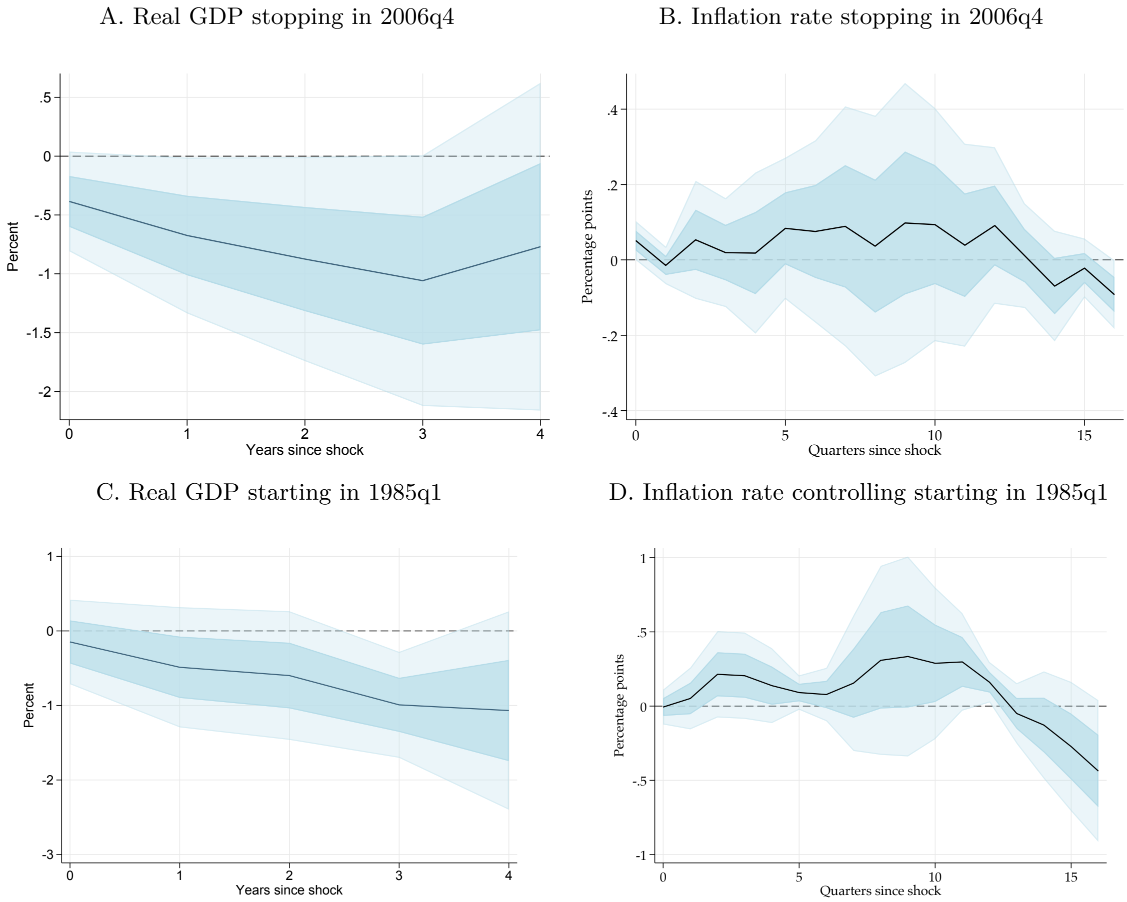


Notes: Each panel reports the interaction coefficients between the monetary policy shock and the dummy identifying the top 20% of the old-age dependency ratio distribution using as dependent variable either the state-level real GDP or the inflation rate. The dark shaded area and the light shaded area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

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 1, 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

Figure 2: Impact of monetary policy on regional variables, different subperiods



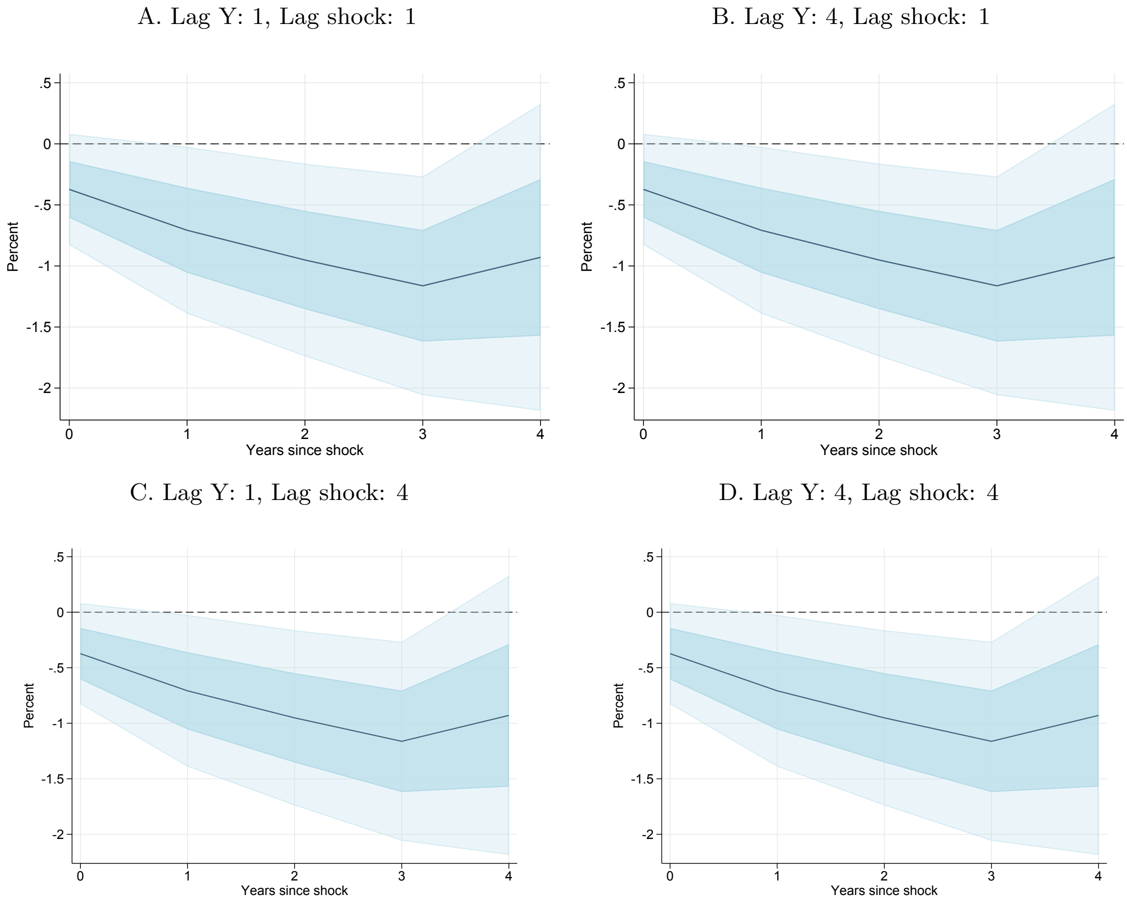
Notes: Each panel reports the interaction coefficients between the monetary policy shock and the dummy identifying the top 20% of the old-age dependency ratio distribution using as dependent variable either the state-level real GDP or the inflation rate. The dark shaded area and the light shaded area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

(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 2. 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 and four lags of the shock, four lags of y and four lags of the shock. Figure 3 and Figure 4 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

Figure 3: Impact of monetary policy on the regional real GDP, different lags



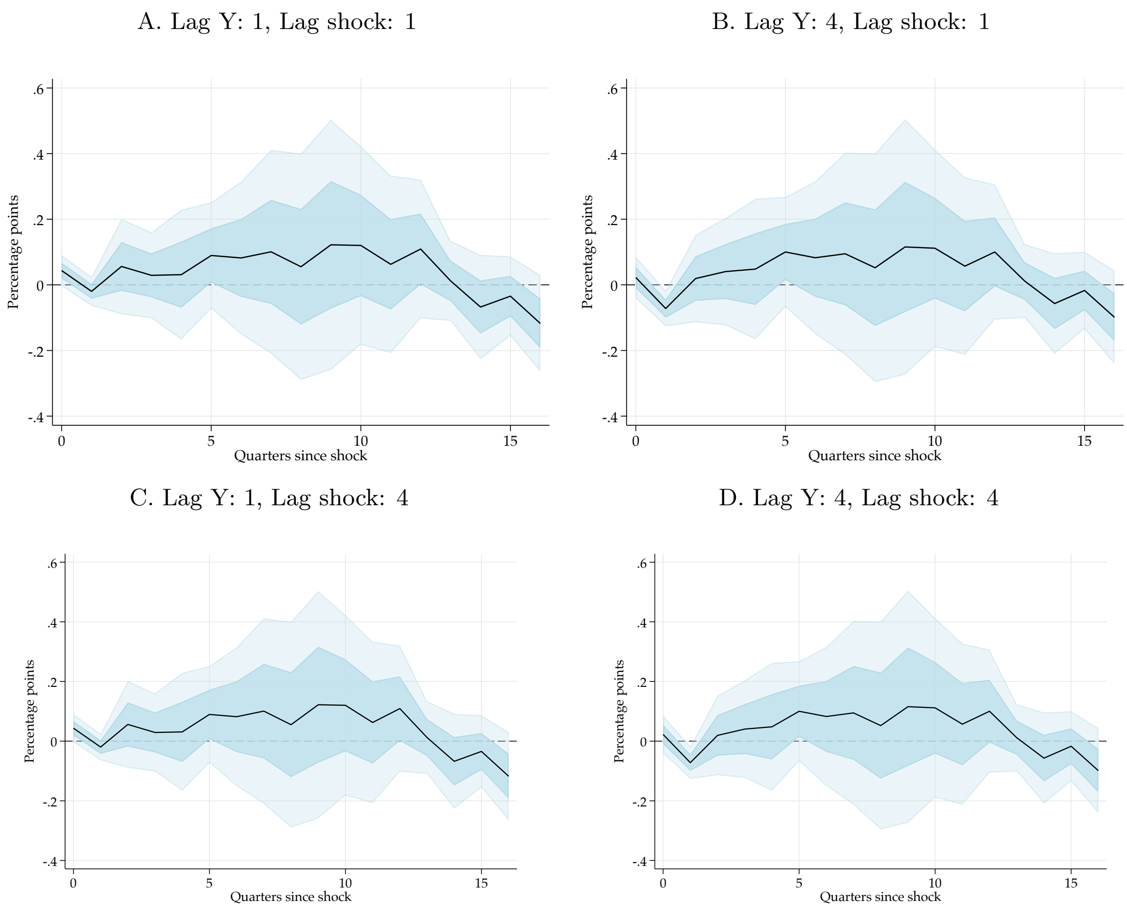
Notes: Each panel reports the interaction coefficients between the monetary policy shock and the dummy identifying the top 20% of the old-age dependency ratio distribution using as dependent variable the state-level real GDP. The dark shaded area and the light shaded area represent the 68% and the 95%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

with the level of the old-age dependency ratio. The impulse response functions are reported in Figure 5. 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 extend the baseline specification by interacting different control variables with the monetary policy shock[2]. 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,

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

Figure 4: Impact of monetary policy on the regional inflation rate, different lags

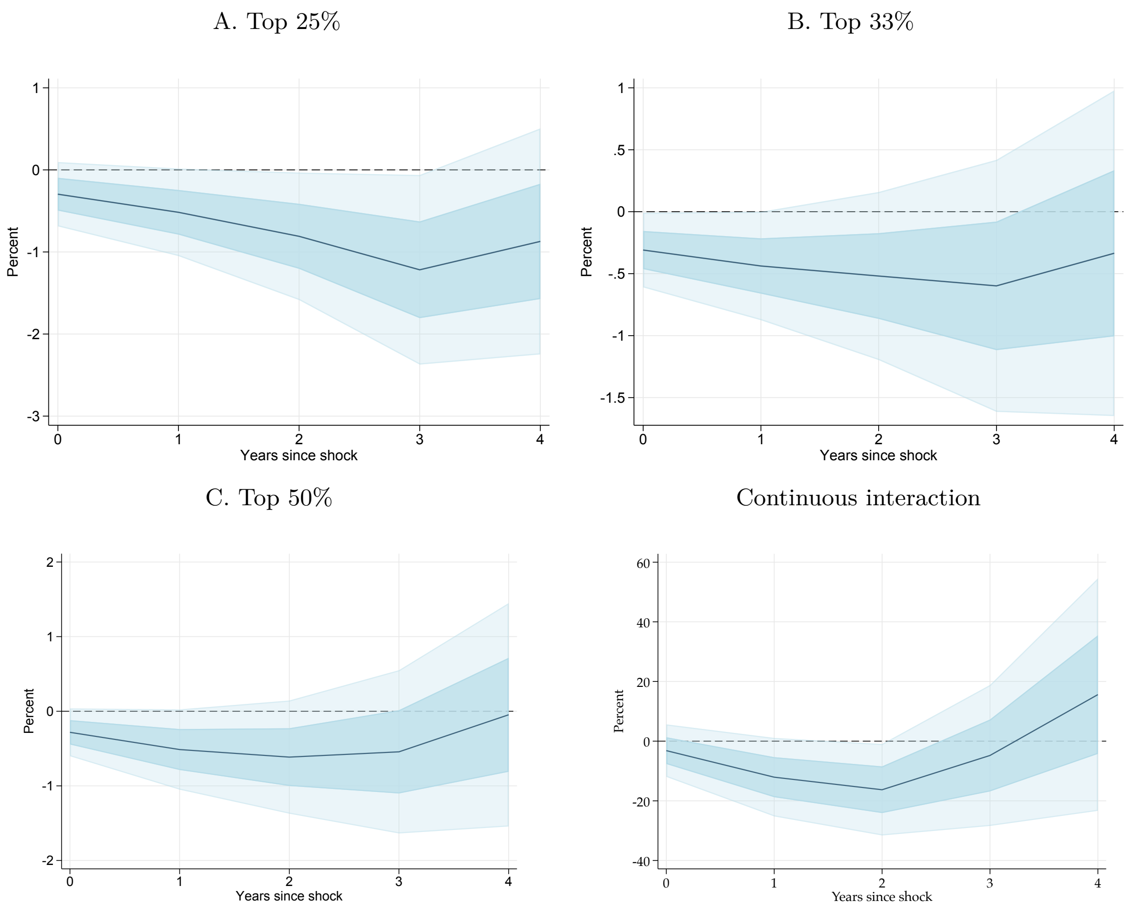


Notes: Each panel reports the interaction coefficients between the monetary policy shock and the dummy identifying the top 20% of the old-age dependency ratio distribution using as dependent variable the state-level inflation rate. The dark shaded area and the light shaded area represent the 68% and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

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 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 6 to and Figure 10.

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

Figure 5: Impact of monetary policy on the regional real GDP, different thresholds

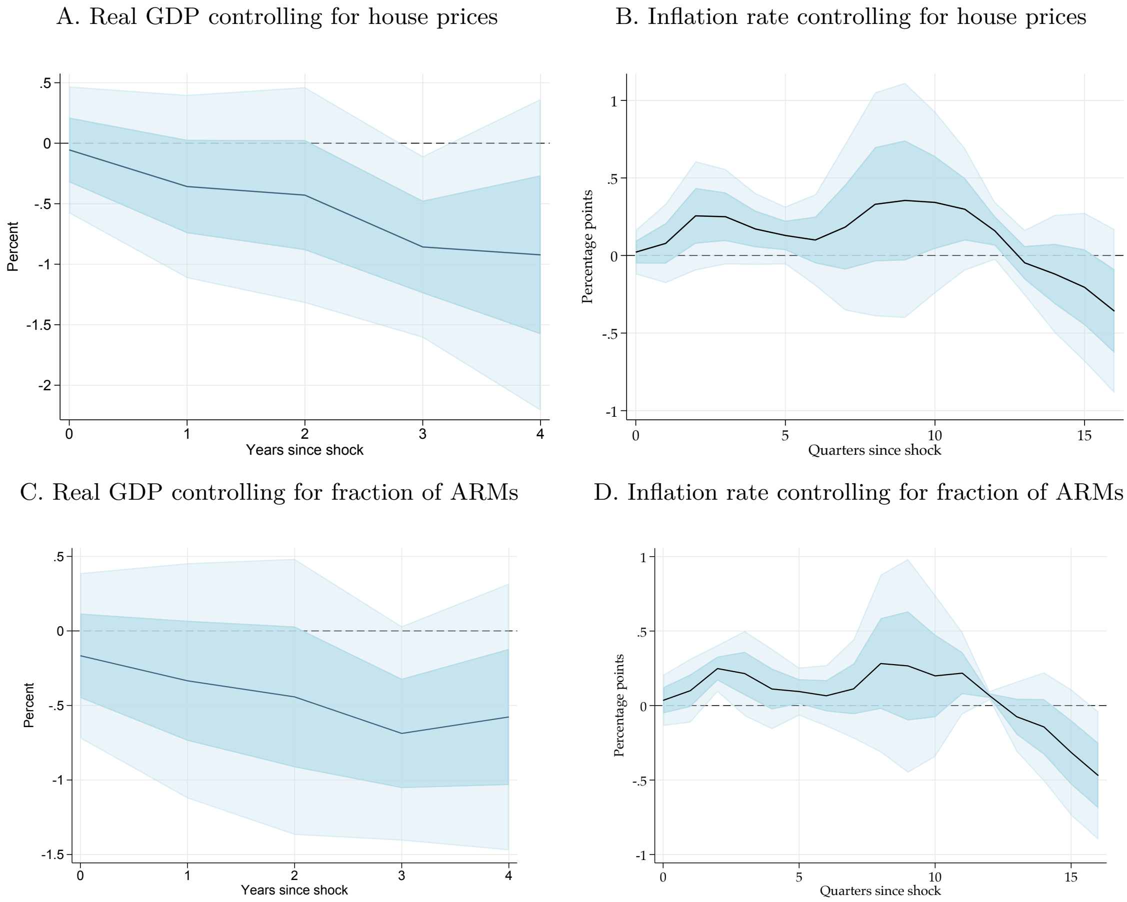


Notes: Each panel reports the interaction coefficients between the monetary policy shock and the dummy identifying the top 20% of the old-age dependency ratio distribution using as dependent variable the state-level real GDP. The dark shaded area and the light shaded area represent the 68% and the 95%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

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 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 11 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.

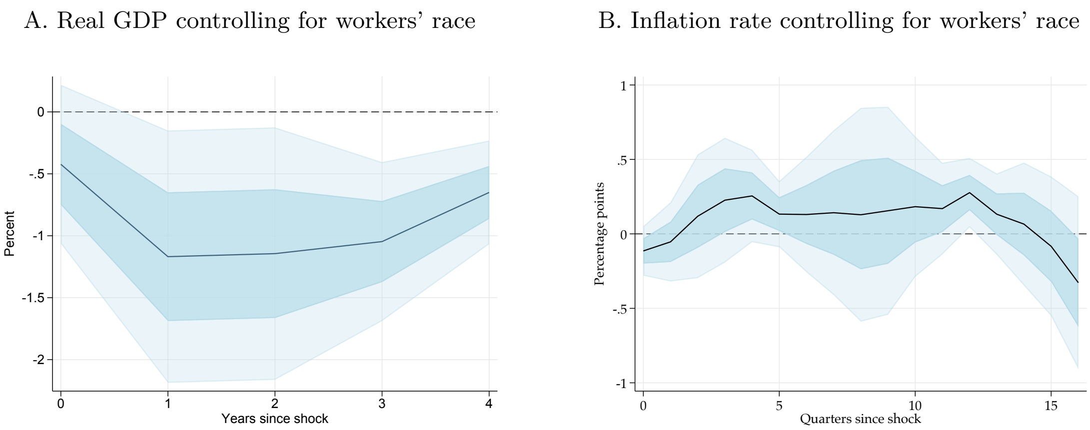
Figure 6: Impact of monetary policy on regional variables, extra controls



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.

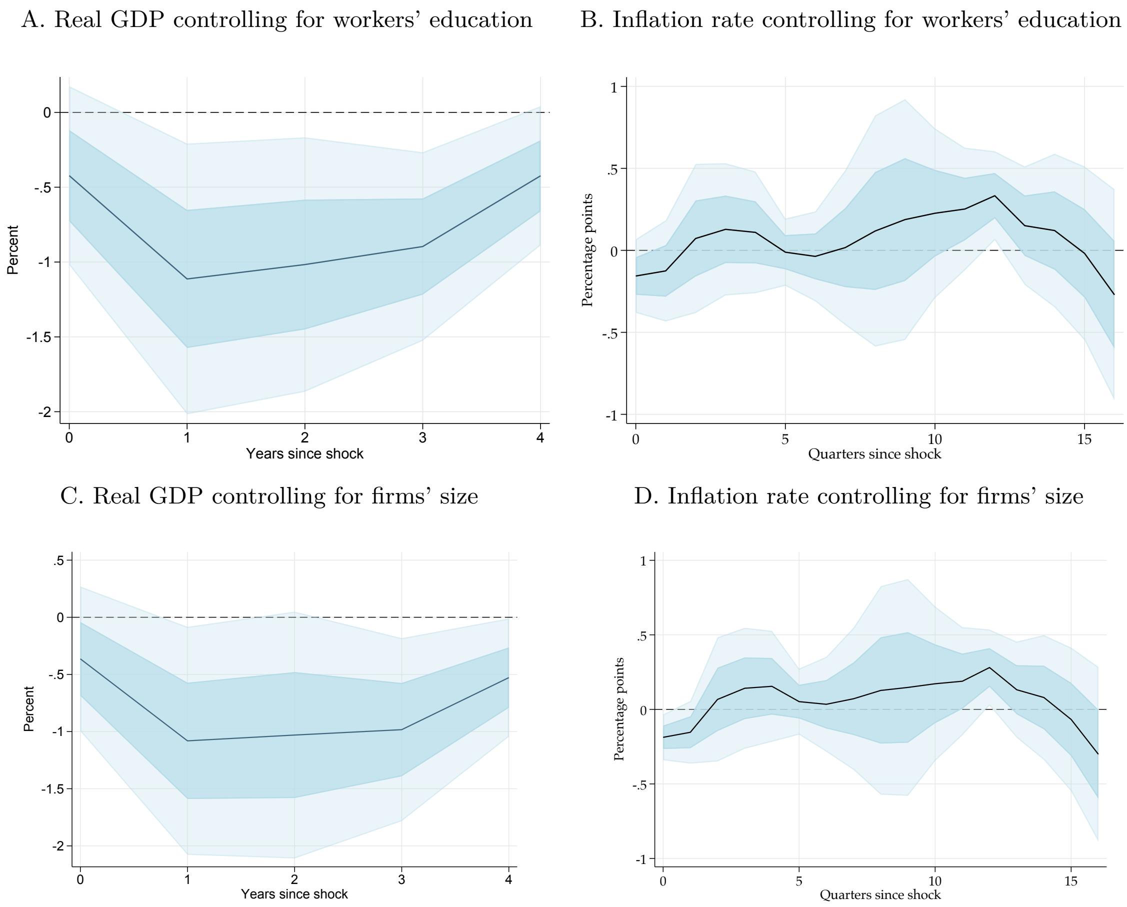
Seventh, spillover effects from other states might bias the results. It could be the case that the stronger response of GDP observed in older states is actually due to an increase in the demand for tradable goods from the surrounding states rather than from the different frequencies of price adjustment 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-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 12. 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 7: 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 8: Impact of monetary policy on regional variables, extra controls

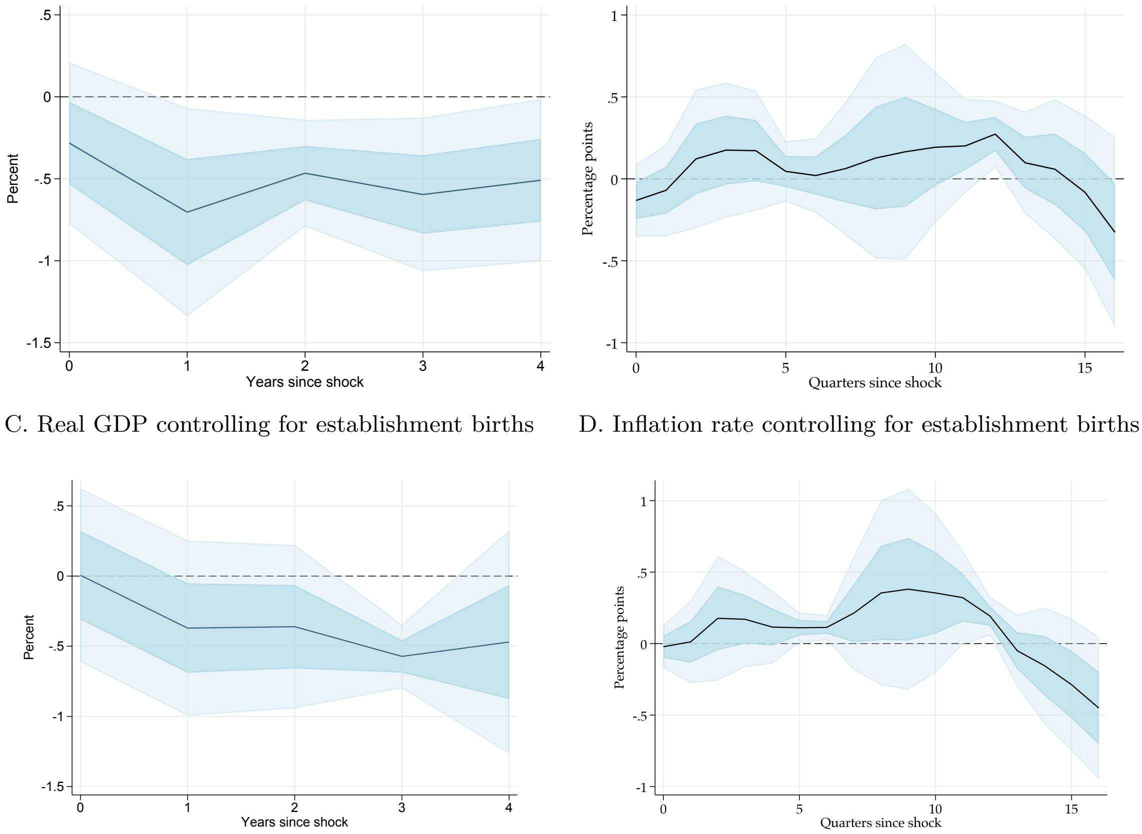


Notes: Each panel reports the interaction coefficients between the monetary policy shock and the dummy identifying the top 20% of the old-age dependency ratio distribution using as dependent variable either the state-level real GDP or the inflation rate. The dark shaded area and the light shaded area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

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

A. Real GDP controlling for firms' age

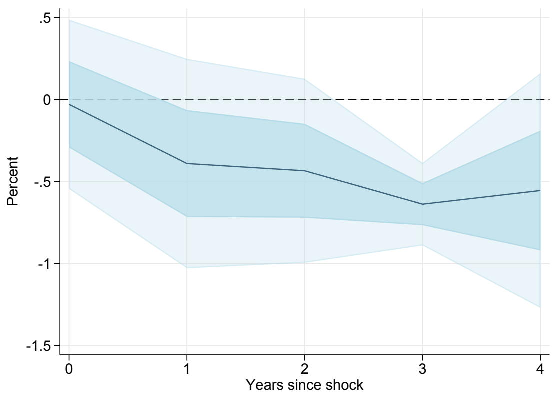
B. Inflation rate controlling for firms' age



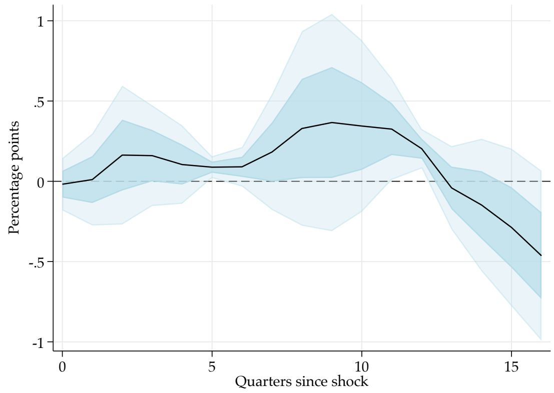
Notes: Each panel reports the interaction coefficients between the monetary policy shock and the dummy identifying the top 20% of the old-age dependency ratio distribution using as dependent variable either the state-level real GDP or the inflation rate.

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

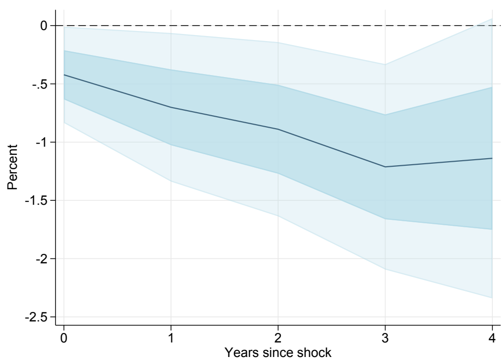
A. Real GDP controlling for establishment deaths



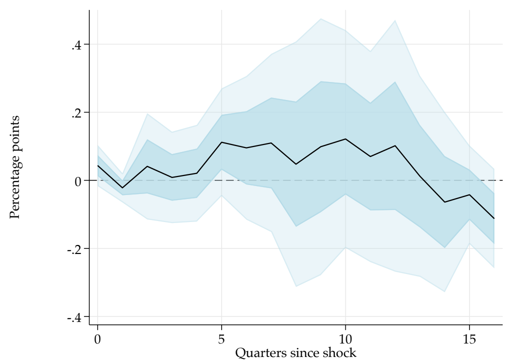
B. Inflation rate controlling for establishment deaths



C. Real GDP controlling for GDP per capita



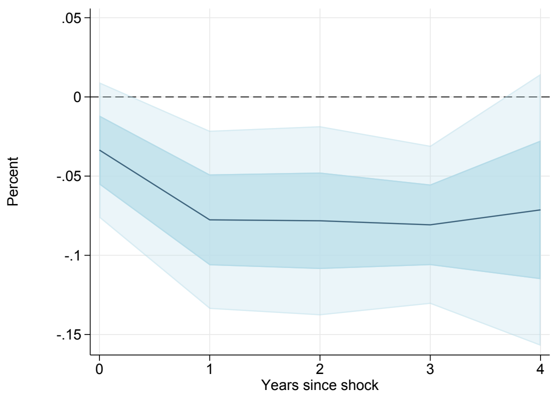
D. Inflation rate controlling for GDP per capita



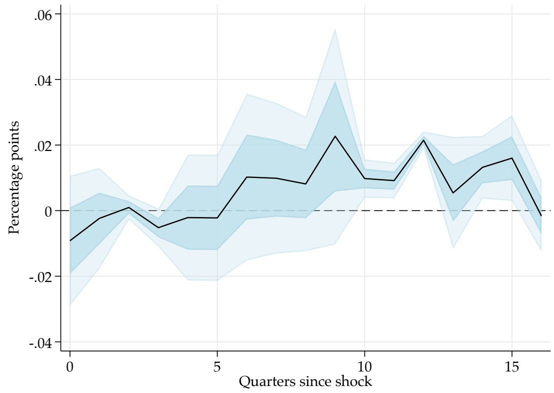
Notes: Each panel reports the interaction coefficients between the monetary policy shock and the dummy identifying the top 20% of the old-age dependency ratio distribution using as dependent variable either the state-level real GDP or the inflation rate. The dark shaded area and the light shaded area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

Figure 11: Impact of monetary policy on regional variables, different monetary shocks

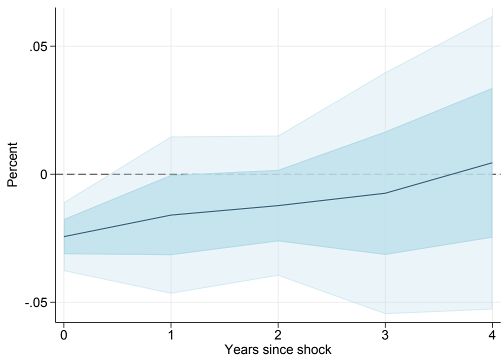
A. Real GDP with shocks from Nakamura and Steinsson (2018)



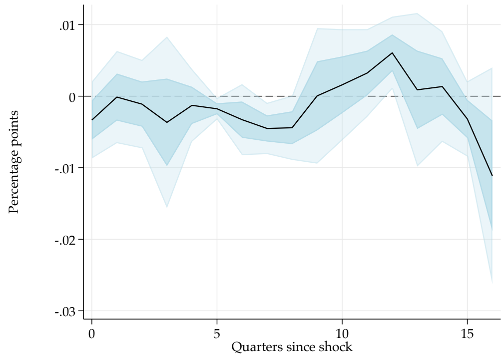
B. Inflation rate with shocks from Nakamura and Steinsson (2018)



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

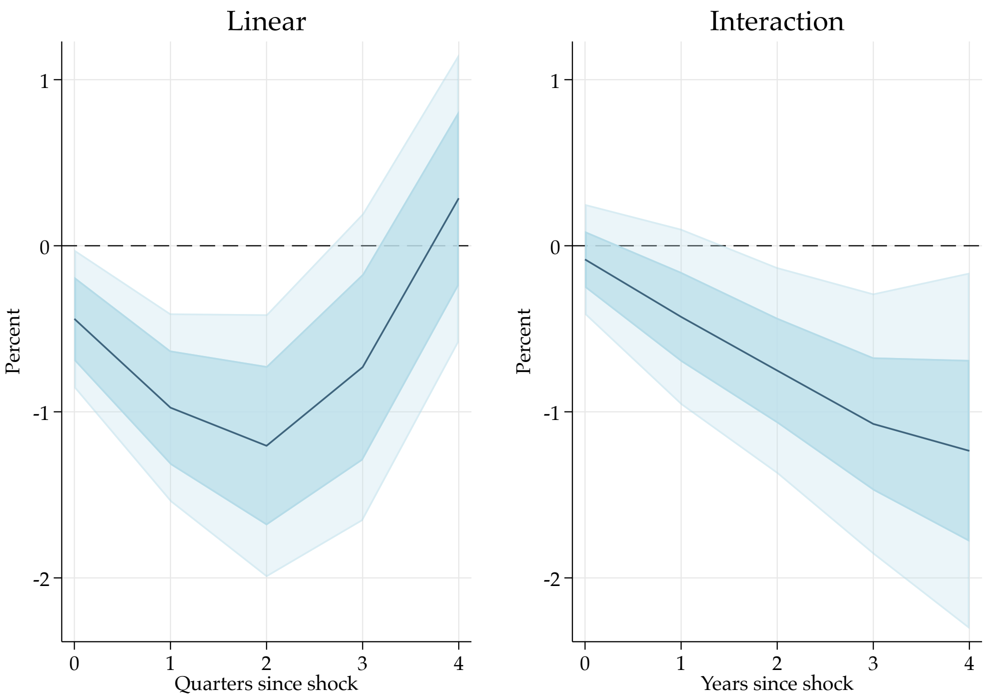


D. Inflation rate with shocks from Miranda-Agrippino and Ricco (2021)



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 12: 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.

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