BANCA D'ITALIA
EUROSISTEMA

Temi di discussione

(Working Papers)

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December 2024

Number 1474

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ISSN 2281-3950 (online)

Designed by the Printing and Publishing Division of the Bank of Italy

MONETARY POLICY SHOCKS AND INFLATION INEQUALITY

by Christoph Lauper* and Giacomo Mangiante**

Abstract

This paper studies how monetary policy shocks influence the distribution of U.S. household-level inflation rates. We find that contractionary monetary policy shocks significantly and persistently decrease inflation dispersion in the economy. Moreover, different demographic groups are affected heterogeneously by monetary policy. Due to the different consumption baskets purchased, low- and middle-income households experience higher median inflation rates, which are at the same time more responsive to a contractionary monetary shock, leading to an overall convergence of inflation rates across income groups. The same result holds for expenditure and salary groups. The expenditures on energy, water and gasoline are the main drivers behind these results. These findings imply that the impact of monetary policy shocks on expenditure inequality is between 20% and 30% more muted once we control for differences in individual inflation rates. Overall, our empirical evidence highlights the importance of inflation heterogeneity in studying the distributional consequences that monetary policies can have.

JEL Classification: E31, E52.

Keywords: monetary policy, inflation inequality, distributional effects.

DOI: 10.32057/0.TD.2024.1474

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1 Introduction

The relationship between monetary policy and heterogeneity has become increasingly important in macroeconomic research, both from a theoretical and empirical point of view. Changes in interest rates do not impact households homogeneously. Renters and homeowners, savers and hand-to-mouths, high-skilled and low-skilled workers are only a few examples of different demographic groups that have been found to bear the consequences of the decisions made by the monetary authorities in completely different ways. Therefore, in the last few years, both economic researchers and central bankers have shifted their focus from aggregate to more granular effects to better understand the different channels through which monetary policy can affect individual households and firms. However, the importance of inflation heterogeneity, i.e., the different inflation rates experienced by households due to the variations in the consumption baskets they purchase, for the distributional effects of monetary policy has so far received limited attention.

This paper studies how monetary policy in the U.S. influences the distribution of individual inflation rates to which different households are exposed. We compute a measure of inflation heterogeneity from 1980 onward, given by the standard deviation of individual inflation rates, and document that contractionary monetary shocks reduce both the median and the cross-sectional standard deviation of the distribution of household-specific inflation rates. We then study how the inflation rates of different demographic groups are heterogeneously affected by monetary shocks. We show that *inflation inequality*, which we define as the cross-sectional standard deviation of the decile-specific inflation rates across expenditure, salary, and income deciles, decreases after a contractionary monetary shock. The reason is that households at the bottom of the distribution are exposed to a higher inflation rate which tends at the same time to decrease more following a monetary shock. The effect is almost entirely driven by expenditures on *Energy*, *Water*, and *Gasoline*. The inflation rate of these sectors, even though they account for a relatively small share of the aggregate consumption bundle, is extremely volatile and highly sensitive to changes in interest rates. Finally, taking inflation heterogeneity into account, we find that the increase in expenditure inequality following a contractionary monetary shock is significantly more muted.

The first contribution of this paper is to evaluate how monetary policy influences the distribution of household-level inflation rates. To compute individual inflation rates, we combine item-level price data from the Bureau of Labor Statistics (BLS) with individual expenditure data from the Consumer Expenditure Survey (CEX) for the U.S. from 1980 onward. We evaluate how the different moments of the inflation rates distribution, i.e., the median and the standard deviation, react to monetary policy shocks by adopting a Local Projection approach à la Jordà (2005). Exogenous variations in interest rate are captured using the Romer and Romer (2004) monetary shocks series. We document that contractionary monetary policy shocks decrease the median inflation rate as well as significantly reduce the dispersion of the distribution.

The second contribution is to study whether the inflation rates of different demographic groups are heterogeneously affected by monetary policy. We demonstrate that contractionary shocks lead to a sizable decrease in inflation inequality. On the one hand, the inflation rates of low- and middle-income households tend on average to be higher than those of high-income households. On the other hand, they are more reactive to shocks and therefore decrease relatively more after a monetary shock. The same result holds for salary and expenditure deciles, confirming the important role of endowments in the dynamics of individual inflation rates.

The third contribution is to assess which sectors are mainly responsible for the decrease in inflation dispersion. The price indices of different sectors have different sensitivity to monetary policy shocks. We document that *Energy*, *Water* and *Gasoline* are by far the most influenced by contractionary shocks and they explain almost entirely the response of inflation dispersion to monetary shocks even though they account for only a relatively small expenditure share. Therefore, the higher responsiveness of the low- and middle-income households' inflation is driven by the larger expenditure share they devote to these categories.

The fourth contribution of the paper is to evaluate how these new findings on inflation heterogeneity influence real expenditure inequality and its response to monetary shocks. We compute two measures of real expenditure at household-level: one deflating nominal expenditure by the aggregate price level (as is common in the literature, neglecting inflation heterogeneity) and one deflating each expenditure category by the relative sectoral price level. As expected, we find that assuming all households are exposed to the same inflation rate overestimates the impact of monetary policy shocks on expenditure inequality. Although the nominal expenditure of low- and middle-income households decreases more after a shock compared to that of high-income households, their inflation rates also decrease relatively more, partially offsetting this decrease in real terms. It is important to underline that real consumption heterogeneity is still found to increase after a contractionary monetary shock corroborating again the evidence of the sizable distributional effects that central banks can have on the economy.

After years of relatively stable price growth, inflation rates worldwide have reached high levels in the post-Covid period. The optimal monetary policy to tackle them is again at the center of attention for academics and policymakers. However, most of the discussion focuses on stabilizing the aggregate inflation rate. The results from this paper suggest that concentrating only on the overall inflation would miss the huge heterogeneity in inflation rates to which households are exposed.

Related literature. This paper contributes to two strands of the literature. The first one is the research agenda on inflation inequality. Households are exposed to different levels of price increases given the heterogeneous consumption baskets they consume. For the U.S., Thesia et al. (1996), Hobijn and Lagakos (2005), Leslie and Paulson (2006), Johannsen (2014), and Orchard (2022) measure inflation inequality using the CEX data which covers the full consumption basket. More recently, Kaplan and Schulhofer-Wohl (2017), Argente and Lee (2021), and Jaravel (2019) compute inflation inequality from scanner data which is available for a much more limited time period but provides information at a higher level of granularity. The differences in inflation rates across households are substantial over time as well as related to demographic characteristics. For instance, high-income households are exposed to lower inflation rates compared to low- and middle-income households. The heterogeneous effects of the post-COVID inflation surge across households are studied by Pallotti et al. (2023), Corsello and Riggi (2023) and Ferreira et al. (2024). See Jaravel (2021) for a review of the growing literature on inflation inequality.

Particularly related to the results of our paper, Cravino et al. (2020) show that the inflation rate of high-income households reacts significantly less than that of middle-income households following a monetary shock. We contribute to this literature by studying how inflation dispersion across households responds to monetary policy shocks. We document that contractionary shocks decrease the cross-sectional dispersion in household inflation rates. Almost the entire effect is due to the higher sensitivity of the prices of *Energy*, *Water*, and *Gasoline* to changes in the interest rate. Combining two results from the existing literature regarding the fact that lower- and middle-income households are exposed to a higher inflation rate, as documented by Kaplan and Schulhofer-Wohl (2017) and Jaravel (2019), and that at the same time, their inflation rate decreases relatively more following a monetary shock, as shown in Cravino et al. (2020), we find that inflation inequality across income, salary, and expenditure deciles decrease in response to a monetary shock.

The second strand is the growing literature on the distributional aspects of monetary policy. With an approach analogous to the one we adopt, Coibion et al. (2017) document that consumption and income inequality in the U.S. increase following a contractionary monetary shock. Similar findings have also been found in other countries and in different time periods, e.g., Mumtaz and Theophilopoulou (2017) for the United Kingdom, Guerello (2018) and Samarina and Nguyen (2023) for the Euro Area, Furceri et al. (2018) for a panel of 32 advanced and emerging economies. A summary of the current empirical and theoretical literature on the relationship between monetary policy and inequality is provided by Colciago et al. (2019).

We show that neglecting inflation heterogeneity results in an overestimation of the impact of monetary policy shocks on expenditure inequality. In response to a contractionary monetary shock, the stronger decrease in the inflation rate of low-income households partially offset the decrease in their nominal consumption resulting in a more muted response in real terms. It follows that the distributional effects of monetary policy on expenditure inequality are more limited once inflation heterogeneity is taken into consideration.

Road map. The paper is structured as follows. Section 2 describes the dataset used, as well as the construction of individual inflation rates and dispersion measures. In Section 3 we discuss the empirical strategy and show the effects of monetary policy shocks on the cross-sectional inflation distribution. Section 4 studies the heterogeneous responses across different demographic groups. In Section 5 we assess the sectoral contributions to the decrease in inflation dispersion following a contractionary monetary shock. Section 6 evaluates how inflation heterogeneity dampens the response of real consumption inequality to monetary shocks. In Section 7, we perform a battery of different robustness checks to evaluate the reliability of our findings. Section 8 concludes.

2 Individual inflation rates

This section describes the computation of individual inflation rates at the household level by exploiting the differences in consumption patterns across households. In line with the literature on inflation inequality, we combine granular data on prices for different categories with detailed information on (individual) consumer expenditure, which allows computing the share of different goods in an aggregate index and therefore provides weights[1]. In the following, we discuss the different steps in detail.

2.1 Inflation data

We use data from the Consumer Price Index (CPI) as computed by the BLS at a monthly frequency. In particular, we use the not-seasonally-adjusted *US City Average for all urban consumers* (CPI-U). The BLS collects price data on 211 different subgroups of goods and services, which they call item strata. This is the most disaggregated level for which it publishes information on prices. However, these item strata over the period from 1980 to today undergo regular revisions, or their definition is changed. Some disappear entirely and some get newly introduced. For this reason and for data availability we need to combine these basic price indices with more aggregate ones. We follow Hobijn and Lagakos (2005) and Johannsen (2014) in creating 21 indices, for which we get consistent inflation rates during our time sample. We call the inflation rates for subgroups of the consumer basket *inflation subindices.*[2] The construction of these inflation rates is subject to a tradeoff between consistent and sufficiently long time series and finely disaggregated time series that capture as much of the difference in inflation as possible. Jaravel (2019) finds that only 20% of inflation inequality is captured when using 22 expenditure categories instead of 256 for the period from 2004 to 2015. In Subsection 7.1 we show that increasing the number of categories considered from 21 to 121 significantly increases the *level* of inflation dispersion across households but does not affect its *sensitivity* to monetary policy shocks.

In Table 1 we report the mean, median, standard deviation, the minimum and the maximum values of the 21 inflation subindices we compute, as well as of the Official CPI-U for the period 1980-2008. The observed sectoral inflation heterogeneity will be one of the key components in explaining the evolution of inflation dispersion. Households spend different shares of their overall expenditure on each category and, since these categories differ in terms of price volatility and price level, this will lead to differences in terms of experienced inflation.[3]

[1] The CEX proves rich enough to provide data on expenditure, going back to 1980.

[2] The list and definitions of these subindices can be found in Appendix A.1.

[3] The biggest limitation of using inflation subindices is that they are not individual prices. While we capture the inflation that is due to different consumption baskets, we are not able to capture inflation differences within a subindex. It is conceivable that taking the category *Food away* as an example, high-end restaurants have different price developments from low-end ones. This problem is circumvented with Nielsen scanner data. The dataset reports product-level information on both prices and quantities so it is more granular than the CEX data. However, two major limitations made the Nielsen data a non-viable solution for our analysis. First of all, the data covers only purchases in department stores, grocery stores, drug stores, convenience stores, and other similar retail outlets which account for approximately 15% of total household expenditures. Moreover, the dataset is available only from 2004 onward.

In what follows, we have to find reliable weights with which we can combine the inflation subindices to get household-level inflation rates across all items.

2.2 Expenditure data

For the computation of expenditure weights, we use the CEX provided by the BLS. This is the same dataset that is used to compute the official CPI of the U.S. The CEX is a quarterly survey of household expenditures and is divided into a diary and an interview survey. The diary survey covers small expenditures on daily items over a period of two weeks. The interview survey is more comprehensive, with detailed questioning every three months yielding up to a year of data for a single household. Since our goal is to get inflation rates that are as comprehensive as possible, we solely rely on data from the interview survey.

There are some limitations to the CEX data. The BLS removes consumption data from the 100th percentile (it is top-coded) to ensure anonymity. Additionally, since we deal with survey data, there are likely more measurement errors in the CEX compared to other data sources.[4] However, the CEX allows us to get a comprehensive picture of virtually all consumer expenditures and it is also sufficiently large in the time dimension (starts in 1980) and along the cross-section (roughly 5000-7000 households each wave).

Like the inflation subindices, we aggregate the expenditure data into 21 groups[5], matching the classification of the CEX with the one from the price indices. In the next step, we aggregate the household-level expenses from monthly to yearly. By doing this, we get rid of seasonal patterns in expenditures, while at the same time "averaging out" extraordinary expenses and hence improving the quality of our data. With this approach, almost the entire variation in individual inflation rates comes from price changes, rather than from changes in consumption patterns. Hence, the variation in individual inflation rates is mainly driven by the dynamics of sectoral inflation rates, as opposed to being driven by changes in the consumption bundle, as we intend. The relevance of the substitution effects is studied in Subsection 7.1 where we compute the expenditure shares at higher frequencies.

[4]See Bee et al. (2013) for an assessment of the quality of our consumer dataset.

[5]In computing household-level inflation rates we have to alter the *Housing* group and omit the *Vehicle* group altogether. In particular, we follow Johannsen (2014) and we use the question on rental equivalence for the owned dwelling expenditures of the homeowners. Moreover, we exclude expenditures on new and used vehicles since in a given year the purchase of a vehicle could dominate all other expenditures. When we compute the inflation rate across deciles, vehicle purchases are included since it is less likely this category can bias the decile-level inflation rates. See Appendix A.3 and Appendix B for more details.

2.3 Computation of individual inflation rates

In the third step, we combine the expenditure data with the inflation data. For this, we compute consumption shares w_j^i for household i and item subgroup j, which are calculated by dividing the yearly consumption expenditure in a certain period by the total expenditure reported in the same period. In the baseline analysis, we use all 21 categories. We compute the individual inflation rate for household i as:

$$\pi_{t-k,t}^i = \sum_{j \in J} w_j^i \pi_{j,t-k,t}, \quad (1)$$

where j denotes the item subgroup as defined in Section 2.2. The inflation rate of the subindex for good j in period t with base period $t-k$ is denoted by $\pi_{j,t,t-k}$. We set $k = 12$, meaning year-on-year inflation rates, which removes seasonality in the inflation subindices. Additionally, we winsorize the individual inflation rates at the 1st and the 99th percentile. In the next step, we analyze the statistical properties of individual inflation rates.

2.4 Properties of individual inflation rates

We assess the validity of the measures of individual inflation computed above by comparing the official CPI inflation rate with the median of individual inflation rates in Figure 1.[6] In the same figures, we also show different percentiles of the calculated household-specific rates of inflation.

[Figure 1 here]

The median of the distribution of household-specific rates of inflation closely tracks the headline value of CPI inflation. Hence, our approach gives, in an aggregate world, very similar results to the official CPI inflation rate. This result shows why for many years economic models mainly focused on the representative agent: The time series of the experienced inflation for the "median household" can be considered a quite good approximation of the aggregate economy.

At the same time, the individual inflation rate percentiles in Figure 1 reveal how much information is lost when ignoring the heterogeneity across households. Not surprisingly, macroeconomic models have been expanded to include heterogeneity in consumption, wages, asset portfolio composition, and many more. However, most models still abstract from inflation

[6] Similar results are obtained for the mean of the distribution.

differences and implicitly assume that households are exposed to the same inflation rate. Figure 1 strongly rejects this assumption.

2.5 Measures of dispersion

To evaluate how monetary policy shocks affect inflation dispersion in the U.S., we construct three different measures of dispersion: the cross-sectional standard deviation, the difference between the 90th percentile and the 10th percentile (depicted as 90th-10th, henceforth), and the cross-sectional interquartile range (IQR). To avoid the change in the survey composition affecting our results, we calculate the variation in the inflation dispersion measures on the households present in both periods. Therefore, when we calculate the change in the cross-sectional standard deviation from t to $t+1$, we do it only for the households that are present during both periods. Sampling weights are applied throughout the analysis.

[Figure 2 here]

Figure 2 shows the historical evolution of the three measures of dispersion, together with U.S. recessions. The three variables are highly correlated, suggesting that a normal distribution approximates the computed individual inflation rates very well. Despite using a different time period and alternative CPI categories, the time series are comparable in magnitude to those found by Johannsen (2014). As one can notice, inflation dispersion tends to increase during U.S. recessions suggesting a sort of correlation with the business cycle in the economy.

3 The effects on inflation dispersion

3.1 Methodology

To study whether and to what extent monetary policy shocks influence aggregate inflation dispersion, we adopt in the baseline specification the Local Projection (LP) method developed by Jordà (2005). As in Cravino et al. (2020), we estimate a series of regressions for the dependent variable over different horizons on the monetary policy shock in period t and controlling for the lags of the shock as well as of the dependent variable:

$$x_{t+h} - x_t = c_h + \beta_h e_t^{RR} + \sum_{j=1}^{J} \theta_{h,j}(x_{t+1-j} - x_{t-j}) + \sum_{i=1}^{I} \gamma_{h,i} e_{t-i} + \epsilon_{t+h}, \qquad (2)$$

where x is the variable of interest and the monetary policy shocks are denoted by e_t^{RR}. In line with the literature, we include 48 lags of the shocks and 6 lags of the dependent variable as controls. The coefficient β_h for $h = 1, ..., H$ gives the response of the dependent variable at time $t+h$ to a monetary policy shock at time t.[7] The impulse responses are computed over a horizon of 48 months using data from 1980M1 to 2008M12. Standard errors are corrected as in Newey and West (1987). For each impulse response, we present the one and 1.65 standard deviation confidence intervals. Unanticipated changes in the short-term interest rate are identified using the monetary policy shock series devised by Romer and Romer (2004, henceforth called R&R shocks) and extended by Coibion et al. (2017).[8]

The R&R shocks stop before 2009 so the zero lower bound period is excluded. In Appendix E we perform some additional analysis using as an alternative measure of monetary shocks the proxy from Bauer and Swanson (2022) which spans from 1988 to 2019. The main results of the paper hold considering the most recent period as well.

3.2 Analysis

We evaluate the overall effects of a contractionary monetary policy shock on inflation dispersion by estimating equation (2) using the cross-sectional standard deviation as the baseline measure of inflation dispersion.[9] The results are reported in Figure 3. The top panel shows the responses of the annual inflation rate computed by the BLS (blue line) as well as of the median inflation rate across households (black line): following a contractionary shock, the annual rate decreases by approximately 1.5 percentage points, a magnitude in line with the literature. As one might have expected looking at Figure 1, the response of the median inflation rate closely matches the response of aggregate inflation.

[Figure 3 here]

In the middle panel of Figure 3, we show the impulse response of our dispersion measure. Inflation dispersion decreases after a contractionary monetary policy shock and remains persistently below zero. Looking at the one and 1.65 standard deviation confidence intervals

[7]As an alternative specification, we also use the R&R shocks as an instrument for the change in interest rate (IV-LP) instead of directly inserting them in the LP and the results remain unchanged.

[8]Coibion (2012) shows how the Romer and Romer (2004) approach might be particularly sensitive to the period in which the Federal Reserve abandoned targeting the federal fund rate between 1979 and 1982. Therefore, in Section 7 we redo the analysis starting the sample in 1985, and showing that our results are not driven by these large monetary policy shocks in the early 80s.

[9]The responses for the difference between the 90th and the 10th percentile of the cross-sectional distribution and the IQR are reported in Figure 10. Given the very high correlation among dispersion measures, the IRFs display similar patterns differing mainly in the magnitude of the response.

we can easily reject the null hypothesis that the coefficients are equal to zero for the horizon considered. Therefore, the impulse response strongly suggests that monetary policy shocks lead to a decrease in the inflation dispersion in the economy.

To quantify the magnitude of the decrease in the inflation dispersion, the bottom panel computes the same impulse response but uses the log of the dispersion measure as the dependent variable, such that the magnitude can be interpreted as a percentage change relative to the steady state. Following a contractionary shock, we find that the cross-sectional standard deviation of inflation rates at the household level decreases by around 40% after 15 months and approximately 20% at the end of the horizon considered. The average inflation rate over the same time period is about 3.75% so a decrease of 1.5 percentage points corresponds to a decrease in 60% of the average value.

4 Heterogeneity across demographic groups

Having shown that monetary policy shocks decrease inflation dispersion in the economy, we now evaluate whether the inflation rate of some demographic groups is more sensitive to contractionary shocks relative to other groups and how this affects the cross-sectional inflation dispersion. We focus in particular on three demographic groups: income, salary, and expenditure deciles.

4.1 Expenditure weights

Heterogeneity in inflation rates comes from the fact that households consume different consumption baskets. As in Cravino et al. (2020), we derive the time-varying decile-specific expenditure weights following the procedure used by the BLS to compute the aggregate CPI which we describe in detail in Appendix B.[10] We report in Table 2 the expenditure weights of the first, fifth, and tenth deciles of income, salary, and expenditure deciles for each of the 21 categories for the period 1980-2008.

Several interesting facts can be noticed: First, the pattern across deciles is quite similar for income, salary, and expenditures. This already anticipates that the decile-level inflation rates of these three groups will react in a consistent way to monetary policy shocks. Second, although the weight for most of the categories either decreases or increases from the first to the tenth deciles, some categories display a U-shape pattern, e.g., *Gasoline* and *Medical*

[10] Appendix E shows that the results are not particularly affected by considering the simple median inflation rate for each decile.

expenses. This is consistent with the findings of Cravino et al. (2020) who document that the highest price volatility is experienced by middle-income households.

4.2 Impulse responses by demographic groups

We study how the inflation rates of different demographic groups react to monetary policy shocks. We start by estimating the LP with R&R shocks using as the dependent variable the cross-sectional standard deviation of the decile-specific inflation rates across income, salary, and expenditure deciles which we define as *inflation inequality*.[11] As one can see from Figure 4, following a contractionary monetary policy shock inflation inequality for the three groups significantly decreases.

[Figure 4 here]

[Figure 5 here]

To better understand the main drivers of this result, we compare the median inflation rates of the different income, salary, and expenditure deciles with their impulse responses over time. The black lines in Figure 5 report the cross-sectional distribution of the impulse responses for the inflation rate of the different income (left panel), salary (middle panel), and expenditure deciles (right panel) 24 and 48 months after a one-percentage-point contractionary monetary policy shock.

Similar to what Cravino et al. (2020) find for income, the annual inflation rate of the households at the top of the income distribution reacts substantially less to monetary policy shocks than the one of those in the middle. The difference between middle- and high-expenditure households is economically sizable and statistically significant as tested in Appendix C. After 24 months, the annual inflation rate of the households in the top decile responds to around 40% less than the inflation rate of the households in the fifth decile. After 48 months, the difference is still around 25%.

How does this relate to inflation inequality? We report in the same panels the median inflation rates across deciles relative to the time period considered (red line, right axis).[12] One can notice how the higher the decile the lower the median inflation rate. This result is consistent with the evidence provided by Jaravel (2019) and Kaplan and Schulhofer-Wohl (2017) using the Nielsen scanner data.

[11] Appendix B explains in detail how the median inflation rates are computed following the same approach adopted by the BLS.

[12] Plotting the cumulative difference in inflation rates across deciles delivers similar results.

On the one hand, given their consumption bundle, high-income households experience a lower median inflation rate than the households on the left side of the distribution. On the other hand, their inflation rate reacts significantly less to monetary policy shocks. These two results combined imply that following a contractionary shock, we observe a convergence of individual inflation rates across the distribution leading to a lower inflation inequality as documented in Figure 4. Similar results can be found focusing on salary and expenditure deciles as shown in the middle and right panels of Figure 5.

Our empirical analysis strongly suggests that monetary policy shocks can have significant and non-negligible distributional effects on the economy. The median inflation rate of higher-income households is lower relative to low- and middle-income deciles. At the same time, their inflation rate is less reactive to unexpected changes in the interest rate. This results in a decrease in inflation inequality following a contractionary shock.

5 Sectoral contribution

In this section, we determine which sectors mainly drive the decrease in inflation dispersion across households. The individual inflation rates are constructed assuming there is no substitution across categories in response to a monetary policy shock.[13] Therefore, the decrease in inflation dispersion is entirely because the inflation of different sectors is heterogeneously sensitive to exogenous changes in the interest rate.[14] To evaluate which sectors are mainly responsible for the results documented in the previous sections, we compute the response of several sectoral inflation rates to a contractionary shock. The results are reported in Figure 6.

[Figure 6 here]

The impact of monetary shocks on the inflation rates is extremely heterogeneous across sectors in line with the empirical evidence from Boivin et al. (2009) and Duarte and Dias (2019). Comparing the sectoral responses to the response of aggregate CPI it emerges that the majority of inflation rates at the sectoral level are only marginally affected by monetary policy shocks. In contrast, the inflation rates of *Public Transportation* and *Energy*, *Water* and *Gasoline* are significantly more responsive.

The fact that monetary policy shocks have a strong impact on energy prices may seem surprising. However, the result is consistent with recent empirical analysis. Del Canto et al.

[13] This is an assumption which we relaxed in Subsection 7.1.

[14] Note that in this empirical exercise, we take the sectoral inflation rates as given. In Appendix D, we examine the link between sectoral inflation rates and underlying shocks to pure inflation and relative prices.

(2023) adopt an internal instrument VAR with Gertler and Karadi (2015)'s monetary shocks and document that the response of inflation in the *Motor fuel* category is almost 10 times larger than the response of the overall CPI, the response of inflation in the category *Fuels and utilities* is almost three times larger. Similarly, Ider et al. (2023) estimate a Bayesian proxy SVAR model for the US (1990-2019) and the Euro Area (1999-2019) and confirm that the ECB and the FED can significantly influence domestic and global energy prices. The response of the energy component of the CPI to a monetary policy shock is again about 10 times larger than the response of the CPI. These magnitudes are in line with the responses we report in Figure 6. Ider et al. (2023) also examine the channels through which the FED's monetary policy surprise may affect domestic and global energy prices. The authors find that the observed decline in the global oil price due to an exogenous increase in the interest rate stems from a decline in the energy demand, which subsequently lowers global energy prices, and thus affects the overall inflation rate. Finally, the significant effects that U.S. monetary shocks have on commodity prices, like oil and food prices, is documented also by Miranda-Pinto et al. (2023) and Degasperi et al. (2024).

Having shown that the sectoral inflation rates heterogeneously respond to monetary shocks, we now assess the contribution of the different sectors to the decrease in inflation dispersion. We start by computing inflation rates at the household level considering only a subset of the overall consumption basket. In particular, we classify each category into *non-durables*, *durables*, or *services*. As before, we then derive the response of the inflation dispersion across households for these three sub-categories, defined as the cross-sectional standard deviation, to a contractionary monetary shock.

[Figure 7 here]

The results are reported in Figure 7. The inflation dispersions of the three sub-categories decrease after a contractionary shock. However, they remarkably differ in the magnitude of their responses. The standard deviation of *non-durables* categories is more reactive whether the standard deviations of *durables* and *services* are less responsive to the shock and barely significant. The observed differences in the responses suggest that the main drivers of the decrease in inflation dispersion can be found within the *non-durables* categories.

[Figure 8 here]

Therefore, we compute the same cross-sectional standard deviation of individual inflation rates but exclude one important expenditure category at a time. The results of this exercise are shown in Figure 8. As one can notice, most expenditure categories like *Housing*, *Health expenditure* and *Transportation*[15] have only a marginal effect on our main results despite accounting for a significant share of the household consumption bundles.[16]

The middle left plot reports the inflation dispersion response when we exclude the categories *Energy*, *Water*, and *Gasoline*. Not surprisingly given the results shown in Figure 6, the omission of these three highly volatile categories leads to a near-complete attenuation of the observed inflation dispersion response. The significance of the *Gasoline* category in influencing the level and evolution over time of inflation inequality has been documented by Hobijn and Lagakos (2005), Cravino et al. (2020), and Orchard (2022). Building upon this prior work, we contribute by demonstrating the substantial role that this particular category plays also in transmitting monetary shocks to individual inflation rates.

To summarize, there is large heterogeneity in the contribution that each sector has to inflation dispersion. Many categories, even though being characterized by large expenditure share, have only a negligible impact. Most of the observed effects are due to the categories *Energy*, *Water*, and *Gasoline*. These categories also mainly explain the documented decrease in inflation inequality as low- and middle-income households spend a significantly higher share of their income on them compared to high-income households as shown in Table 2.

Conventional wisdom in monetary economics often advocates that central banks should look through fluctuations in energy and food prices. The reason is that inflation rates in these sectors are highly volatile, and price changes tend to be temporary and mostly driven by sector-specific shocks. In a seminal paper, Aoki (2001) investigates optimal monetary policy in a representative agent model with two sectors — one with perfectly flexible prices and the other with sticky prices. He shows that optimal policy involves stabilizing the price index of the sticky-price sector, i.e., the "core" CPI, thereby simultaneously stabilizing the aggregate output gap. This result is extended to a model with sticky prices in both sectors by Benigno (2004). In this framework, output gap stabilization is no longer optimal but it remains close to optimal. Benigno (2004) also studies the optimal inflation index and shows that the central bank should give a larger weight to the sector with stickier prices, again focusing mainly on the "core" categories of CPI.

However, stabilizing prices in the sector with stickier prices is no longer the optimal policy once heterogeneity in consumption baskets is introduced. This is shown by Lan et al.

[15] *Housing* are defined as the sum of *Rented Dwellings*, *Owned Dwellings* and *Other Lodging*. *Transportation* is equal to the sum of *Public Transportation* and *Other Vehicle Expenses*.

[16] We report the average expenditure weights across different deciles for income, salary, and expenditures in Table 2.

(2024) who develop a multi-sector, two-agent New Keynesian model with heterogeneous consumption baskets to study how optimal monetary policy differs in this framework. In the model, households' price indices have different exposures to sectoral shocks, leading to cyclical inequality in their cost of living, even under flexible prices. The difference in price indices and real wages across households distorts their labor supply and consumption decisions, giving rise to misallocation (or inequality). Therefore, optimal policy requires striking a balance between stabilizing inequality and stabilizing aggregate demand and inflation. As a result, the pursuit of "core" inflation stabilization, as suggested in Aoki (2001) and Benigno (2004), becomes suboptimal.

It becomes optimal for the central bank to tolerate some fluctuations in the aggregate output gap to reduce the inflation volatility faced by households, thereby reducing fluctuations in the cost-of-living inequality. This can be achieved by stabilizing the prices of goods produced in the sector with more flexible prices. Therefore, the central bank benefits from adopting a more aggressive stance in stabilizing inflation in the stickier-price sector.

The policy implications that we can draw from our empirical evidence support the findings of Lan et al. (2024). *Energy*, *Water* and *Gasoline* are found to be the main drivers behind the changes in inflation heterogeneity. Therefore, monetary authorities should not only focus on stabilizing the "core" components of the CPI, but should also pay close attention to variations in the inflation rates of more flexibly priced sectors and possibly respond to them in order to minimize fluctuations in cost-of-living inequality.

6 Real expenditure inequality

Does the identified inflation inequality have any effect on the estimated impact of monetary shocks on real expenditure inequality? To answer this question, we follow Coibion et al. (2017) as closely as possible and compute a broad measure of household expenditure which includes non-durables, durables, and services.[17] Few expenses are excluded since the relative sub-category price index is not easily identifiable, e.g., occupational expenses, mortgage, and property taxes.

[17] In particular, the categories considered are: Food at Home, Food Away, Alcohol at Home, Alcohol Away, Apparel, Gasoline, Personal Care (services and durables), Reading, Tobacco, Household Furnishings and Operations, Energy, Water, Other Lodging, Public Transportation, House expenditures (services and durables), Rental expenditures (services and durables), Rent paid, Heath insurance, Health expenditures (services and durables), Education, Vehicles purchase, Vehicle expenditures (services and durables), Miscellaneous.

To evaluate the role played by inflation inequality, we create two different series for real expenditure. In line with the literature, one is created by deflating each category by the aggregate CPI-U. The other one is obtained by deflating each item group by its relative price index. We then aggregate the expenditures at quarterly levels to reduce sampling error and to avoid having unusual purchases bias the analysis. We also winsorize at the bottom and top 1 percent of the distribution. Expenditure inequality across households is computed as the cross-sectional standard deviation of log levels, the Gini coefficient of levels, and the difference between the 90th percentile and the 10th percentile of log levels. Finally, all series are seasonally adjusted.

Inequality is defined as $Ineq_t^{IH}$ and $Ineq_t^{NoIH}$ respectively for when inflation heterogeneity is taken into account by deflating each category by the relative price index and for when it is neglected. As an example, the standard deviations at time t across households i are equal to $Std(logC_{i,t}^{IH})$ and $Std(logC_{i,t}^{NoIH})$ with:

$$C_{i,t}^{IH} = \sum_{j \in J} \frac{C_{i,j,t}}{P_{j,t}}, \qquad C_{i,t}^{NoIH} = \sum_{j \in J} \frac{C_{i,j,t}}{P_t}, \tag{3}$$

where $C_{i,j,t}$ is the nominal consumption of household i relative to category j at time t, $P_{j,t}$ is the price index of the category j at time t and P_t is the aggregate price index. [18]

To make our results as comparable as possible, we use the same econometric procedure adopted by Coibion et al. (2017), i.e., local projection with Romer and Romer (2004) shocks at a quarterly frequency, over the same time period, 1980Q1:2008Q4.[19] Since the series is quarterly, we include as controls 20 lags for the shocks and 2 lags for the dependent variable and we compute the impulse responses over 20 quarters.

[Figure 9 here]

Figure 9 plots the results. The black solid lines report the impulse responses of the three measures of expenditure inequality obtained by deflating the expenditure categories by the aggregate CPI. The shape and the magnitude of the responses are very close to those obtained

[18]It is important to note that the inequality measures used here do not account for variations in the cost of living across households. Due to the lack of data on the specific prices paid by individual households, we assume that all households face identical sectoral inflation rates. As a result, the observed differences in inequality are entirely driven by variations in consumption bundles. The aim of this exercise is to compare the potential distributional effects of monetary policy when all expenditure categories are deflated by a common price index, as has been standard practice in the literature, against an alternative approach that incorporates sectoral inflation heterogeneity.

[19]Similar results are obtained adopting our empirical specification.

by Coibion et al. (2017). After a contractionary monetary policy shock, expenditure inequality persistently and significantly increases.

However, neglecting inflation heterogeneity across consumption baskets leads to an overestimation of the overall effect. As shown by the red solid lines which report the responses of the expenditure inequality measures obtained by deflating each category by their respective price index, when the expenditure categories are properly deflated, the estimated effect of monetary policy on inequality is approximately 20% lower for standard deviation and 30% for the Gini coefficient and the 90th-10th percentile difference. It is worth mentioning that the estimated coefficients are still positive and significant which implies that monetary policy still has redistributive effects on the economy.

This result can be explained by combining the new empirical evidence from the previous sections. Along the income distribution, a contractionary monetary shock has heterogeneous effects on nominal consumption. The nominal consumption of low- and middle-income households decreases more than that of high-income households because they are more sensitive to the monetary policy shock, e.g., they are financially constrained, they are more likely to lose their job in an economic downturn, etc. However, at the same time, the cost of their consumption basket decreases more strongly as well. Hence, the overall effect on expenditure is partially offset in real terms. This results in a more muted, but still positive and significant, increase in real expenditure inequality.

7 Robustness

To strengthen the validity of our findings in the previous sections, we show that our results are robust across a wide range of alternative specifications. First, we evaluate the importance of substitution effects. Second, we assess the sensitivity of our results to different lag specifications. Third, we perform the same analysis starting our sample in 1985M1 to control for the Volcker disinflation period. More robustness checks can be found in Appendix E.

7.1 Substitution effects

Throughout the paper, we conduct our analysis under the assumption that changes in prices mainly drive differences in inflation dispersion and that variations in expenditure shares play only a marginal role. Both the inflation rate at household-level as well as at the decile level are computed using expenditure weights aggregated over multiple time periods to control for seasonal effects as well as to avoid unusual purchases by the households biasing our results. The weights for the household-level inflation rate rely on the entire time series of expenditure (maximum 12 months) whereas the weights at the decile level are computed following the BLS which updates its expenditure weight reference period approximately every ten years, and since 2002, every two years (more details can be found in Appendix B).

Cravino et al. (2020) tested whether substitution effects are important for the CEX by using the difference between the Laspeyres and Paasche price index as a proxy for the substitution bias from 1987 to 2004. These authors showed that the difference between the two indices is negligible over time demonstrating that the substitution bias must be very small.

Furthermore, using the Nielsen data, Jaravel (2019) evaluates whether the observed inflation heterogeneity along the income distribution stems from the fact that high-income households purchase different goods or whether they pay more for the same goods, for instance, because they buy from different shops. The inflation difference is then decomposed into a *between* and a *within* component. The former corresponds to the inflation difference that we would observe if households differ only in terms of the expenditure shares across categories and if they experience the same within-category inflation. Vice versa, the latter refers to the difference that would arise in case of households experience the same within-category inflation, but have different expenditure shares. The between component accounts for more than 70% of the inflation difference.

Given the importance for our results of the assumption that inflation dispersion is mainly driven by changes in prices rather than in expenditure shares, we also test whether substitution effects are a potential source of bias. We do this through two robustness checks: First, we assess if the granularity of the expenditure categories we choose plays any role. Second, we compute our measures of inflation inequality across deciles by using annual, quarterly, and monthly expenditure shares instead of using multiple years of consumption data like the BLS.

Following the literature, in computing the individual inflation rates we adopt a rather conservative aggregation in the number of categories considered. Not only do we have data for *Food and Beverage*, the most aggregate item category, but also have data for the sub-category *Eggs*, the most disaggregate. In choosing the baseline aggregation, we face a trade-off between using as disaggregate data as possible to fully capture inflation dispersion and the quality of the price index. Many price series started significantly after 1980, especially the most disaggregated goods and services indices.

We show that the main results are unaffected by increasing or decreasing the number of categories considered. We compute the household-level inflation dispersion using 14, 31, and 121 expenditure categories.[20] The evolution over time of the dispersion measures is reported in Figure 11.

The number of categories considered significantly affects the overall level of inflation dispersion. Relatively to the baseline inflation dispersion with 21 categories, the magnitude is slightly smaller with 14 categories and is slightly larger with 31. With 121 categories the cross-sectional standard deviation is almost twice as high compared to the baseline. However, the measures of inequality are extremely positively correlated. The correlation with the baseline specification is 0.97, 0.98, and 0.86 for the measures with 14, 31, and 121 categories respectively.

In Figure 12 we compare the response from our baseline specification with 21 categories (blue line) against the three alternative aggregations. When using price indices at a slightly more granular level (middle panel, 31 categories) or an even more conservative number of categories (top panel, 14 categories), the magnitude and the shape of the responses are basically the same as that obtained in our baseline specification. Considering 121 categories the response is still significantly and persistently negative following a contractionary shock. The magnitude of the response is almost twice as much as the one of the baseline response but since the size of the inflation dispersion measure has doubled as well, in percentage terms the results are similar. This suggests that the number of categories considered in computing individual inflation rates is important for measuring the *level* of inflation inequality but not its *sensitivity* to monetary policy shocks.

As a second test for the role of substitution effects, we compute the expenditure weights for the decile-level inflation rates at annual, quarterly, and monthly frequencies. It is important to notice that by allowing the weights to vary at a much higher frequency than the biannual frequency adopted by the BLS in the last decades, our dispersion measures will not only capture potential adjustments in the consumption bundles due to the shocks but also measurement errors and unusual purchases will account for a larger share.

[20]For this last specification some of the price indices were introduced after 1980 so it is an unbalanced panel. The 14 categories are Food, Alcohol, Housing, Apparel, Gasoline, Other Vehicle Expenses, Public Transportation, Medical, Entertainment, Personal Care, Reading, Education, Tobacco, and Other Expenses. The 31 categories are Food at Home, Food Away from Home, Alcohol, Rental expenditures (durables), Rental expenditures (services), Rent Paid, Rent Equivalent, House Expenditures (durables), House Expenditures (services), Other House related expenses, Other Lodging, Energy, Water, Phone, Household Furnishings and Operations, Jewelry, Clothing (durables), Clothing (services), Gasoline, Vehicle Expenditure (durables), Vehicle Expenditure (services), Public Transportation, Medical, Entertainment, Personal Care (durables), Personal Care (Services), Reading, Education, Tobacco, and Other Expenses.

We report in Figure 13 the response of the cross-sectional standard deviation of the median inflation rates across income deciles as well as the one standard deviation confidence interval (black line and gray area). For comparison, the blue lines refer to the impulse response of the cross-sectional standard deviation as well as the relative confidence interval computed following the BLS methodology as shown in Figure 4.

Not surprisingly, moving from annual to quarterly and especially to monthly weights makes the responses more volatile. The responses with time-varying weights are still negative and significant: inflation inequality across expenditure deciles remarkably decreases after a monetary shock. The magnitude is even more negative relative to the baseline. This might suggest that substitution effects move in the same direction as our inflation heterogeneity channel: following a contractionary shock, inflation rates of the expenditure categories purchased by low- and middle-income households decrease more strongly than the other categories so their overall inflation rates react more. Moreover, the same households might even increase their consumption of these categories since they are now relatively cheaper, leading to second-order effects. Similar evidence is found for the dispersions in median inflation across the salary and expenditure deciles whose responses are reported in Figure 14 and Figure 15 respectively.

Since we cannot further disentangle substitution effects from measurement errors in the survey or unrepresentative purchases made by households, we prefer to interpret these results with caution. Overall these findings confirm that substitution effects do not cancel out the impact of contractionary shocks on inflation dispersion and that heterogeneity in prices across, rather than within, expenditure categories is the main driver of our results.

7.2 Different lag specification

We re-estimate equation (2) with an alternative lag specification. In Figure 16 we run the LP regression including 36 and 60 lags for the monetary policy shocks as well as 4 and 8 lags for the cross-sectional standard deviation of the individual inflation. Similar results are also obtained for the other measures of dispersion. Increasing or reducing the number of lags has little to no effect on the impulse responses: after a contractionary monetary policy shock, inflation dispersion significantly decreases.

7.3 Volcker disinflation

Coibion (2012) shows how few episodes in the early 80s can be the main drivers of the impulse responses computed using LP with R&R shocks. Since then, it has been common practice for researchers to test their results excluding the period between 1979 and 1982 in which the Federal Reserve abandoned targeting the federal fund rate. Figure 17 reports the IRFs obtained using the baseline specification but starting the sample in 1985M1. In this case, the results are also robust.

8 Conclusion

Central bankers and policymakers are more and more strongly advocating the importance of the conduct of a more inclusive monetary policy where the potential negative spillovers deriving from the monetary authorities' decisions are taken into account. Similarly, macroeconomic research has shifted its focus from the aggregate effects of monetary shocks towards the different channels through which households and firms might be heterogeneously affected by it. Our results suggest that the inflation heterogeneity that arises from the different consumption baskets the agents purchase is of pivotal importance for understanding the distributional consequences of monetary policy.

This paper studies how monetary policy shocks affect the distribution of household-level inflation rates. We rely on individual expenditure data from the CEX and combine it with category-level inflation rates from the BLS to obtain household-level inflation rates. We compute different moments of the individual inflation rates distribution and we evaluate how monetary policy shocks influence the median and the cross-sectional standard deviation of the distribution. Inflation dispersion across households significantly and persistently decreases in response to a contractionary monetary policy shock.

We also evaluate how the inflation rate of different demographic groups is heterogeneously affected by monetary policy. We find that the inflation rates of low- and middle-income households are significantly more reactive to monetary shocks than those of high-income households. Since at the same time, they experience a higher median inflation rate, contractionary shocks lead to an overall convergence of inflation inequality across income groups. The same is true for expenditure and salary deciles. *Energy*, *Water* and *Gasoline* are found to explain almost entirely the observed effects despite accounting for a relatively small expenditure share.

Finally, we demonstrate that assuming that households are exposed to the same inflation rate results in an overestimation of the impact of monetary shocks on expenditure inequality. Following a contractionary shock, low-income households experience a stronger decrease in nominal consumption relative to high-income households. However, the price level of low-income households' consumption bundles decreases relatively more than that of high-income households, partially offsetting the impact on their real purchasing power. Accounting for inflation heterogeneity reduces the estimated response of expenditure inequality to monetary shocks by around 20-30% depending on the measure of inequality considered.

In conclusion, our research provides substantial evidence that designing optimal monetary policies as well as studying their distributional effects cannot abstract from also considering the different inflation rates to which agents are exposed. Indeed, the economic agents experience significantly different inflation rates both in the long run as well as in response to shocks. Inflation heterogeneity in the economy is sizable and related to demographic characteristics. Finally, taking into account inflation heterogeneity is particularly relevant when it comes to assessing the impact of monetary policy on other forms of inequalities.

Acknowledgments

We would like to thank Florin Bilbiie, Jean-Paul Renne, and Andreas Tischbirek for their valuable comments and guidance. We are particularly indebted to Ting Lan for providing the data on the income-percentile-specific consumer price indices. We are also grateful to Philippe Bacchetta, Andrea Brandolini, Kenza Benhima, Aurélien Eyquem, Yuriy Gorodnichenko, Andrei Levchenko, Stefano Neri, Christina Patterson, Ricardo Reis, Fabrizio Venditti and fellow UNIL Ph.D. students for helpful suggestions that significantly improved the paper. Finally, we would like to thank the participants of the conferences organized by the International Association for Applied Econometrics, the Swiss Society of Economics and Statistics, the Society of Economics of the Household, the Ph.D. - Economics Virtual Seminar, the VMACS (Virtual Macro Seminar), the Berkeley GEMS, the Lausanne Macro Reading Group, the 9th Italian Congress of Econometrics and Empirical Economics, the 61st Annual Conference of the Italian Economic Association and the 15th Economics Graduate Students Conference for precious feedback. The views expressed are those of the authors and do not necessarily reflect those of the Banca d'Italia or the Eurosystem.

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A Data sources

This section documents in greater detail the data sources used and the properties of the underlying data.

A.1 Price Indices

Since individual inflation rates are a weighted average of sectoral price indices, Table 1 displays the CPI subindices used, as well as their respective statistical properties.

Table 1: Item-level CPI statistics

CPI series (Item Code)	Mean	Std. Dev.	Min.	Max.
Food at Home (SAF11)	3.223	2.176	-2.904	10.524
Food Away from Home (SEFV)	3.598	1.751	1.422	10.675
Alcoholic Beverages (SAF116)	3.388	1.936	0.66	10.961
Rented Dwellings (SEHA)	4.028	1.706	0.694	8.938
Owned Dwellings (SEHC)	3.533	1.067	0.724	6.437
Other Lodging (SE2102-SEHB)	4.876	4.358	-9.313	19.395
Energy (SAH21)	3.744	6.739	-15.168	23.602
Water (SEHG01)	5.442	2.295	0.579	14.217
Phone (SAE2)	-0.812	1.733	-4.611	2.516
Household F&O (SAH3)	1.587	2.051	-2.295	8.545
Apparel (SAA)	1.154	2.46	-4.069	7.378
Gasoline (SETB)	3.531	17.378	-54.864	52.006
Other Vehicle Exp. (SETC-SETD-SETE-SETF)	4.397	2.235	0.208	11.936
Public Transportation (SETG)	4.867	6.313	-12.946	27.742
Medical care (SAM)	5.723	2.347	2.447	11.778
Entertainment (SAR)	2.921	2.048	-0.407	9.391
Personal Care (SAG1)	3.335	1.798	1.028	8.904
Reading (SERG)	3.82	2.682	-0.196	11.825
Education (SAE)	6.929	2.033	4.3	13.126
Tobacco (SEGA)	7.962	6.42	-8.483	33.332
Other Expenses (SEGD)	5.588	2.397	0.972	11.893
CPI-U (SA0)	**3.615**	**2.481**	**-2.119**	**13.764**

Notes: This table displays descriptive statistics about each item-level inflation rate, as measured by year-on-year changes of the respective index. The source of this data is the U.S. Bureau of Labor Statistics.

A.2 Consumer expenditure survey data

This section provides further details about the construction of the dataset we use in the empirical analysis. We download the raw data for the period 1980-2005 from the ASCII files available from the Inter-university Consortium for Political and Social Research (ICPSR) whereas from the year 2006 onward we use the data provided by the BLS. For each quarter, the Interview Survey is structured as follows: the expenditure data is recovered from the disaggregated MTAB files, income data is derived from the FMLY files and additional information regarding the households can be found in the MEMB files.

In line with the literature, we aggregate together expenditures about the same month which is reported in different interviews. Then, we drop households that report zero expenditure on food as well as those that report negative expenditure for categories that cannot be negative according to the data codebook, such as expenditure for elderly care. Respondents younger than 25 years and older than 75 are excluded. To correct for sample breaks caused by slight changes in the questionnaire (food at home (1982Q1-88Q1), food away from home (2007Q2), and personal care services (2001Q2)) we regress each expenditure series on a time trend and indicators for the corresponding sample breaks and then subtract the effect of the dummies from the original series. For all these transformations, we rely heavily on Coibion et al. (2017).

Finally, the CEX data started to include the imputed income in 2004. To impute income data before that year, we follow the approach adopted by Fisher et al. (2013) and Coibion et al. (2017): for households recording a bracketed range, we use the median point of the bracket. Furthermore, we estimate the remaining income observations by regressing income on a set of observable characteristics such as age, age squared, the reference person's gender, race, education, number of weeks worked full or part-time in the last 12 months, unadjusted family size, the number of children under 18, the number of people over 64, the number of earners at the annual level and with sampling weights as well as using fixed effects for the income reporting date. To account for the sampling uncertainty, we add residuals drawn randomly with replacement from the sampling distribution to the predicted values. We then trim values above the top-coding threshold at the top coding value.

We then calculate expenditure shares from the cleaned expenditure data, which constitute the weights used to calculate individual inflation rates. We find substantial variation in the weights that can be explained to a large part by either income, salary, or expenditure deciles. Table 2 shows the weights for the 1st, 5th, and 10th deciles.

A.3 Matching of expenditure and inflation data

We match the expenditure categories with the respective price indices. Following Hobijn and Lagakos (2005), for the category *Other Vehicle Expenses* which does not have a perfect match with the available CPI sub-categories, we create the CPI index by combining the series that match this category (that is, SETC, SETD, SETE, and SETF). As sectoral weights, we use

Table 2: Expenditure weights for the first, fifth and tenth decile of income, salary, and expenditure

	Income deciles			Salary deciles			Expenditure deciles		
	1st	5th	9th	1st	5th	9th	1st	5th	9th
Food at Home	14.5	13.0	9.8	13.7	12.8	9.9	22.6	14.7	7.8
Food Away	8.1	8.2	7.7	8.8	8.3	7.7	9.3	8.5	7.2
Alcohol	1.0	1.1	1.2	1.1	1.1	1.2	1.0	1.1	1.0
Rented Dwellings	9.4	8.4	1.9	8.5	8.6	2.0	21.0	7.9	1.4
Owned Dwellings	18.8	17.4	21.4	15.5	16.2	21.5	7.4	19.8	17.7
Other Lodging	0.8	0.6	1.5	1.0	0.6	1.5	0.1	0.1	1.2
Energy	5.3	5.0	3.8	4.9	4.7	3.8	6.8	5.8	2.9
Water	0.8	0.8	0.7	0.8	0.8	0.7	0.9	1.0	0.6
Phone	2.7	2.7	2.0	2.7	2.7	2.0	4.0	3.0	1.5
Household F&O[21]	4.3	4.5	5.1	7.8	4.7	7.0	1.2	3.0	10.6
Apparel	4.1	4.3	5.9	4.6	4.8	6.1	2.6	3.6	6.4
Gasoline	4.1	5.0	4.0	4.7	5.3	4.1	4.8	5.7	3.2
Other Vehicle Expenses	7.9	10.6	11.7	9.5	11.6	12.0	5.6	11.1	10.8
Public Transportation	1.1	1.0	1.8	1.2	1.0	1.8	0.7	0.4	2.8
Medical	5.8	6.6	4.7	5.7	5.2	4.3	4.3	5.6	5.8
Entertainment	4.2	4.8	6.9	4.8	5.3	6.9	2.6	3.9	8.9
Personal Care	0.9	0.9	0.9	0.9	0.9	0.9	0.9	1.0	0.7
Reading	0.4	0.5	0.6	0.5	0.5	0.6	0.4	0.5	0.4
Education	2.5	1.0	2.7	3.2	1.3	2.8	0.2	0.4	4.3
Tobacco	1.0	1.2	0.5	1.2	1.2	0.5	2.3	1.3	0.4
Other Expenses	1.1	1.2	1.2	1.1	1.1	1.0	0.3	0.6	2.3

Notes: This table displays the first, fifth, and ninth deciles for the weight of income, salary, and expenditure shares. While our methodology uses these shares at a monthly frequency, this table displays the average over the period 1980-2008.

the average over the time period considered of the official weights provided by the BLS, as displayed in the table "Relative Importance in the CPI". Finally, since *Other Lodging* changed the name, we use *Lodging away from home* until 1997 (MUUR0000SE2102) and *Lodging while out of town* (SEHB) until the end of the sample. In all cases, the CPI series we use are the not-seasonally-adjusted *US City Average for all urban consumers* series. Table 3 displays the categories in the CEX, as well as the categories in the CPI data that were used to match the two data sets.

Table 3: Matching between CEX expenditure category and CPI

BLS Expenditure Category	CPI Series (Item Code)
Food at Home	SAF11
Food Away from Home	SEFV
Alcohol	SAF116
Owned Dwellings	SEHC
Rented Dwellings	SEHA
Other Lodging	MUUR0000SE2102-SEHB
Energy	SAH21
Water	SEHG01
Phone	SAE2
Household Furnishings and Operations	SAH3
Apparel	SAA
Gasoline	SETB
Other Vehicle Expenses	SETC-SETD-SETE-SETF
Public Transportation	SETG
Medical	SAM
Entertainment	SAR
Personal Care	SAG1
Reading	SERG
Education	SAE
Tobacco	SEGA
Other Expenses	SEGD

Notes: This table displays the expenditure category from the CEX, as well as the respective category code in the CPI index series.

B Decile-level expenditure weights

Before computing the decile-level expenditure weights, some adjustments need to be performed. In line with the literature and the BLS procedure, the expenditure weight for the owners' equivalent rent of primary residence is based on the following CEX question: "If someone were to rent your home today, how much do you think it would rent for monthly, unfurnished and without utilities?" The homeowners' answer to this question is stored in the variable RENTEQVX in the characteristics files.

Moreover, as we mention in the main text, vehicle purchases are likely to bias the estimated expenditure shares. Indeed, they are large in size and not representative of the usual household consumption bundle. Therefore, in line with Johannsen (2014), we drop this category when computing household-level inflation rates. Following Cravino et al. (2020), we include expenditures on used cars and trucks when computing the decile-level inflation but we reduce the spending to half to reflect only the dealer value added.

Households are also interviewed a different number of times and for at most four consecutive quarters, which corresponds to twelve months' worth of spending information. However, this does not necessarily match the calendar year. To control for this, we compute the decile-based inflation rate closely following the BLS procedure as in Cravino et al. (2020). First, we sort households into deciles based on their annual income, salary, median, and mean expenditure. We then compute the average expenditure for each item category at every decile in the calendar year. For instance, a respondent interviewed in February will report personal consumption for January, but also for November and December of the previous year. Similar to what the BLS does for the computation of the official CPI, to account for the relative contribution of each household to the decile-mean value of a calendar year, we weight the consumption by the number of months a household reports expenditures during a calendar year (the BLS calls this variable MO_SCOPE).

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

$$X_j^d = \frac{\sum_i fwt_i^d \sum_t c_{i,j,t}^d}{\sum_i fwt_i^d \; MO\_SCOPE_i^d} \times 12, \tag{4}$$

where fwt_i^d is the frequency weight for household i at decile d, $c_{i,j,t}^d$ refers to the annual consumption on category j by household i at decile d and $MO\_SCOPE_i^d$ identify the number of months per year household i reported its expenditure. The decile-level expenditure weight for category d can then be computed as:

$$w_j^d = \frac{X_j^d}{\sum_j X_j^d}. \tag{5}$$

C Differences in responses across deciles

We evaluate whether the responses of the decile-level median inflation rates to a monetary policy shock are statistically different from each other. To do so, we estimate equation (2) using as dependent variable the difference between the inflation rate of the 10th and 1st decile of each group and the inflation rate of the 5th decile. The first column of Figure 18 reports the responses of the difference in median inflation rate for the 10th and the 5th decile and the second column for the 1st and the 5th decile. The first row shows the responses for the differences across expenditure deciles, the second row for salary deciles, and the last row for income deciles.

[Figure 18 here]

As it can be noticed in Figure 5, both the median inflation rates of the 10th as well as of the 1st deciles of income, salary, and expenditures react much less to a monetary policy shock than the 5th deciles resulting in a positive and significant response of their differences. The U-shaped response across deciles is in line with what was found by Cravino et al. (2020) who document that the price volatility along the income distribution is hump-shaped with the households at the top of the distribution experiencing the lowest volatility (resulting in the flattest impulse response) and middle-income households being exposed to slightly more price volatility than lower-income households.

D Pure Inflation and Relative Goods' Prices

The present work exploits differences in sectoral inflation rates. These inflation rates are taken as given, without further analysis of the drivers behind this data. To shed more light on the drivers behind these inflation rates, we rely on the work of Reis and Watson (2010). They use a dynamic factor model in order to derive underlying factors in the dataset of sectoral inflation rates. A dynamic factor model is well suited to derive the common components in this set of correlated but distinct time series.

Applying the factor model of Reis and Watson (2010), we derive three drivers of inflation derived from sector prices.[22] First, there is a pure inflation factor ν_t, that affects all sectoral inflation rates equally. Second, they find a factor that influences relative prices, called ρ_t. This factor captures fundamental shocks that affect some price setters, but not others. Third, idiosyncratic inflation stems from sectoral price changes that are uncorrelated with other sectors.

This decomposition allows us to distinguish between different underlying drivers of sectoral inflation rates. In the second step, we want to measure the importance of the three underlying factors to sectoral inflation rates. To do so, we regress sectoral inflation rates on the three factors individually and measure the importance of each factor by its respective R^2, as is displayed in the three left columns of Table 4. Additionally, we also calculate the contribution to the R^2 of the three factors. In the three right columns, we report the difference in R^2 in a regression on all three factors, when the respective factor is removed.

Table 4: Regressing sectoral inflation rates on factor data

	R^2_ν	R^2_ρ	R^2_u	$Contr_\nu$	$Contr_\rho$	$Contr_u$
Food at Home	15	35	3	18	37	0
Food Away	61	23	5	65	26	0
Energy	12	12	13	21	13	7
Gasoline	0	12	24	19	12	19
Rented Dwellings	63	6	1	66	8	0
Owned Dwellings	34	2	7	51	14	5
Water	72	2	1	71	1	0
Medical	80	0	1	81	1	0

Notes: This table reports the explanatory power of the pure inflation factor ν, the relative price factor ρ, and the idiosyncratic factor u, as defined by Reis and Watson (2010) on sectoral inflation rates. For brevity, we only report sectors that have a median expenditure share above 5% according to Table 2. The three left columns show the R^2 of a simple regression on the three factors. The three right columns report the difference in R^2 when the respective factor is removed from a regression on all three factors. The results are sorted by the contribution of the relative price factor ρ.

As Table 4 shows, the sectors *food home* and *food away* are strongly correlated with the relative price factor, while *energy* and *gasoline* are strongly correlated with both ρ and u. The other sectors, that are usually considered to be part of core inflation, are clearly dominated by

[22]The original article by Reis and Watson (2010) is based on quarter-on-quarter inflation rates using data from the Personal Consumption Expenditures (PCE) price index. To make this exercise comparable to the results in this paper, we use quarter-on-quarter inflation rates from (4-digit) CPI inflation rates. We also adjust the sample period to the analysis in this article, that is from 1960-1999 (original paper) to 1980-2008.

the pure inflation factor and contribute less to changes in inflation dispersion. By construction, the pure inflation factor ν should have no or very little effect on inflation dispersion.[23] The results in Table 4 show, however, that the relative price factor and the idiosyncratic factor account for a disproportionate share of the differential changes in sectoral inflation rates on which the results in this article are based.

This result is important as it connects our findings with potential underlying drivers. Relative price changes, which are a dominant driver of aggregate inflation as shown by Reis and Watson (2010), are also driving our results. The expenditure categories *energy* and *gasoline*, which account for a higher share of the consumption bundle of low- and middle-income households, are also mainly driven by relative price changes and idiosyncratic shocks.

E Further robustness checks

As a further robustness check, Figure 19 reports the impulse responses excluding all U.S. recession periods from the analysis (1981M07:1982M11, 1990M07:1991M03, 2001M03:2001M11). The results remain qualitatively unchanged relative to the baseline specification.

[Figure 19 here]

As a second set of checks, we assess whether our results are specific to the shock series we chose, i.e., Romer and Romer, 2004. The first alternative measure of monetary shocks we use is the high-frequency proxy proposed in Bauer and Swanson (2022). The proxy is computed from changes in future prices in a narrow window around FOMC announcements and orthogonalized with respect to the public information about the economic and inflation outlook. The shock series is available from 1988M2 to 2019M12.

[Figure 20 here]

The second alternative measure of monetary shocks is the series developed by Miranda-Agrippino and Ricco (2021). The authors show that monetary surprises are a combination of a true shock and information about the state of the economy that imperfectly informed agents infer from monetary policy decisions. Therefore, to remove the information content of

[23]Note that the pure inflation factor theoretically affects all sectors' inflation rates equally, and should thus have no effect on inflation dispersion. However, there are differences between the dynamic factor model and our approach both in terms of methodology and data. Also, the present paper captures the dynamics related to exogenous monetary policy shocks, while the dynamic factor model captures the overall dynamics in the dataset.

monetary policy surprises, the surprises are regressed on a set of variables that aim to control for the central bank's superior information about the economy. The residuals are considered to be monetary policy surprises cleaned from any informational effects and are available from 1991M1 to 2009M12.

The results are presented in Figure 20. The figure reports the responses of the cross-sectional standard deviation to the alternative contractionary shocks. All the regressions include the same controls as in the baseline specification. In both cases, inflation dispersion decreases. Overall, the results from alternative monetary policy shocks confirm our main findings and point towards a distributional role played by monetary policy in terms of inflation dispersion.

Moreover, one might be concerned that part of the inflation heterogeneity we measured is driven by differences in consumption patterns across U.S. states rather than along the income distribution. Since the BLS does not provide price indices at the state level, but only at the division level (Northeast, Midwest, South, and West), we compute the cross-sectional standard deviation of inflation for the four divisions using expenditure weights as well as price indices at division level.[24]

The responses across U.S. divisions are reported in Figure 21. There are some regional differences in the shape of the responses of inflation dispersion to contractionary shocks. However, the magnitude and significance of the results are comparable to the baseline specification. The decrease is more muted only for the West division.

[Figure 22 here]

In the main analysis, the decile-specific inflation rates are computed following the BLS procedure. The advantage of this approach is that for each decile all the individual expenditure information is combined to form the expenditure weights. In this way, outliers are less likely to bias the analysis. An alternative approach to the BLS methodology would be to simply consider the median of the individual inflation rates within each decile.

In Figure 22 we report the responses of inflation inequality for income, salary, and expenditures to a contractionary monetary shock. Inflation inequality is measured as the standard deviation of the median inflation rates across deciles. Following a monetary shock

[24] A more limited number of price indices are available at the division level. Therefore, we used the following expenditure categories: Food at Home, Food Away from Home, Alcohol, Rented Dwellings, Owned Dwellings, Household Furnishings and Operations, Utility, Apparel, Private Transportation, Public Transportation, Gasoline, Medical, Education, and Miscellaneous.

the inflation inequality responses are still negative and statistically significant confirming the baseline results.

Finally, the baseline measure of inflation dispersion is computed using data from the interview module of the CEX but not the diary module. As the two modules of the CEX interview different households, they cannot be combined to measure inflation at the household level. However, the two modules can be jointly used to compute inflation rates for different demographic characteristics. This exercise was done by Cravino et al. (2020) who studied the differential sensitivity of inflation rates to monetary policy shocks along the income distribution.

Cravino et al. (2020) compute income-percentile specific CPIs by combining both modules of the CEX with micro price data.[25] Using this data, we define an alternative measure of inflation inequality as the cross-sectional standard deviation in inflation rates across the income percentiles.

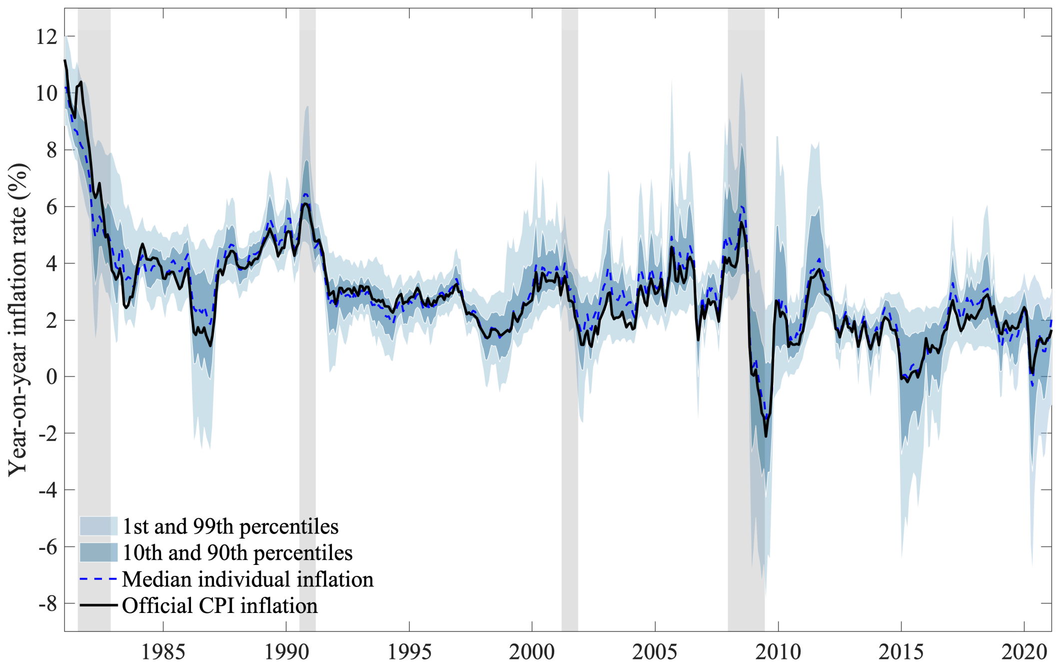
[Figure 23 here]

The response of this new measure of inflation inequality to a monetary shock is reported in Figure 23. The shape and magnitude of the response are comparable to our baseline response. Therefore, the main result of the present article is robust to include information from both the interview and the diary modules of the CEX: inflation inequality decreases following a contractionary monetary policy shock.

[25] We contacted the authors who kindly shared their percentile-specific CPI data with us.

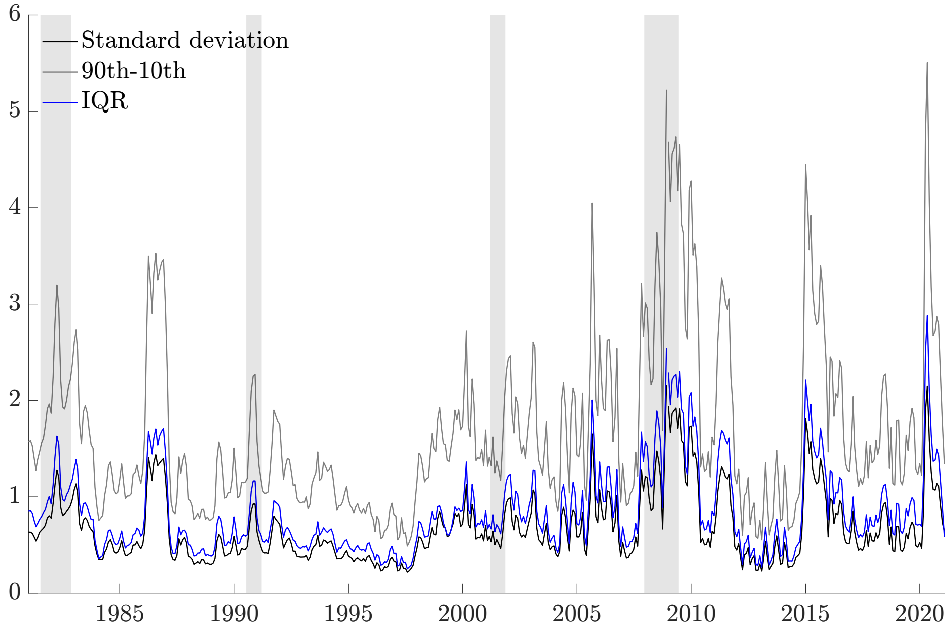
F Figures

Figure 1: Official CPI inflation, cross-sectional distribution, and median individual inflation rate over time



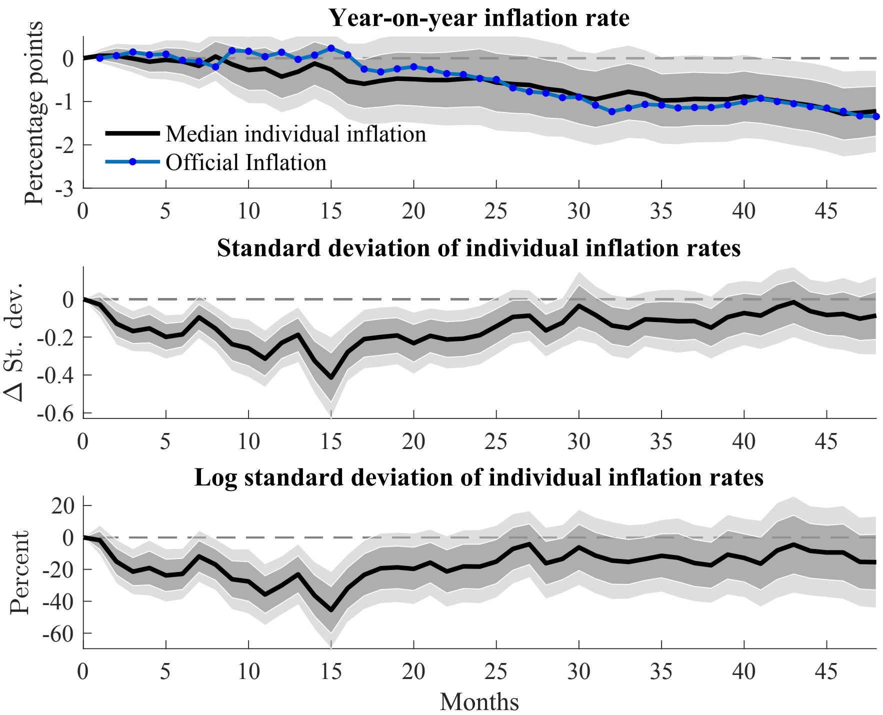
Notes: This figure shows the evolution over time of the official CPI inflation as well as the median and selected percentiles (1st, 10th, 90th, and 99th) of the winsorized cross-sectional distribution in individual inflation rates. The gray shaded areas depict U.S. recessions.

Figure 2: Historical series of inflation dispersion measures



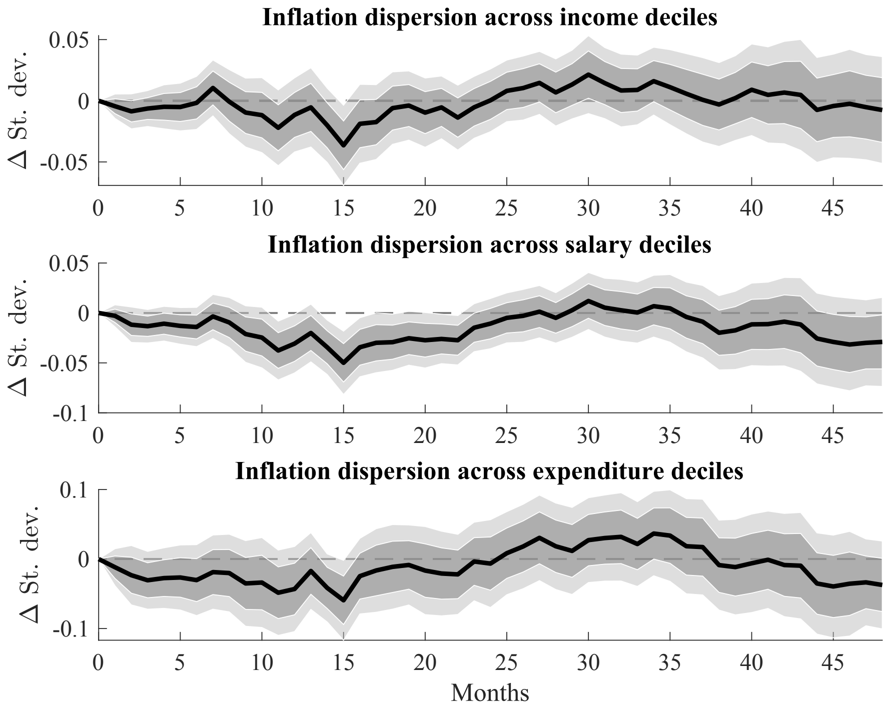
Notes: This figure shows the evolution of inflation dispersion measured using the cross-sectional standard deviation, the difference between the 90th and the 10th percentile of the cross-sectional distribution, and the IQR. All the series refer to the period 1981M1:2020M12. The gray shaded areas depict U.S. recessions.

Figure 3: Impulse responses of the year-on-year inflation rate as well as the median and the standard deviation of the individual inflation rate distribution



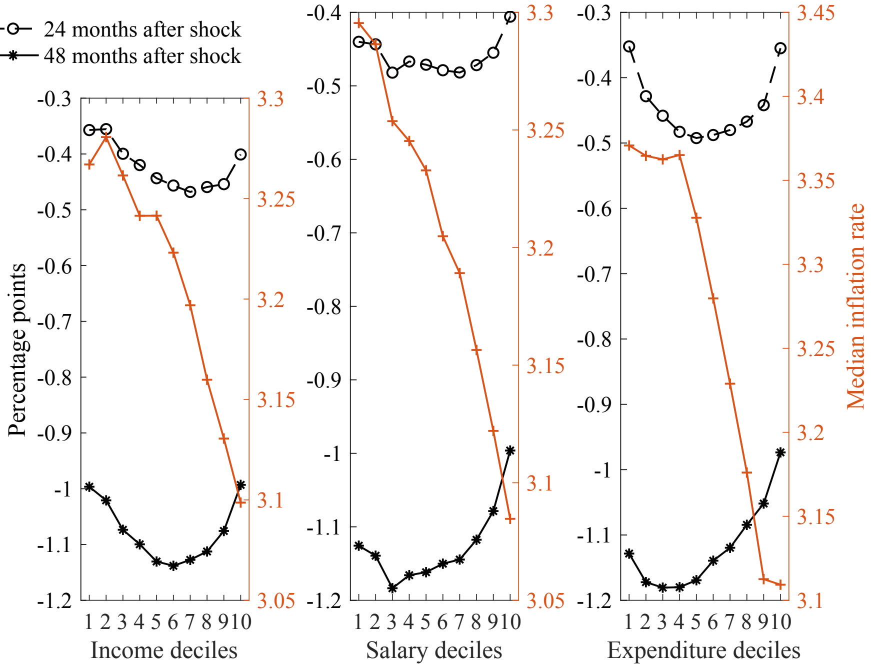
Notes: The top panel of this figure shows impulse responses to a percentage point contractionary monetary policy shock, as well as one and 1.65 standard deviation confidence intervals for the official annual inflation rate (black line) and the median inflation rate (blue line) of the individual inflation rate distribution. The middle panel reports the impulse response using as the dependent variable the dispersion in inflation, measured by the cross-sectional standard deviation and the bottom panel the log of the dispersion measure such that it can be interpreted as a percent change relative to the steady state. The horizontal axis is in months. Impulse responses are computed at a monthly frequency using data for the period 1980M1:2008M12.

Figure 4: Impulse responses of inflation dispersion across income, salary, and expenditure deciles



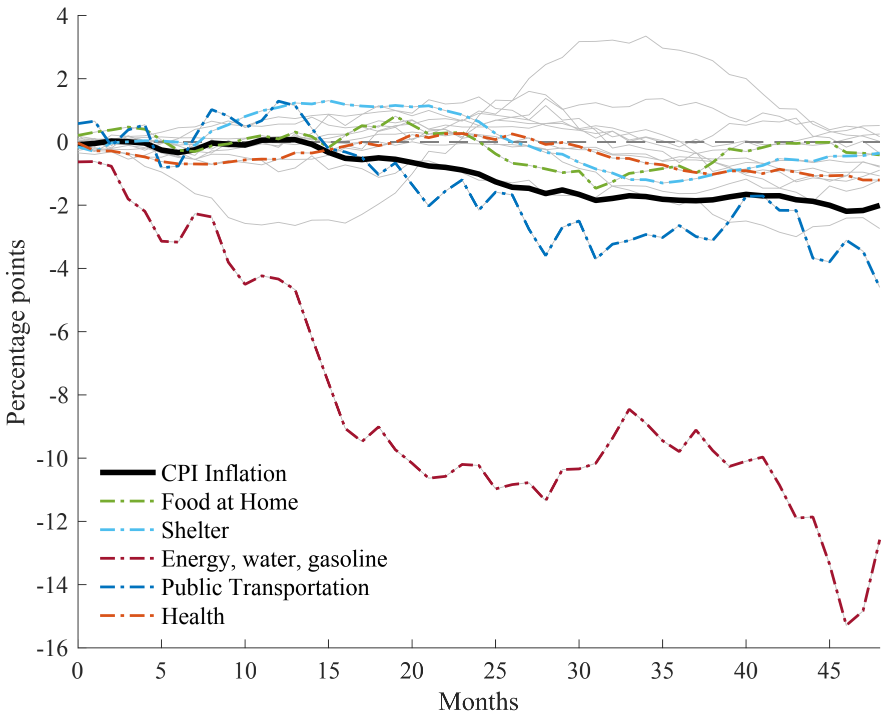
Notes: This figure shows impulse responses to a percentage point contractionary monetary policy shock, as well as one and 1.65 standard deviation confidence intervals for inflation inequality across income (top), salary (middle), and expenditure deciles (bottom). Inflation inequality is measured using the cross-sectional standard deviation of the decile-specific inflation rates. The horizontal axis is in months. Impulse responses are computed at a monthly frequency using data for the period 1980M1:2008M12.

Figure 5: Impulse responses of the decile-specific inflation rate across income, salary, and expenditure deciles



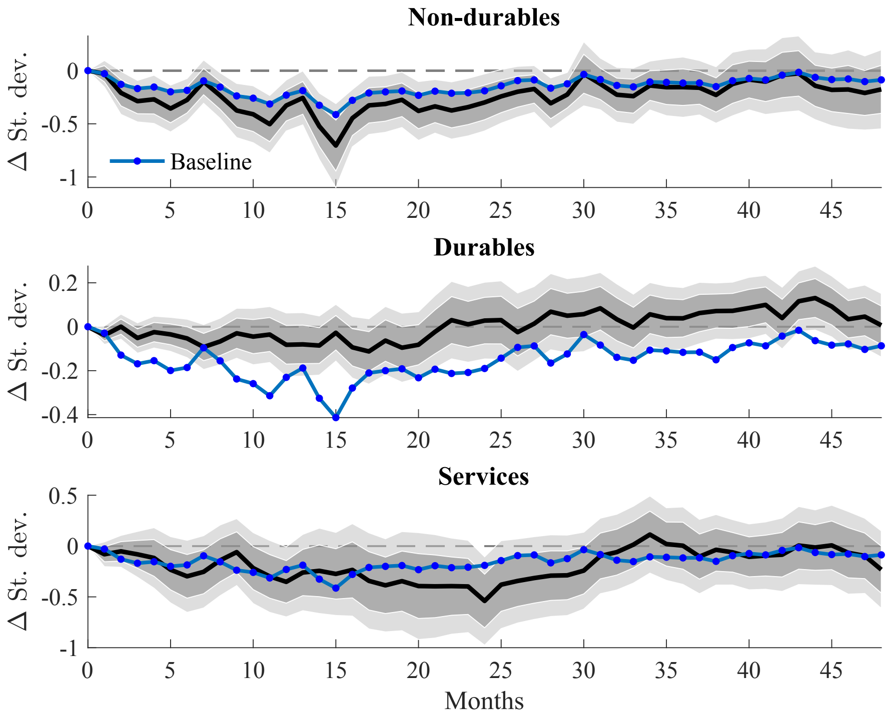
Notes: This figure reports the cross-sectional distribution of the decile-specific inflation rate responses of the different income (left panel), salary (middle panel), and expenditure deciles (right panel) 24 and 48 months after a one-percentage-point contractionary monetary policy shock. The red lines refer to the median inflation rate across deciles (left axis). Impulse responses are computed at a monthly frequency using data for the period 1980M1:2008M12.

Figure 6: Sectoral inflation rates impulse responses



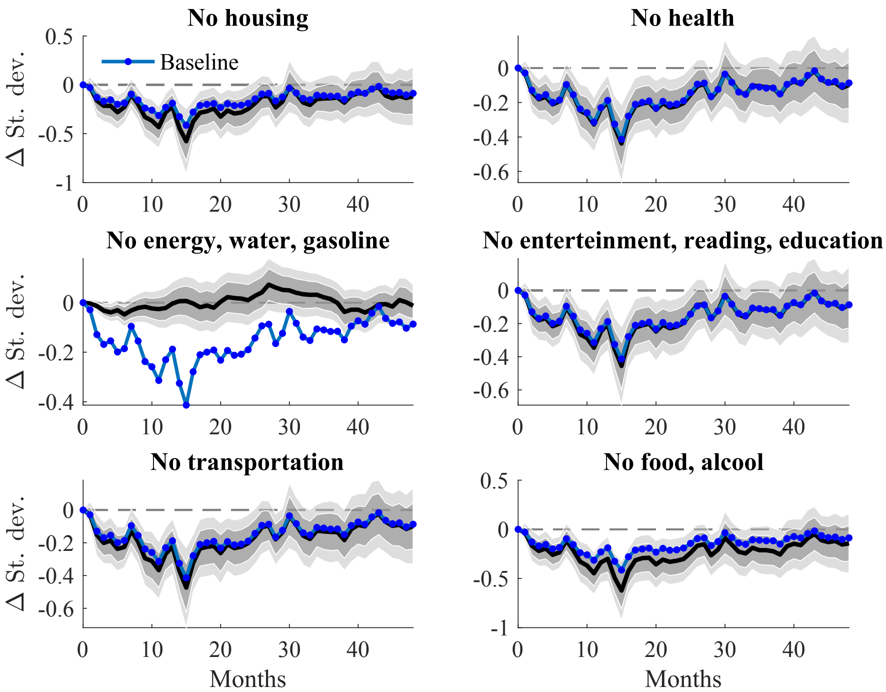
Notes: This figure shows impulse responses of some of the different sectoral inflation rates that compose the Official CPI inflation (thick black line) to a one percentage point contractionary monetary policy shock. Impulse responses are computed at a monthly frequency using data relative to the period 1980M1:2008M12

Figure 7: Impulse responses of inflation dispersion for different sub-categories of expenditure



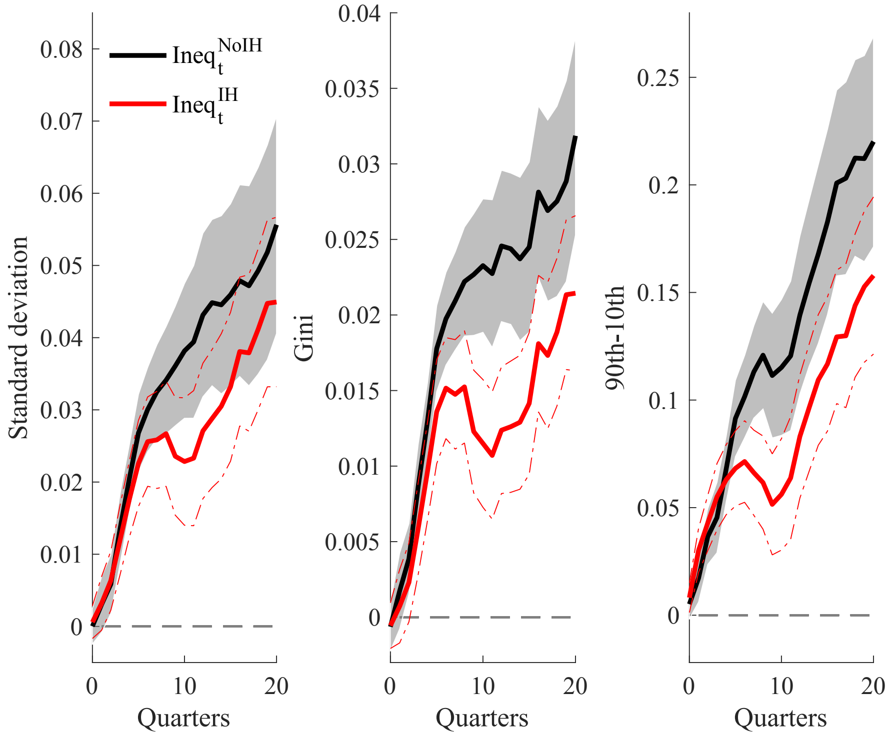
Notes: This figure shows impulse responses to a percentage point contractionary monetary policy shock, as well as one and 1.65 standard deviation confidence intervals for the dispersion in inflation, measured by the cross-sectional standard deviation. The top panel uses the standard deviation in inflation rates for non-durable categories, the middle panel for durables, and the bottom panel for services. The solid blue line refers to the baseline impulse response obtained using the baseline categories. The horizontal axis is in months. Impulse responses are computed at a monthly frequency using data for the period 1980M1:2008M12.

Figure 8: Impulse responses of inflation dispersion excluding different categories of expenditure



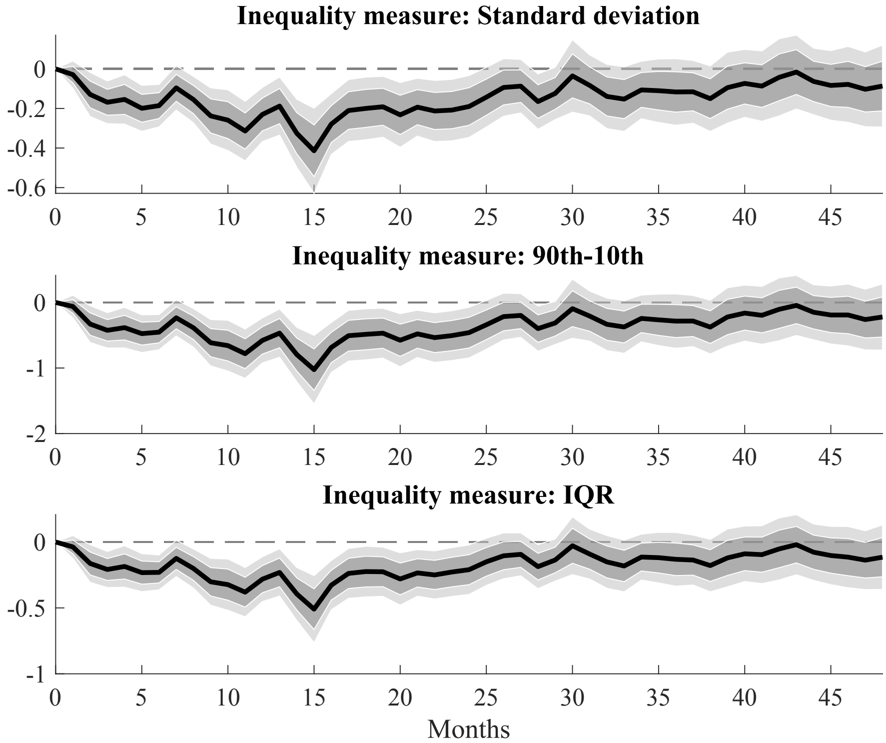
Notes: This figure shows impulse responses to a percentage point contractionary monetary policy shock, as well as one and 1.65 standard deviation confidence intervals for the dispersion in inflation, measured by the cross-sectional standard deviation. Each panel uses the standard deviation in inflation rates computing excluding expenditure categories from the consumption bundle of the households. The solid blue line refers to the baseline impulse response obtained using the baseline categories. The horizontal axis is in months. Impulse responses are computed at a monthly frequency using data for the period 1980M1:2008M12.

Figure 9: Impulse responses of expenditure inequality



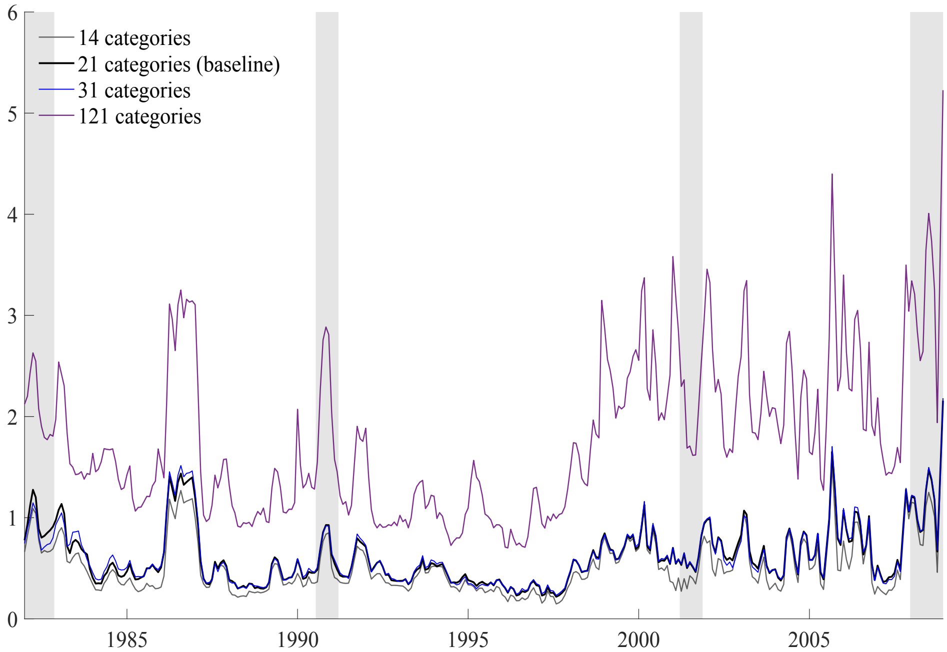
Notes: This figure shows impulse responses to a one percentage point contractionary monetary policy shock, as well as one standard deviation confidence intervals for expenditures inequality. The horizontal axis is in quarters and inequality is measured using the cross-sectional standard deviation (left), Gini coefficient (middle), and the log difference between the 90th and 10th percentiles of the cross-sectional distribution (right). The black solid line and the dark grey shaded areas depict the impulse response obtained by deflating the expenditure categories by the aggregate CPI, the red solid line and the dashed red lines refer to the impulse obtained by deflating each category by their respective price index. Impulse responses are computed at the quarterly frequency using data for the period 1980Q1:2008Q4.

Figure 10: Impulse responses of inflation dispersion



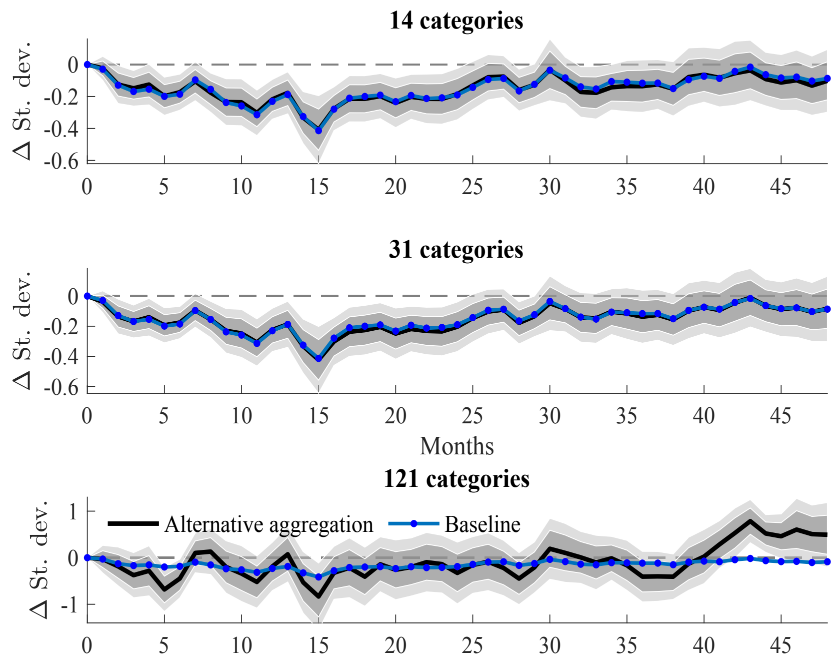
Notes: This figure shows impulse responses to a percentage point contractionary monetary policy shock, as well as one and 1.65 standard deviation confidence intervals for the respective inflation dispersion measures. The horizontal axis is in months. Dispersion is measured using the cross-sectional standard deviation (top), the difference between the 90th and the 10th percentile of the cross-sectional distribution (middle), and the IQR (bottom). Impulse responses are computed at a monthly frequency using data for the period 1980M1:2008M12.

Figure 11: Historical series of inflation dispersion measures



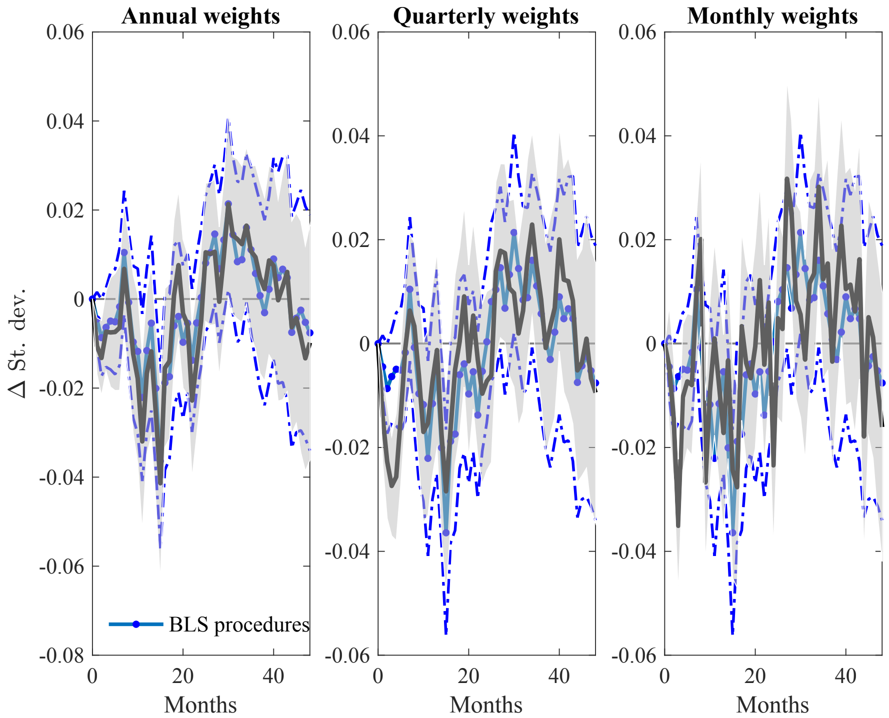
Notes: The plot shows the evolution of inflation dispersion measured using the cross-sectional standard deviation computed using 14, 21, 31, and 121 expenditure categories. All the series refer to the period 1981M1:2009M12. The gray shaded areas depict U.S. recessions.

Figure 12: Impulse responses of the cross-sectional standard deviation of inflation (alternative aggregations)



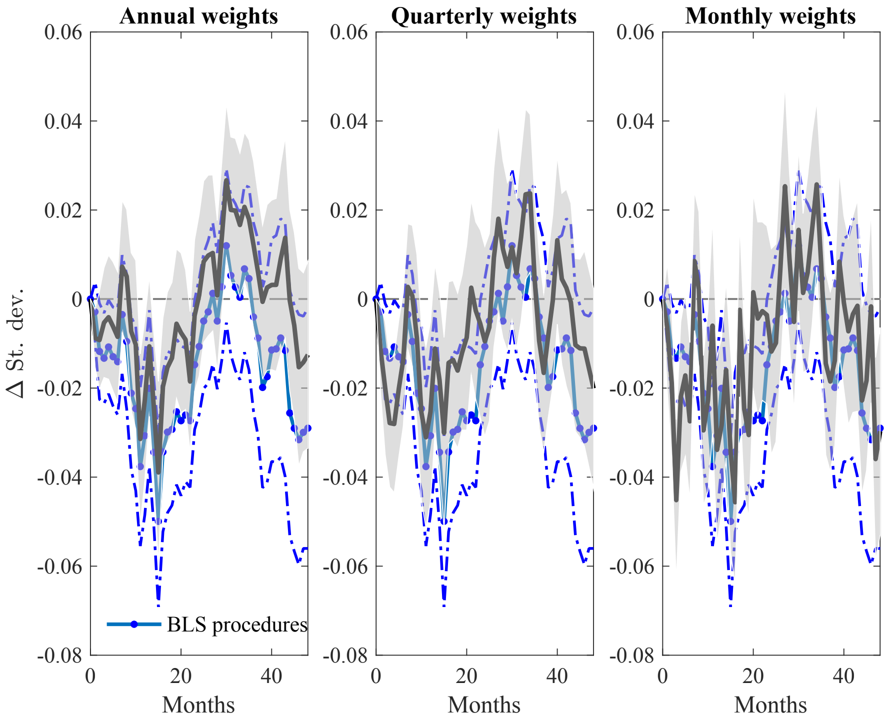
Notes: This figure shows impulse responses of alternatively aggregated inflation rates to a one percentage point contractionary monetary policy shock, as well as one and 1.65 standard deviation confidence intervals for the respective inflation dispersion measures. The solid blue line refers to the impulse response obtained using the baseline categories. Impulse responses are computed at a monthly frequency using data relative to the period 1980M1:2008M12.

Figure 13: Impulse responses of inflation inequality across income deciles with time-varying weights



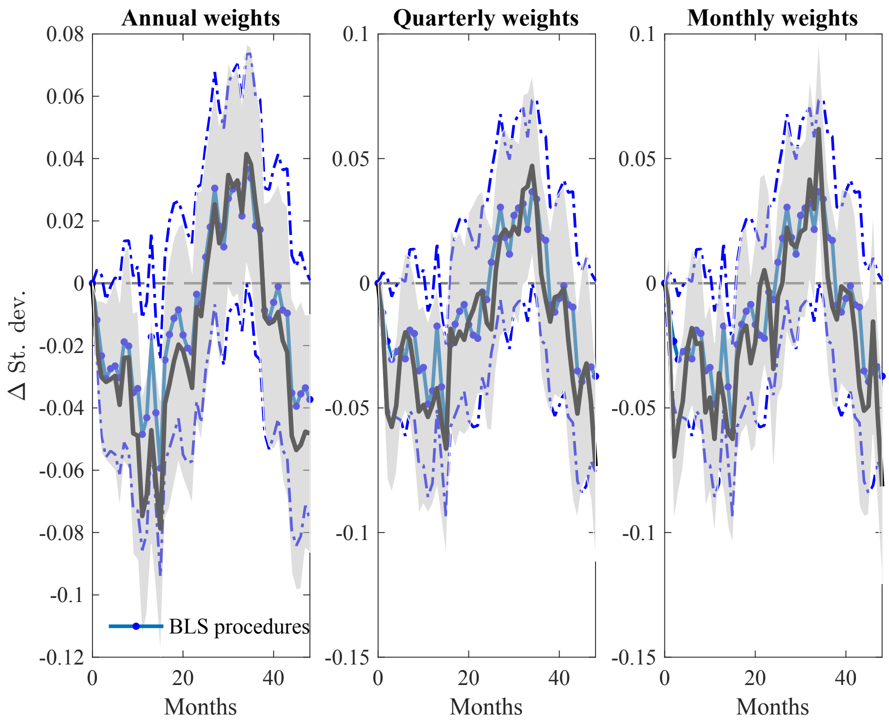
Notes: This figure shows impulse responses to a percentage point contractionary monetary policy shock (black line) as well as one standard deviation confidence interval (gray area) for inflation inequality across income deciles. Inflation inequality is measured using the cross-sectional standard deviation of the decile-specific inflation rates. The expenditure weights are time-varying and computed at annual (left panel), quarterly (middle panel), and monthly (right panel) frequencies. The solid blue line refers to the baseline impulse response obtained following the BLS methodology for the expenditure weights, the blue dashed lines are the one standard deviation confidence interval. The horizontal axis is in months. The top panel uses the standard deviation in inflation rates for non-durable categories, the middle panel for durables, and the bottom panel for services. Impulse responses are computed at a monthly frequency using data for the period 1980M1:2008M12.

Figure 14: Impulse responses of inflation inequality across salary deciles with time-varying weights



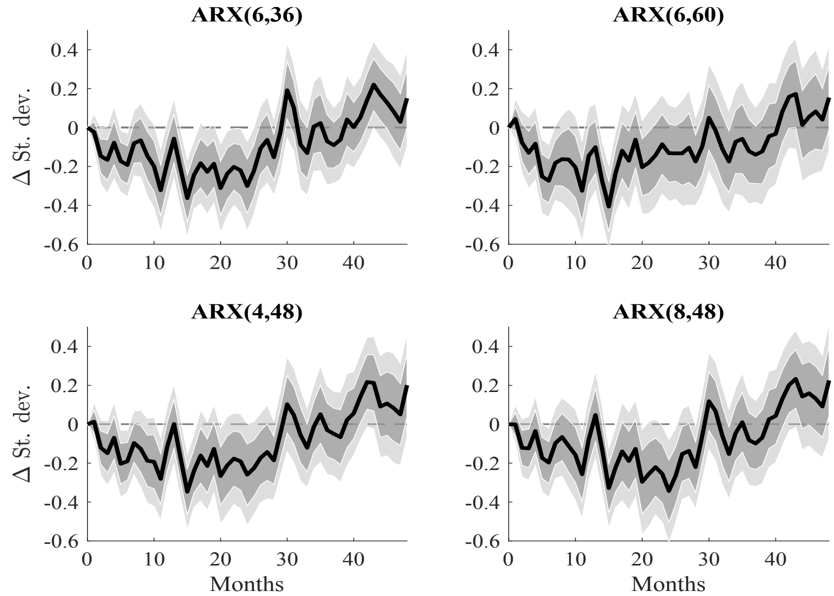
Notes: This figure shows impulse responses to a percentage point contractionary monetary policy shock (black line) as well as one standard deviation confidence interval (gray area) for inflation inequality across salary deciles. Inflation inequality is measured using the cross-sectional standard deviation of the decile-specific inflation rates. The expenditure weights are time-varying and computed at annual (left panel), quarterly (middle panel), and monthly (right panel) frequencies. The solid blue line refers to the baseline impulse response obtained following the BLS methodology for the expenditure weights, the blue dashed lines are the one standard deviation confidence interval. The horizontal axis is in months. The top panel uses the standard deviation in inflation rates for non-durable categories, the middle panel for durables, and the bottom panel for services. Impulse responses are computed at a monthly frequency using data for the period 1980M1:2008M12.

Figure 15: Impulse responses of inflation inequality across expenditure deciles with time-varying weights



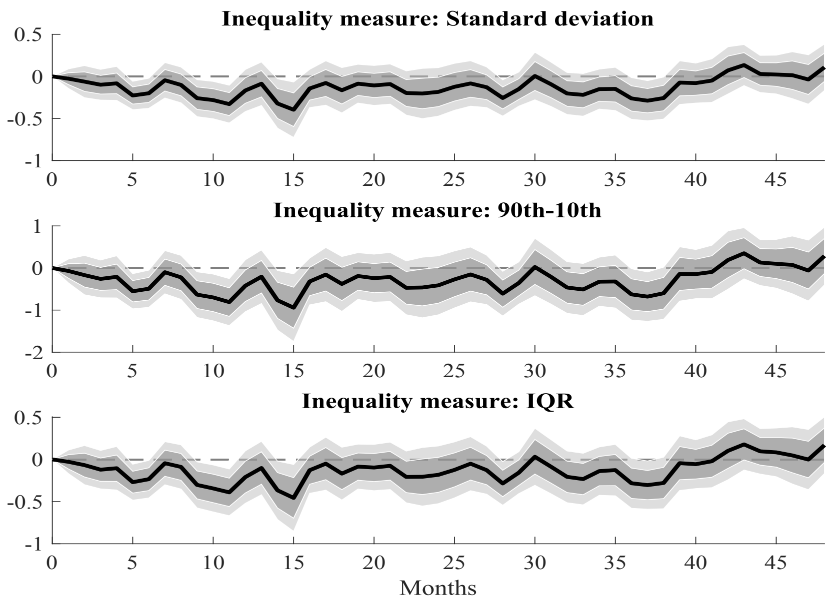
Notes: This figure shows impulse responses to a percentage point contractionary monetary policy shock (black line) as well as one standard deviation confidence interval (gray area) for inflation inequality across expenditure deciles. Inflation inequality is measured using the cross-sectional standard deviation of the decile-specific inflation rates. The expenditure weights are time-varying and computed at annual (left panel), quarterly (middle panel), and monthly (right panel) frequencies. The solid blue line refers to the baseline impulse response obtained following the BLS methodology for the expenditure weights, the blue dashed lines are the one standard deviation confidence interval. The horizontal axis is in months. The top panel uses the standard deviation in inflation rates for non-durable categories, the middle panel for durables, and the bottom panel for services. Impulse responses are computed at a monthly frequency using data for the period 1980M1:2008M12.

Figure 16: Impulse responses of inflation dispersion for different lag specifications



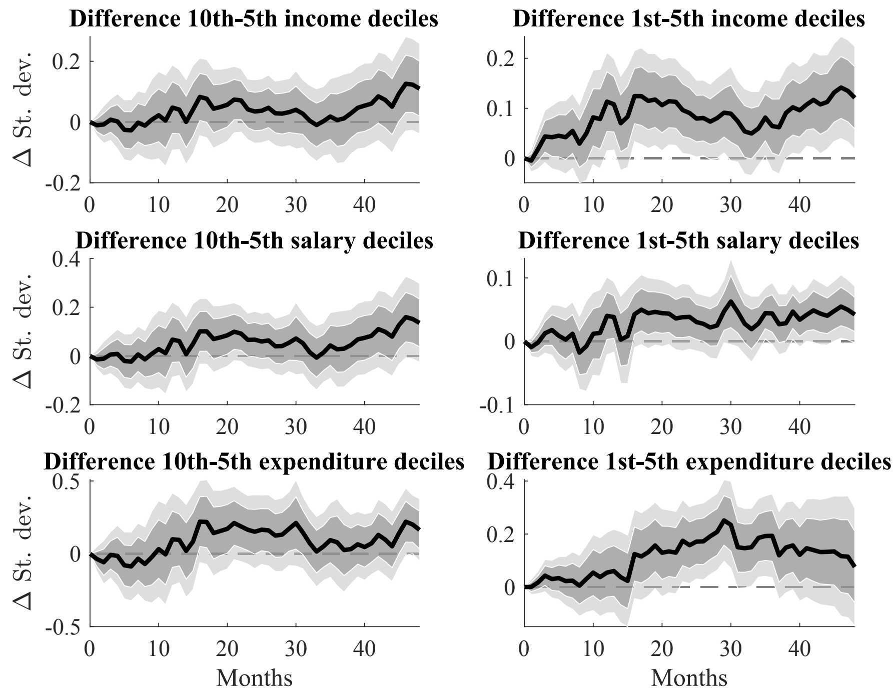
Notes: This figure shows the impulse responses to a one percentage point contractionary monetary policy shock, as well as one and 1.65 standard deviation confidence intervals of the cross-sectional standard deviation. The horizontal axis is in months. In an $ARX(p,r)$-model, we control for p lags of the dependent variable, and for r lags of the shock variable. Impulse responses are computed at a monthly frequency using data relative to the period 1980M1:2008M12.

Figure 17: Impulse responses of inflation dispersion (without Volcker period)



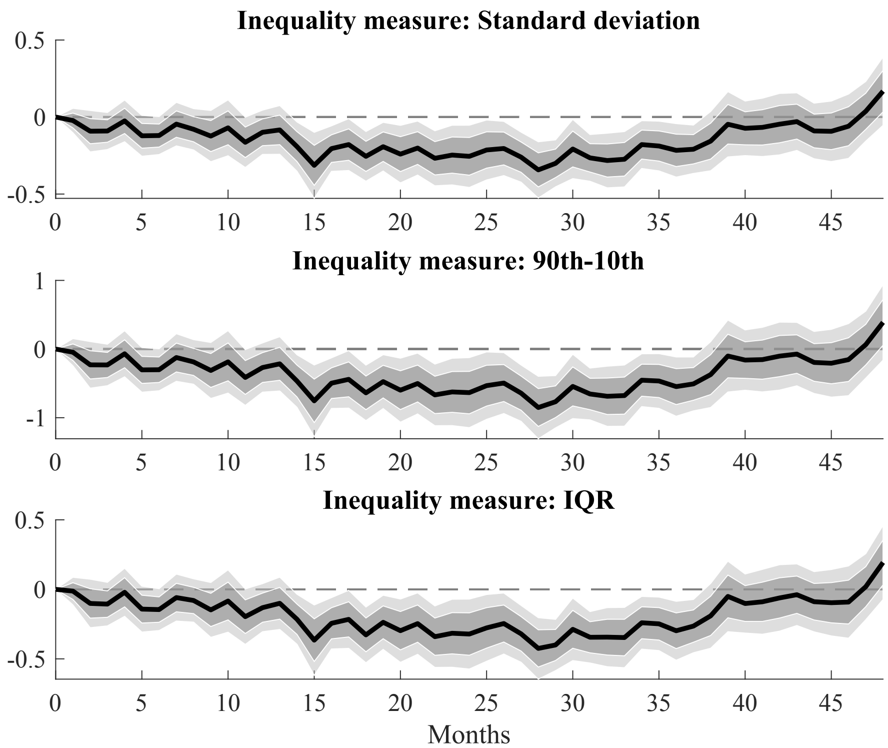
Notes: This figure shows impulse responses to a one percentage point contractionary monetary policy shock, as well as one and 1.65 standard deviation confidence intervals for the respective inflation dispersion measures. The horizontal axis is in months. Dispersion is measured using the cross-sectional standard deviation (top), the difference between the 90th and the 10th percentile of the cross-sectional distribution (middle), and the IQR (bottom). Impulse responses are computed at a monthly frequency using data relative to the period 1985M1:2008M12 in order to exclude the Volcker disinflation period.

Figure 18: Differences in impulse responses across deciles



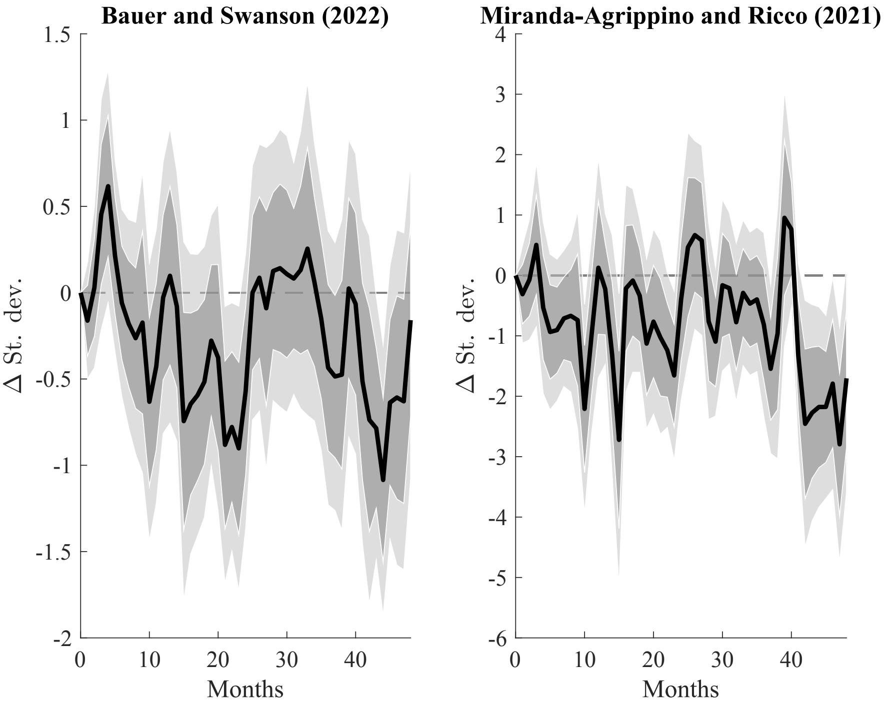
Notes: This figure shows impulse responses to a percentage point contractionary monetary policy shock, as well as one and 1.65 standard deviation confidence intervals for the difference in decile-specific inflation rates across deciles of the demographic groups. The first column reports the responses of the difference in inflation rate for the 10th and the 5th decile, and the second column for the 1st and the 5th decile. The first row shows the responses for the difference across expenditure deciles, the second row for salary deciles, and the last row for income deciles. The horizontal axis is in months. Impulse responses are computed at a monthly frequency using data for the period 1980M1:2008M12.

Figure 19: Impulse responses of inflation dispersion (without recession periods)



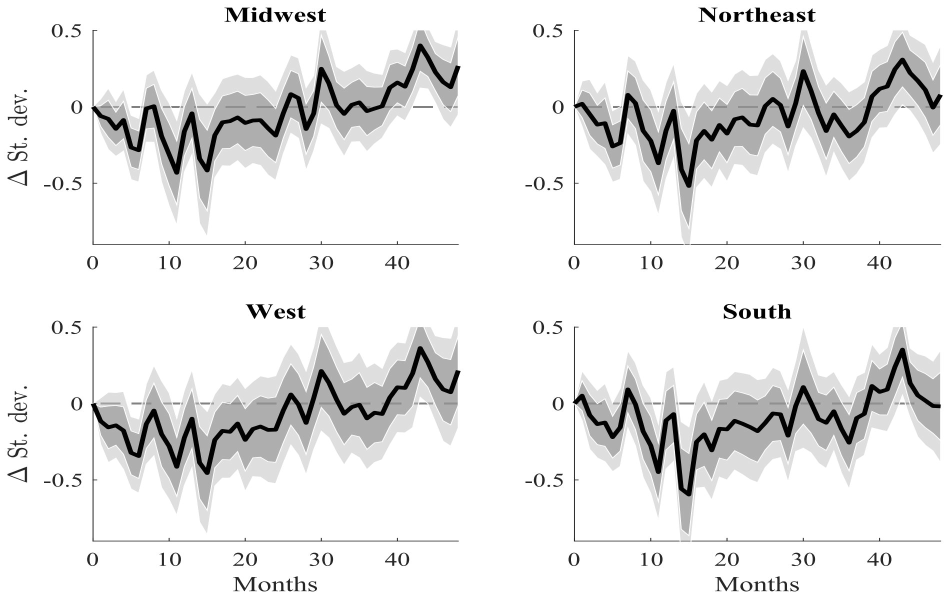
Notes: This figure shows impulse responses to a one percentage point contractionary monetary policy shock, as well as one and 1.65 standard deviation confidence intervals for the respective inflation dispersion measures. The horizontal axis is in months. Dispersion is measured using the cross-sectional standard deviation (top), the difference between the 90th and the 10th percentile of the cross-sectional distribution (middle), and the IQR (bottom). Impulse responses are computed at a monthly frequency using data relative to the period 1980M1:2008M12

Figure 20: Impulse responses of inflation dispersion, Bauer and Swanson (2022) and Miranda-Agrippino and Ricco (2021) monetary shocks



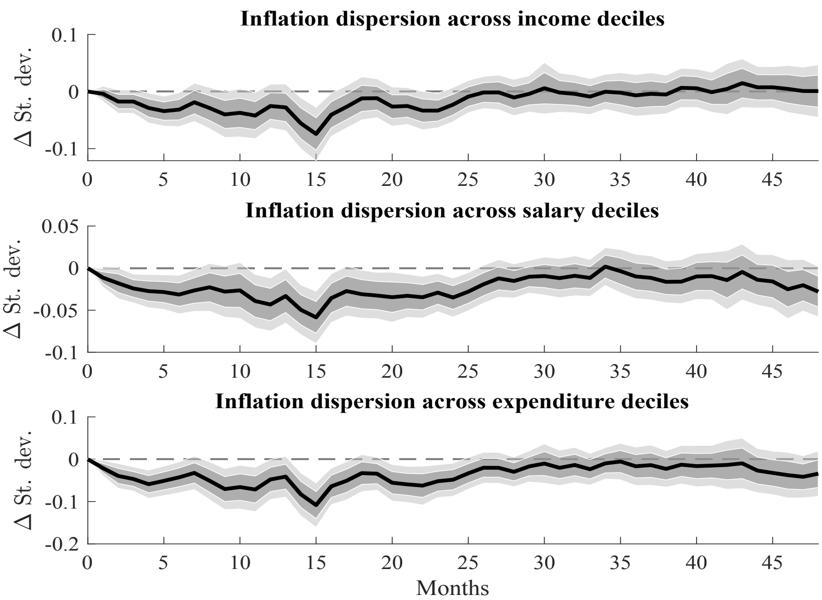
Notes: This figure shows impulse responses to a percentage point contractionary monetary policy shock, as well as the 1.65 standard deviation confidence intervals. On the left panel we use the monetary shocks computed by Bauer and Swanson (2022). On the right panel the monetary shocks computed by Miranda-Agrippino and Ricco (2021). The horizontal axis is in months. Impulse responses are computed at a monthly frequency.

Figure 21: Impulse responses of inflation dispersion across U.S. divisions



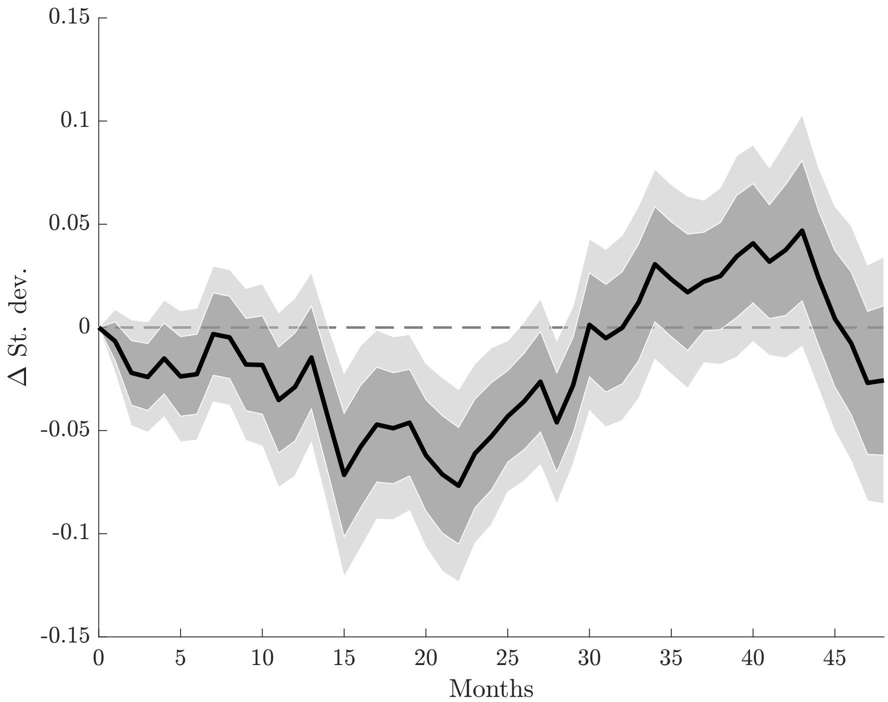
Notes: This figure shows impulse responses to a one percentage point contractionary monetary policy shock, as well as one and 1.65 standard deviation confidence intervals for the inflation dispersion measured as the cross-sectional standard deviation for the four US regions. Impulse responses are computed at a monthly frequency using data relative to the period 1980M1:2008M12.

Figure 22: Impulse responses of the dispersion across the median inflation rates for income, salary, and expenditure deciles



Notes: This figure shows impulse responses to a percentage point contractionary monetary policy shock, as well as one and 1.65 standard deviation confidence intervals for inflation inequality across income (top), salary (middle), and expenditure deciles (bottom). Inflation inequality is measured using the cross-sectional standard deviation of the median inflation rate for each decile. The horizontal axis is in months. Impulse responses are computed at a monthly frequency using data for the period 1980M1:2008M12.

Figure 23: Impulse responses of inflation inequality derived from the income-percentile-specific CPI data from Cravino et al. (2020)



Notes: This figure shows impulse responses to a percentage point contractionary monetary policy shock, as well as the 1.65 standard deviation confidence intervals. Inflation inequality is defined as the cross-sectional standard deviation across the income-percentile-specific CPI from Cravino et al. (2020). The horizontal axis is in months. Impulse responses are computed at a monthly frequency using data for the period 1980M1:2008M12.

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