Monetary policy shocks and inflation inequality

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Abstract

This paper studies how monetary policy shocks influence the distribution of household-level inflation rates. We find that (i) contractionary monetary policy shocks significantly and persistently decrease inflation dispersion in the economy, and that (ii) the expenditures on *Energy*, *Water* and *Gasoline* are the main drivers behind this result. Moreover, (iii) different demographic groups are heterogeneously affected 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. These findings imply that (iv) 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.

Keywords: monetary policy, inflation inequality, distributional effects
JEL classification: E31, E52

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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 rate 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 influences the distribution of the individual inflation rates to which different households are exposed. We compute a measure of the inflation rate at the household level and we document that contractionary monetary shocks reduce the median as well as the cross-sectional standard deviation of the distribution of inflation rates. The decrease in inflation dispersion is almost entirely driven by expenditures on *Energy*, *Water*, and *Gasoline*. The inflation rate of these sectors, despite the fact that they account for a relatively small share of the aggregate consumption bundle, is extremely sensitive to changes in interest rate. We then study how the inflation rates of different demographic groups are heterogeneously affected by monetary shocks. We show that *inflation inequality*, defined 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. Finally, we find that the increase in expenditure inequality in response to monetary shocks is significantly more muted once inflation heterogeneity is taken into account.

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 assess which sectors are mainly responsible for the decrease in inflation dispersion. The price indexes 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.

The third 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 to be higher than that one of high-income households. On the other hand, it is more reactive to shocks and therefore decreases 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 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 monetary shock corroborating again the evidence of the sizable distributional effects that central banks can have on the economy.

After years of relatively stable and low price growth, inflation rates worldwide have reached historically high levels in the post-Covid period. Which are the optimal monetary policies to be implemented to tackle it are 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.

The level as well as the sensitivity of household-level inflation rates to changes in interest rate are strongly correlated with demographic characteristics. Therefore, abstracting from also considering how the individual inflation rates adjust in response to shocks would lead to systematic biases by the monetary authorities against specific demographic groups. For instance, since low-income households experience a higher inflation rate relative to high-income households, they would benefit from a more aggressive monetary policy than the one implemented by focusing only on the aggregate inflation rate. This problem could even be exacerbated by the fact that central banks usually design their policies targeting a specific subset of the price indexes. As we document, core measures of inflation, i.e., excluding energy and food, greatly underestimate the overall level of inflation dispersion in the economy. Finally, the empirical findings we provide suggest that central banks should pay close attention to inflation heterogeneity as whether it is taken into account or not has important implications for the magnitude of the distributional effects caused by the monetary authorities' decisions.

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 are available for a much more limited time period but provides information at a higher level of granularity. The differences in inflation rates across households have been found to be 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. 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 of 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 main results in terms of the impact of monetary policy shocks on the cross-sectional inflation distribution. Section 4 studies the heterogeneous responses across different demographic groups. Section 5 evaluates how inflation heterogeneity influences the response of real consumption inequality to monetary shocks. In section 6, we perform a battery of different robustness checks to evaluate the reliability of our findings. Section 7 concludes.

2 Individual inflation rates

In this section, we compute individual inflation rates at the household level by exploiting the differences in consumption patterns across households. There are three steps needed for the computation of any inflation rate. First, we need information on prices for different goods. Second, we need detailed information on (individual) consumer expenditure, which allows computing the share of different goods in an aggregate index and therefore provides weights[1]. Third, statistical agencies have to decide on a methodology to combine price data to get a meaningful measure of inflation. In the following, we discuss each step separately.

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 6.1 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 10th and the 90th percentile 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

[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.

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]. 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

[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.

[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.

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 6.1 where we compute the expenditure shares at higher frequencies.

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:

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

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.

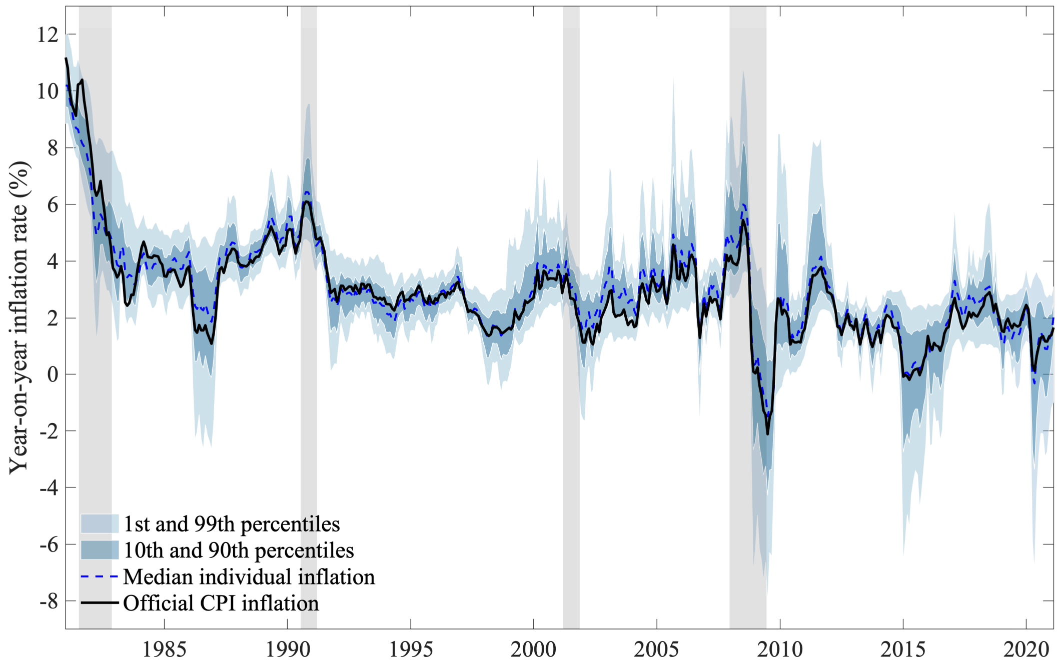
2.4 Properties of individual inflation rates

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.

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.

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

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



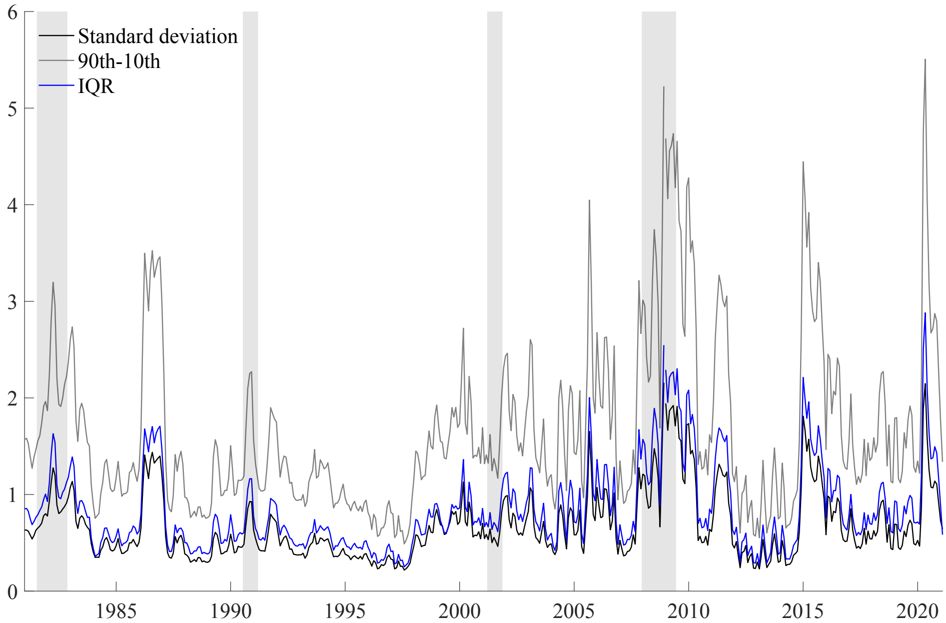
Notes: The plot shows the evolution over time of the official CPI inflation as well as the median and selected percentiles (1st, 10th, 90th, and 99th) of the cross-sectional distribution in individual inflation rates. The gray shaded areas depict U.S. recessions.

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 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 which are present during both periods. Sampling weights are applied throughout the analysis.

Figure 2: Historical series of inflation dispersion measures



Notes: In the plot, we show 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 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 Monetary policy shocks and inflation dispersion

In this section, we present the results of our empirical analysis. We first study whether and to what extent monetary policy shocks influence aggregate inflation dispersion. We then investigate which expenditure categories drive the main results of our analysis.

3.1 Methodology

In the baseline specification, we adopt 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 control. 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 D 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

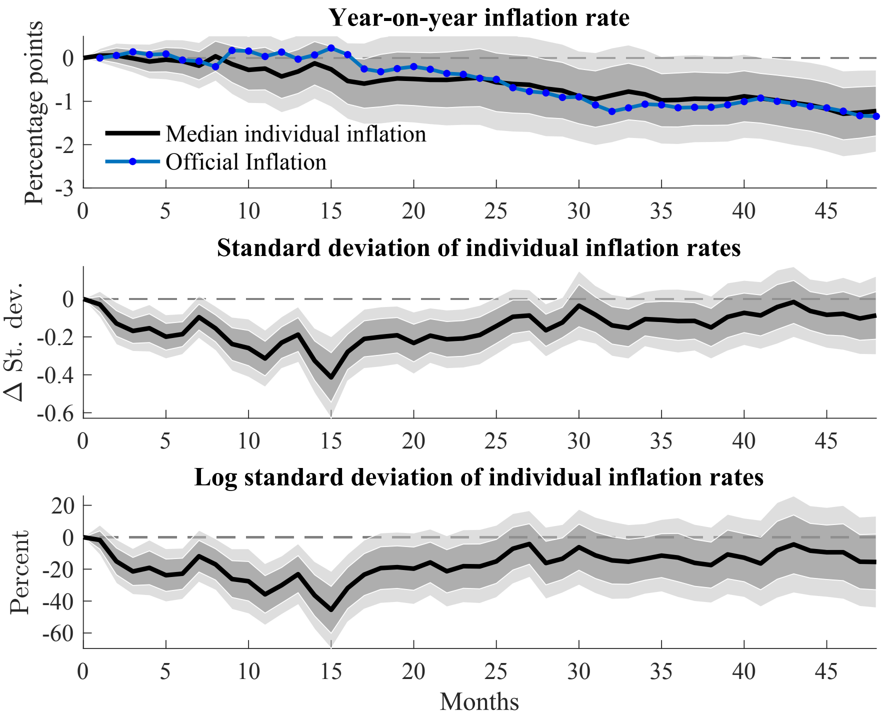
We evaluate the overall effects of a contractionary monetary policy shock on inflation dispersion by estimating equation (2) using the cross-sectional standard deviation as the baseline measure of inflation dispersion[9]. The results are reported in Figure 3. The top panel shows the responses of the 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.

[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 basically 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 6 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 15. Given the very high correlation among dispersion measures, the IRFs display similar patterns differing mainly in the magnitude of the response.

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: In the top panel the figure plots the 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.

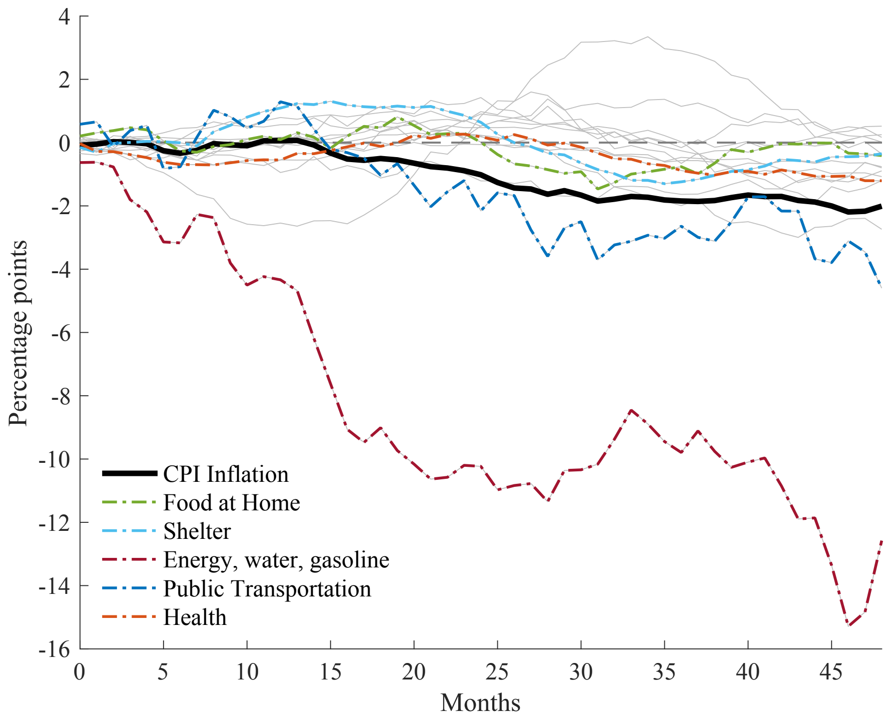
In the middle panel, we show the impulse response of our dispersion measure. Inflation dispersion decreases after a contractionary monetary policy shock and remains persistently below zero. Looking at the one and 1.65 standard deviation confidence intervals we can easily reject the null hypothesis that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

3.3 Sectoral contribution

The individual inflation rates are constructed assuming there is no substitution across categories in response to a monetary shock[10]. Therefore, the decrease in inflation dispersion is entirely due to the fact that the inflation of different sectors is heterogeneously sensitive to exogenous changes in the interest rate. 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 4.

Figure 4: Sectoral inflation rates impulse responses



Notes: The figure plots the 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

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

[10] Assumption which we relaxed in subsection 6.1.

policy shocks. In contrast, the inflation rates of *Public Transportation* and *Energy*, *Water* and *Gasoline* are significantly more responsive. This result is in line with Ider et al. (2023) which estimate a Bayesian Proxy SVAR model for the U.S. (1990-2019) and the Euro Area (1999-2019) and document that the response of the energy component of inflation to a monetary shock is 10 times larger compared to the response of the headline consumer price index. Why the price indexes of some categories are more sensitive than others to monetary shocks is beyond the scope of this paper but we can expect it to be related to several factors like the different levels of price stickiness, labor intensity, etc.

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.

The results are reported in Figure 5. 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 clearly suggest that the main drivers of the decrease in inflation dispersion can be found within the *non-durables* categories.

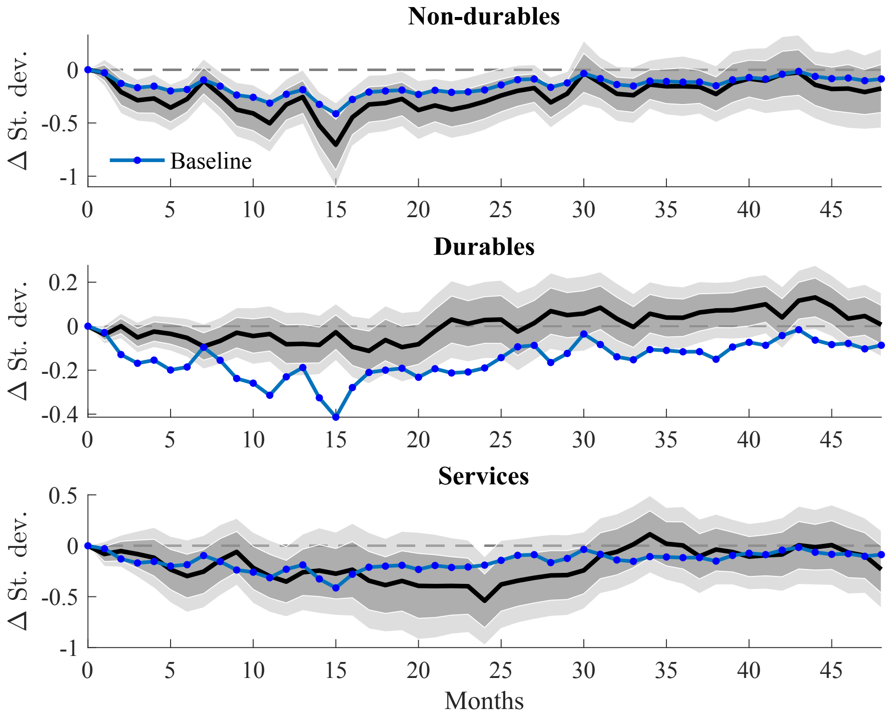
Therefore, we compute the same cross-sectional standard deviation of individual inflation rates but excluding one important expenditure category at a time. The results of this exercise are shown in Figure 6. As one can notice, most expenditure categories like *Housing*, *Health expenditure* and *Transportation*[11] have only a marginal effect on our main results despite accounting for a significant share of the household consumption bundles[12].

The middle left plot reports the inflation dispersion response when we exclude the categories *Energy*, *Water*, and *Gasoline*. This new specification is close to the definition of Core CPI that the Federal Reserve Bank uses to decide which monetary policy to adopt. Not surprisingly given the results shown in Figure 4, removing three of the most volatile categories cancels out the response of inflation dispersion almost entirely.

[11] *Housing* is 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*.

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

Figure 5: Impulse responses of inflation dispersion for different sub-categories of expenditure



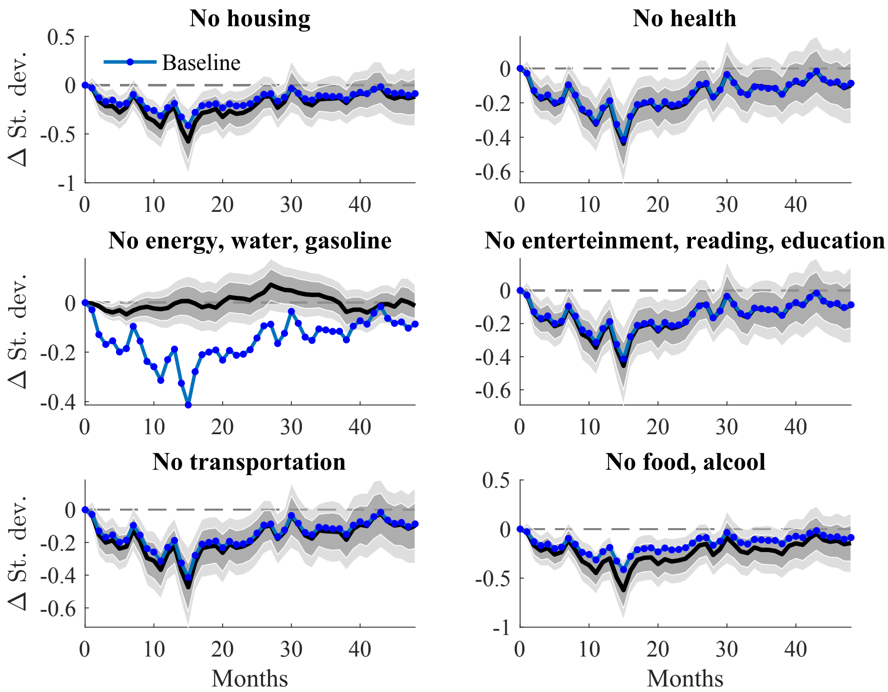
Notes: The figure plots impulse responses to a percentage point contractionary monetary policy shock, as well as one and 1.65 standard deviation confidence intervals for the dispersion in inflation, measured by the cross-sectional standard deviation. The top panel uses the standard deviation in inflation 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.

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*. This empirical evidence suggests that central banks should not neglect the importance of these small and extremely volatile categories in setting their policy rate since most of the variation in inflation dispersion comes actually from them.

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.

Figure 6: Impulse responses of inflation dispersion excluding different categories of expenditure



Notes: The figure plots 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.

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[13]. 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 categories 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*

[13] Appendix D 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. Finally, looking at the differences in weights across deciles, we can already anticipate the inflation rate of which deciles will be more sensitive to monetary shocks. In the previous section, we demonstrate that most of the variation in inflation dispersion comes from *Gasoline* and *Energy* and that low- and middle-income households consume a significantly higher share of their income in these categories with respect to high-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*[14]. As one can see from Figure 7, following a contractionary monetary policy shock inflation inequality for the three groups significantly decreases.

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 8 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.

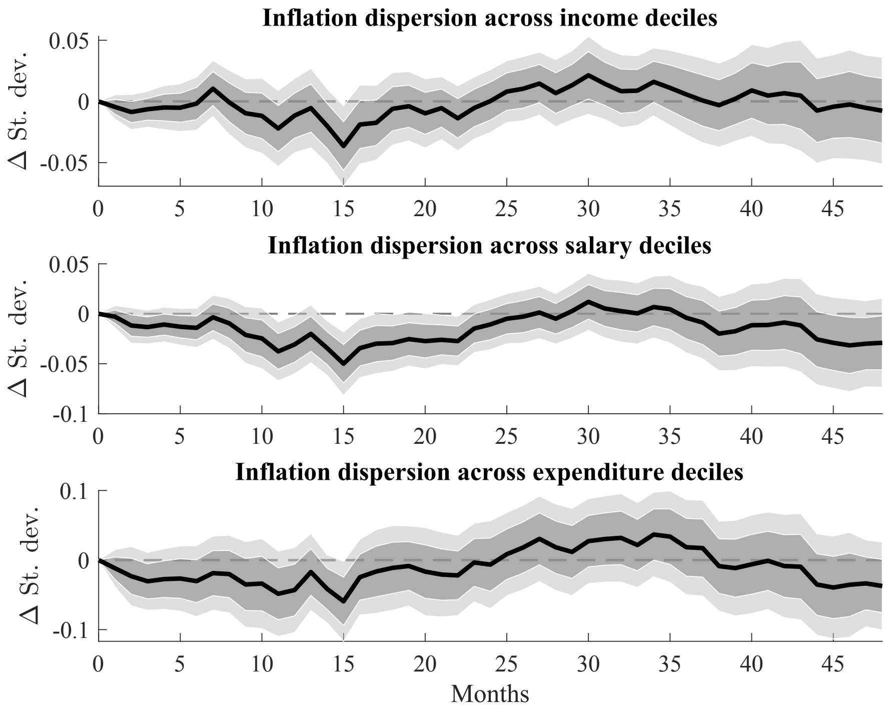
Similar to what Cravino et al. (2020) find for income, the annual inflation rate of the households at the top of the income distribution reacts substantially less to monetary policy shocks than the one of those in the middle. The difference between middle- and high-expenditure households is economically 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, left axis)[15]. One can notice how the higher the decile the lower the median inflation rate. This result is

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

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

Figure 7: Impulse responses of inflation dispersion across income, salary, and expenditure deciles



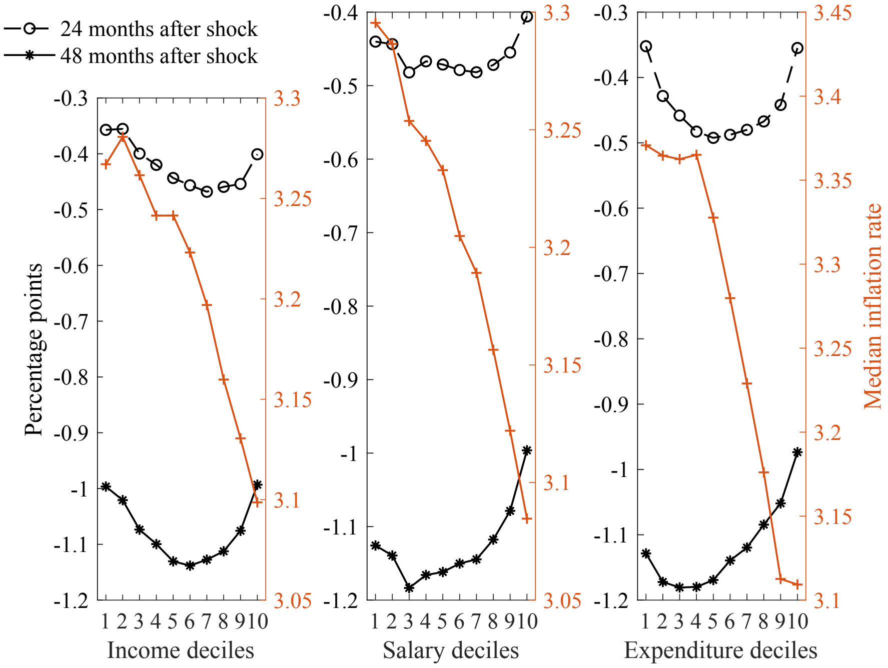
Notes: The figure plots impulse responses to a percentage point contractionary monetary policy shock, as well as one and 1.65 standard deviation confidence intervals for inflation inequality across income (top), salary (middle), and expenditure deciles (bottom). Inflation inequality is measured using 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.

consistent with the evidence provided by Jaravel (2019) and Kaplan and Schulhofer-Wohl (2017) using the Nielsen scanner data.

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 7. Similar results can be found focusing on salary and expenditure deciles as shown in the middle and right panels of Figure 8.

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.

Figure 8: Impulse responses of the decile-specific inflation rate across income, salary, and expenditure deciles



Notes: The 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.

5 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 close as possible and compute a broad measure of household expenditure which includes non-durables, durables, and services[16]. Few expenses are excluded since the relative sub-category price index is not easily identifiable, e.g., occupational expenses, mortgage, and property taxes.

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

[16]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.

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.

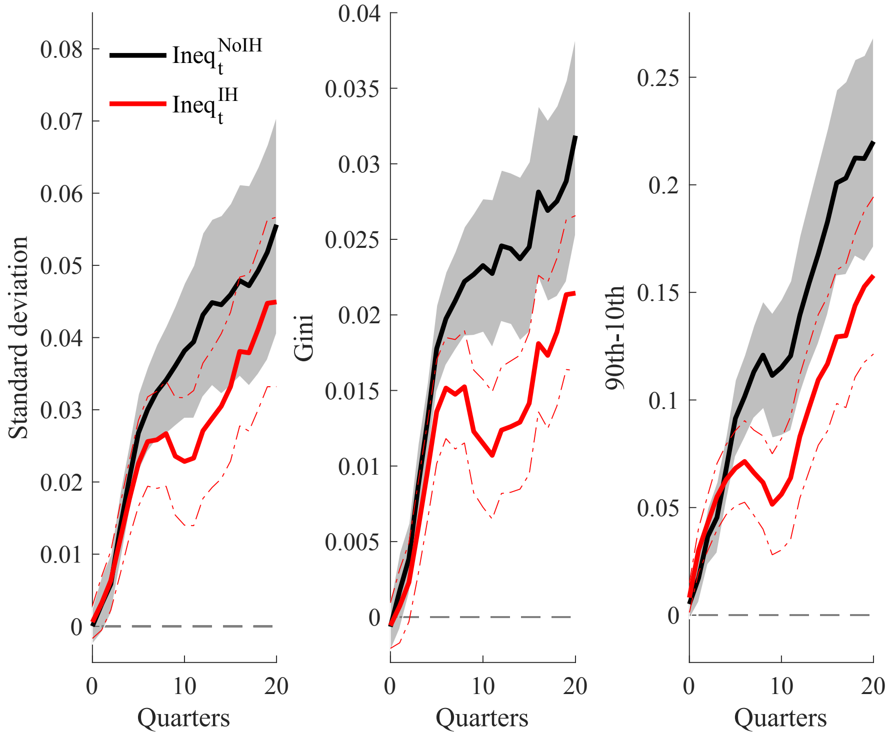
To make our results as comparable as possible, we use the same econometric procedure adopted by Coibion et al. (2017), i.e., local projection with Romer and Romer (2004) shocks at a quarterly frequency, over the same time period, 1980Q1:2008Q4[17]. Since the series is quarterly, we include as controls 20 lags for the shocks and 2 lags for the dependent variable and we compute the impulse responses over 20 quarters.

Figure 9 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 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.

[17]Similar results are obtained adopting our empirical.

Figure 9: Impulse responses of expenditure inequality



Notes: The figure plots 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.

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.

6 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 D. The figures are reported in Appendix E.

6.1 Substitution effects

Throughout the paper, we conduct our analysis under the assumption that differences in inflation dispersion are mainly driven by changes in prices 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. Not all price series are available since the early 80s and this is true, especially for the most disaggregate goods and services.

We show that the main results are basically unaffected by increasing or decreasing the number of categories considered. We compute the household-level inflation dispersion using 14, 31, and 121 expenditure categories[18]. The evolution over time of the dispersion measures is reported in Figure 16.

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 17 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

[18]For this last specification some of the price indexes were available later than 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.

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.

We report in Figure 18 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 7.

Not surprisingly, moving from annual to quarterly and especially to monthly weights makes the responses more volatile. The responses with time-varying weights are clearly 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 19 and Figure 20 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.

6.2 Different lag specification

We re-estimate equation (2) with an alternative lag specification. In Figure 21 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.

6.3 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 22 reports the IRFs obtained using the baseline specification but starting the sample in 1985M1. In this case, the results are also robust.

7 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.

In this paper, we study 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. *Energy*, *Water* and *Gasoline* are found to explain almost entirely the observed effects despite accounting for a relatively small expenditure share.

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 that 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.

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 of their consumption bundles decreases relatively more as well partially offsetting the effect in real terms. 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. Therefore, focusing only on aggregate inflation or measures of inflation that exclude important components might lead to the implementation of systematically suboptimal policies for specific demographic groups. Finally, taking into account inflation heterogeneity is particularly relevant when it comes to assessing the impact of monetary policy on other forms of inequalities.

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A Data sources

In this section, we document 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)[19]	Mean	Median	Standard Deviation	p10	p90
Food at Home (SAF11)	3.05	2.72	1.84	1.01	5.60
Food Away from Home (SEFV)	3.36	3.05	1.41	1.99	4.61
Alcoholic Beverages (SAF116)	3.24	2.73	1.84	1.64	5.29
Rented Dwellings (SEHA)	3.94	3.60	1.53	2.46	6.15
Owned Dwellings (SEHC)	3.65	3.33	1.01	2.42	5.13
Other Lodging (MUUR0000SE2102-SEHB)	5.15	4.65	3.50	1.51	9.69
Energy (SAH21)	3.29	2.41	5.74	-3.19	10.82
Water (SEHG01)	5.34	5.23	2.38	2.82	7.79
Phone (SAE2)	-1.06	-1.08	1.70	-3.31	1.13
Household F&O[21] (SAH3)	1.43	1.34	1.77	-0.39	2.70
Apparel (SAA)	1.00	0.82	2.32	-1.83	4.49
Gasoline (SETB)	3.31	2.93	13.79	-13.63	20.98
Other Vehicle Expenses (SETC-SETD-SETE-SETF)	3.02	2.34	2.10	0.79	6.75
Public Transportation (SETG)	4.47	4.06	5.08	-0.93	9.54
Medical care (SAM)	5.72	4.82	2.21	3.45	9.01
Entertainment (SAR)	1.47	1.34	0.74	0.59	2.64
Personal Care (SAG1)	3.23	2.79	1.57	1.87	5.01

[20]The official series ID, as defined by the BLS, is a combination of "CUUR0000", which stands for the unadjusted CPI-U inflation rate for the whole US, and the Item Code, as shown in the table.

[21]Household Furnishings and Operations

Table 1: Item-level CPI statistics (continued)

CPI series (Item Code)[20]	Mean	Median	Standard Deviation	p10	p90
Reading (SERG)	3.64	3.36	2.50	0.86	7.01
Education (SAE)	2.40	2.40	0.96	1.10	3.70
Tobacco (SEGA)	7.56	7.11	6.08	2.27	12.75
Other Expenses (SEGD)	5.73	4.93	2.84	3.29	11.48
CPI-U (SA0)	**3.42**	**3.04**	**1.72**	**1.68**	**5.01**

A.2 Consumer expenditure survey data

In this section, we provide 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 which 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.

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

	Income deciles			Salary deciles			Expenditure deciles		
	1st	5th	10th	1st	5th	10th	1st	5th	10th
Food at Home	18.7	14.2	11.1	16.5	14.0	11.1	22.0	14.3	9.9
Food Away	7.2	7.5	7.3	7.7	7.6	7.2	8.0	7.3	6.9
Alcohol	1.0	1.1	1.2	1.1	1.2	1.2	1.1	1.1	1.1
Rented Dwellings	15.6	12.4	6.0	13.7	12.4	6.0	21.8	10.6	5.9
Owned Dwellings	15.4	17.1	22.6	14.5	16.8	22.8	6.5	19.3	22.6
Other Lodging	0.5	0.6	1.4	0.7	0.6	1.3	0.3	0.6	1.5
Energy	6.2	5.4	4.3	5.7	5.2	4.3	6.6	5.6	3.7
Water	0.9	1.0	0.9	0.9	0.9	0.9	0.9	1.0	0.8
Phone	3.4	3.0	2.3	3.2	3.0	2.3	3.8	3.0	2.1
Household F&O[22]	3.3	4.5	7.0	3.9	4.7	7.0	2.5	4.4	8.1
Apparel	4.0	4.3	5.6	4.4	4.6	5.7	3.7	4.2	5.7
Gasoline	4.2	5.3	4.4	5.0	5.6	4.5	4.3	5.4	3.8
Other Vehicle Expenses	4.3	6.8	7.2	5.5	7.2	7.3	3.7	6.8	7.0
Public Transportation	1.0	1.0	1.7	1.1	1.0	1.6	1.0	0.9	1.8
Medical	5.0	6.2	5.0	5.4	5.2	4.6	4.9	6.2	5.6
Entertainment	3.8	4.9	6.5	4.5	5.2	6.5	3.4	4.8	7.0
Personal Care	0.9	1.0	1.0	1.0	1.0	1.0	0.9	1.0	0.9
Reading	0.4	0.5	0.6	0.5	0.5	0.6	0.4	0.5	0.6
Education	1.6	0.8	2.3	2.1	1.0	2.4	1.3	0.9	2.9
Tobacco	1.7	1.4	0.6	1.7	1.4	0.6	2.3	1.3	0.6
Other Expenses	0.8	1.1	1.1	0.9	1.1	0.9	0.6	1.0	1.5

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 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

[22] Household Furnishings and Operations

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: 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

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 these spendings 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 10 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.

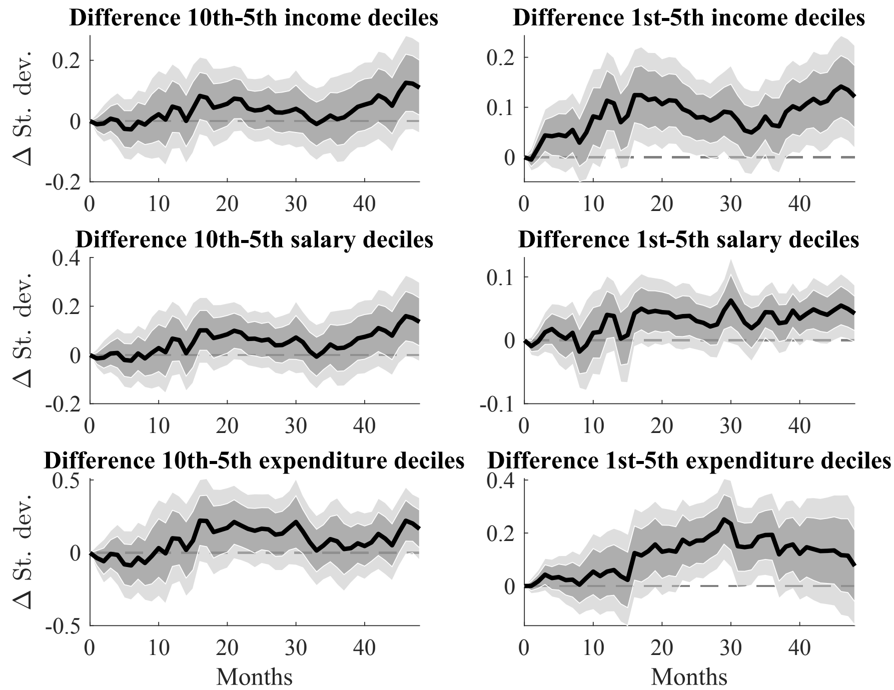
As it can be noticed in Figure 8, both the median inflation rates of the 10th as well as of the 1st deciles of income, salary, and expenditures react much less to a monetary policy shock than the 5th deciles resulting in a positive and significant response of their differences. The U-shaped response 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 Further robustness checks

As a further robustness check, Figure 11 reports the impulse responses excluding all U.S. recession periods from the analysis (1981M07:1982M11, 1990M07:1991M03, 2001M03:2001M11). The results remain qualitatively unchanged with respect to the baseline specification.

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 alternative measure of monetary shocks we use is the high-frequency proxy proposed in Bauer and Swanson (2022). The proxy is computed from

Figure 10: Differences in impulse responses across deciles



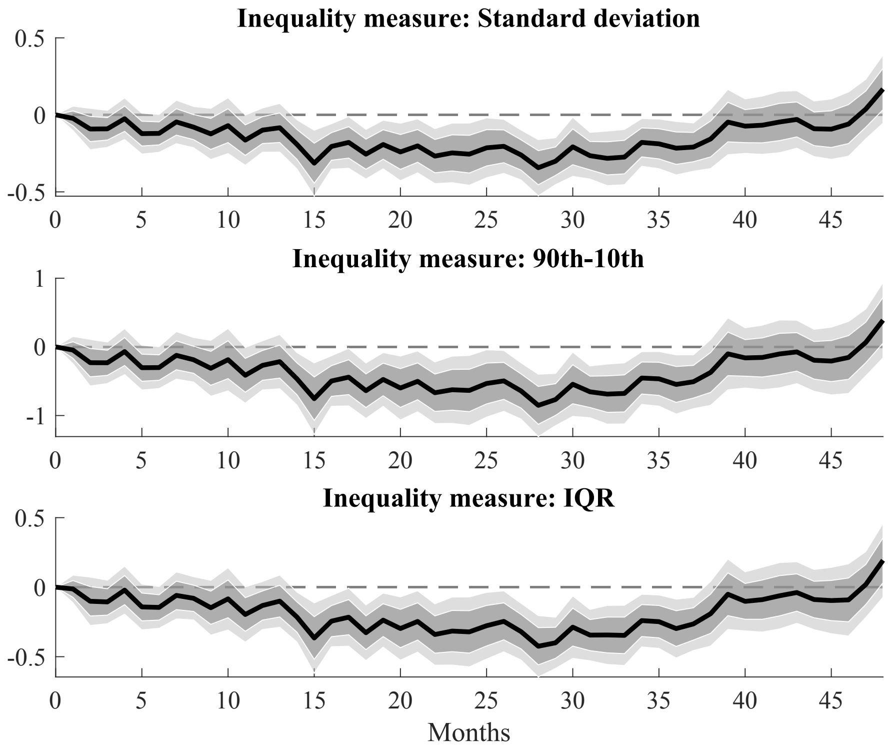
Notes: The figure plots impulse responses to a percentage point contractionary monetary policy shock, as well as one and 1.65 standard deviation confidence intervals for the difference in decile-specific inflation rates across deciles of the demographic groups. The first column reports the responses 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.

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 1988 to 2019.

The results are presented in Figure 12. The top panel reports the response of the cross-sectional standard deviation to a contractionary shock and the bottom panel shows the response of inflation inequality across expenditure deciles. All the regressions include the same controls as in the baseline specification. In response to contractionary monetary policy shocks inflation dispersion as well as inequality decrease. 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

Figure 11: Impulse responses of inflation dispersion (without recession periods)



Notes: The figure plots 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

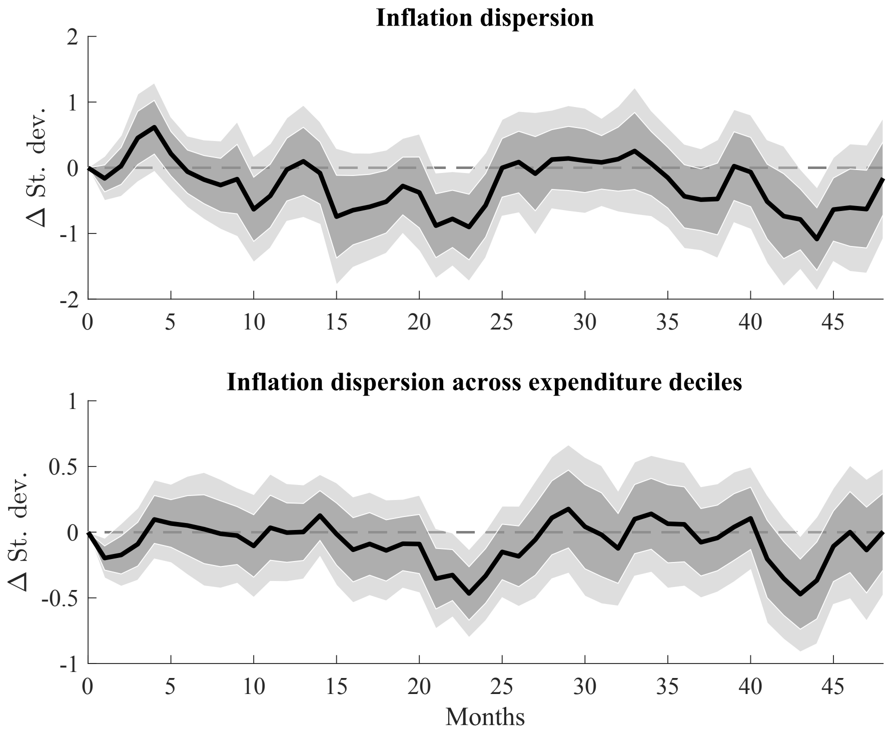
standard deviation of inflation for the four divisions using expenditure weights as well as price indices at division level[23].

The responses across U.S. divisions are reported in Figure 13. 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.

Finally, 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.

[23] 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.

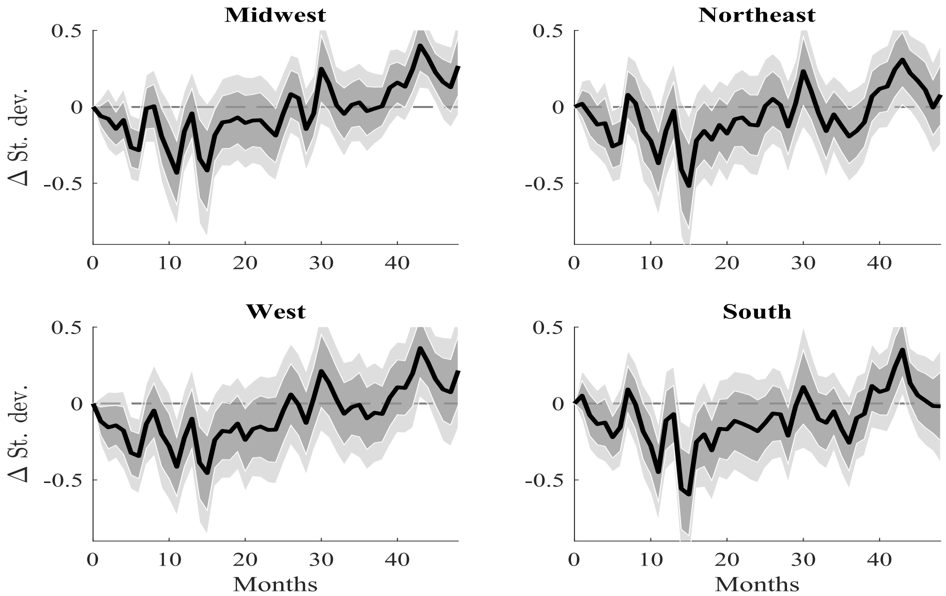
Figure 12: Impulse responses of inflation dispersion and inequality, Bauer and Swanson (2022) monetary shocks



Notes: The figure plots impulse responses to a percentage point contractionary monetary policy shock, as well as the 1.65 standard deviation confidence intervals. The horizontal axis is in months. Impulse responses are computed at a monthly frequency using data for the period 1988M2:2019M12.

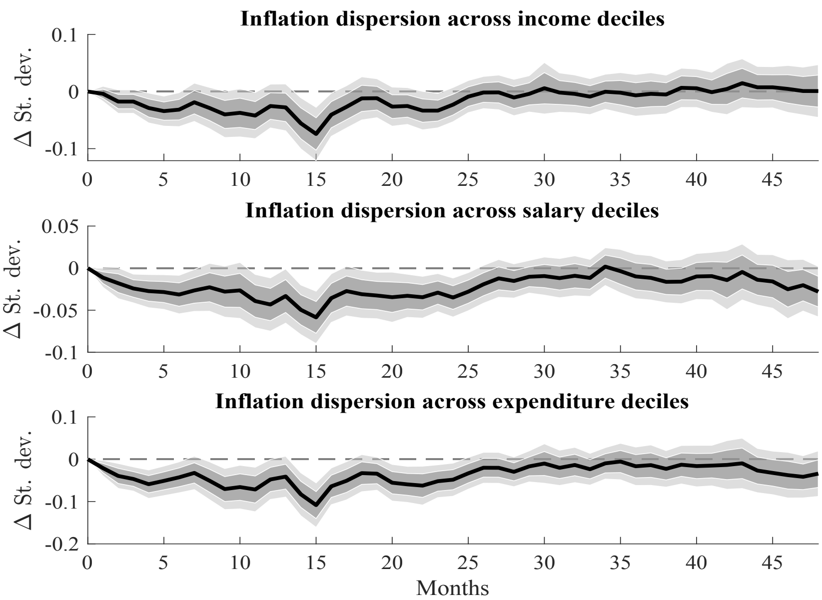
In Figure 14 we report the responses of inflation inequality for income, salary, and expenditures to a contractionary monetary shock. Inflation inequality is measured as the standard deviation of the median inflation rates across deciles. Following a monetary shock the inflation inequality responses are still negative and statistically significant confirming the baseline results.

Figure 13: Impulse responses of inflation dispersion across U.S. divisions



Notes: The figure plots 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.

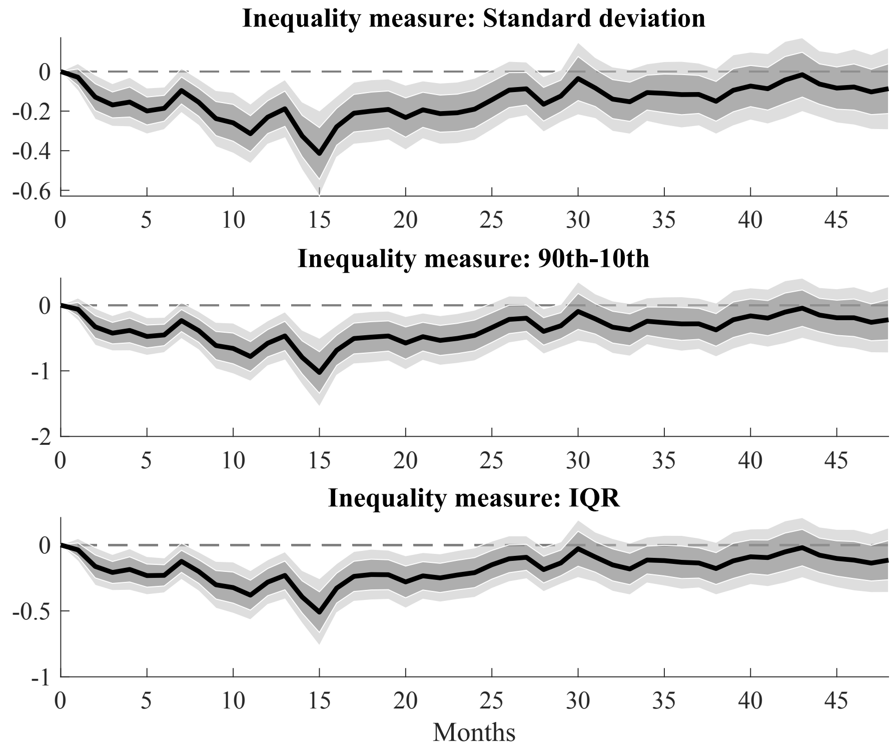
Figure 14: Impulse responses of the dispersion across the median inflation rates for income, salary, and expenditure deciles



Notes: The figure plots 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.

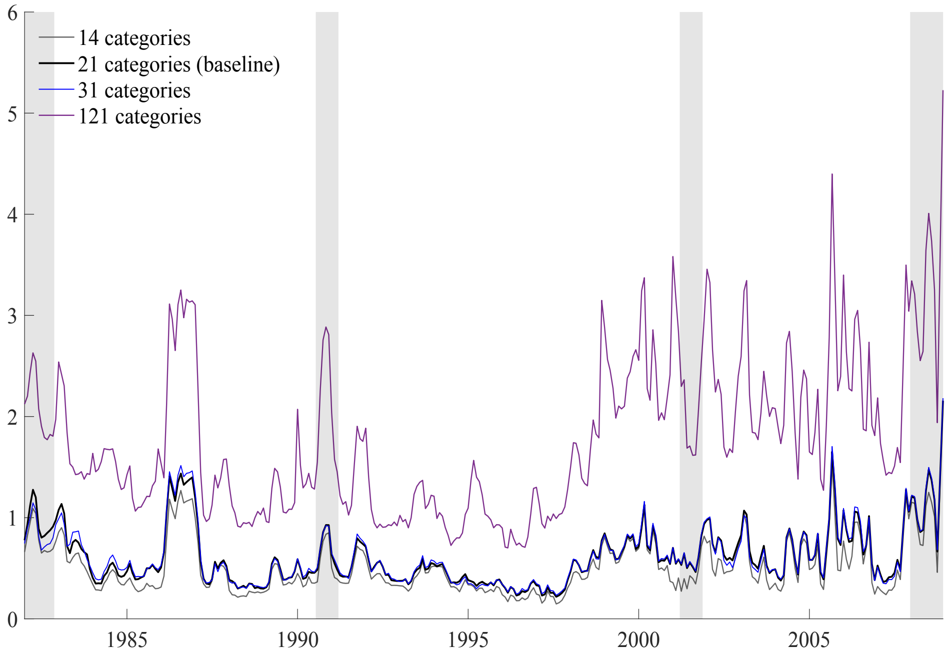
E Robustness plots

Figure 15: Impulse responses of inflation dispersion



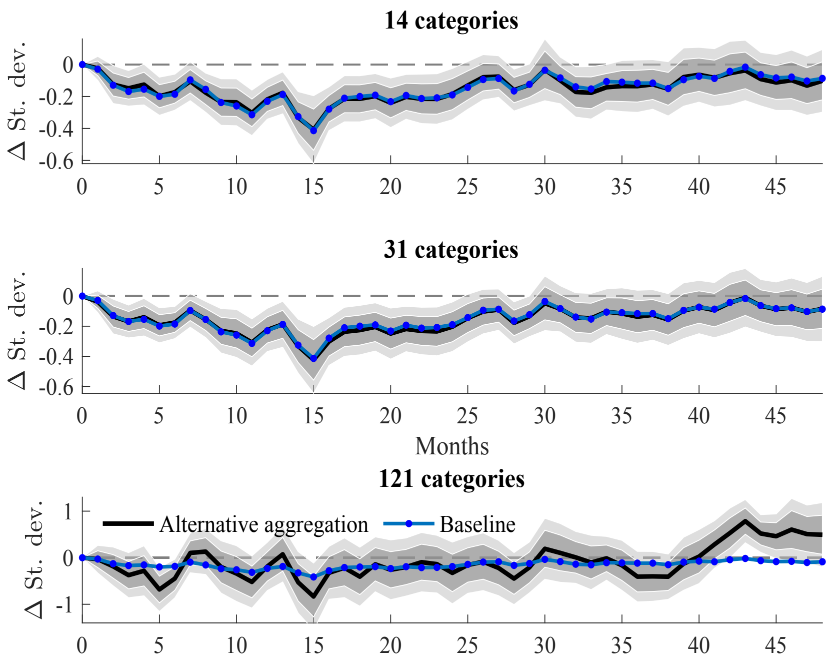
Notes: The figure plots impulse responses to a percentage point contractionary monetary policy shock, as well as one and 1.65 standard deviation confidence intervals for the respective inflation dispersion measures. The horizontal axis is in months. Dispersion is measured using the cross-sectional standard 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 16: Historical series of inflation dispersion measures



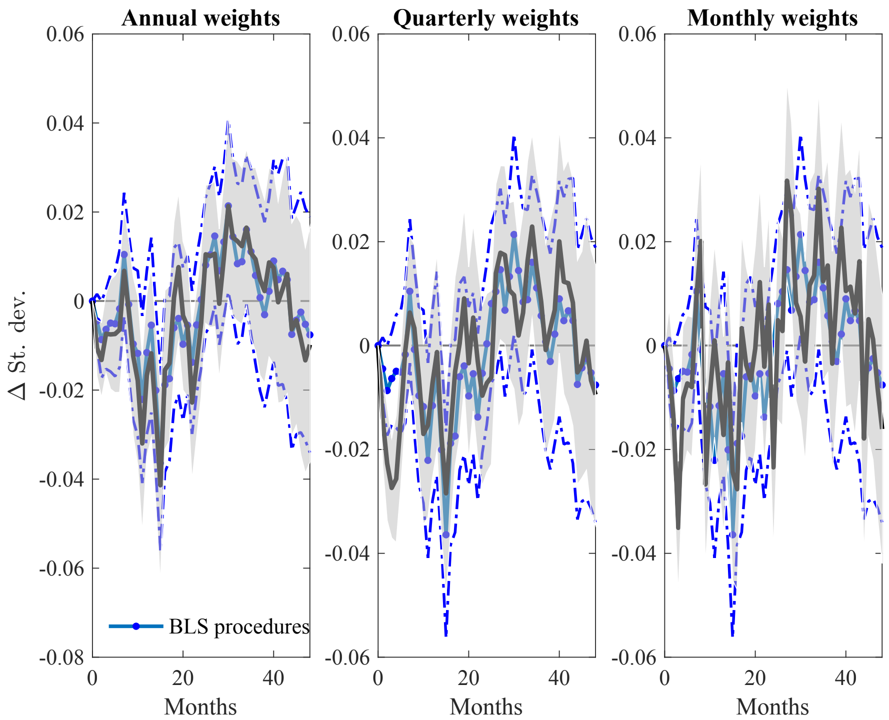
Notes: The plot shows the evolution of inflation dispersion measured using the cross-sectional standard deviation computed using 14, 21, 31, and 121 expenditure categories. All the series refer to the period 1981M1:2009M12. The gray shaded areas depict U.S. recessions.

Figure 17: Impulse responses of the cross-sectional standard deviation of inflation (alternative aggregations)



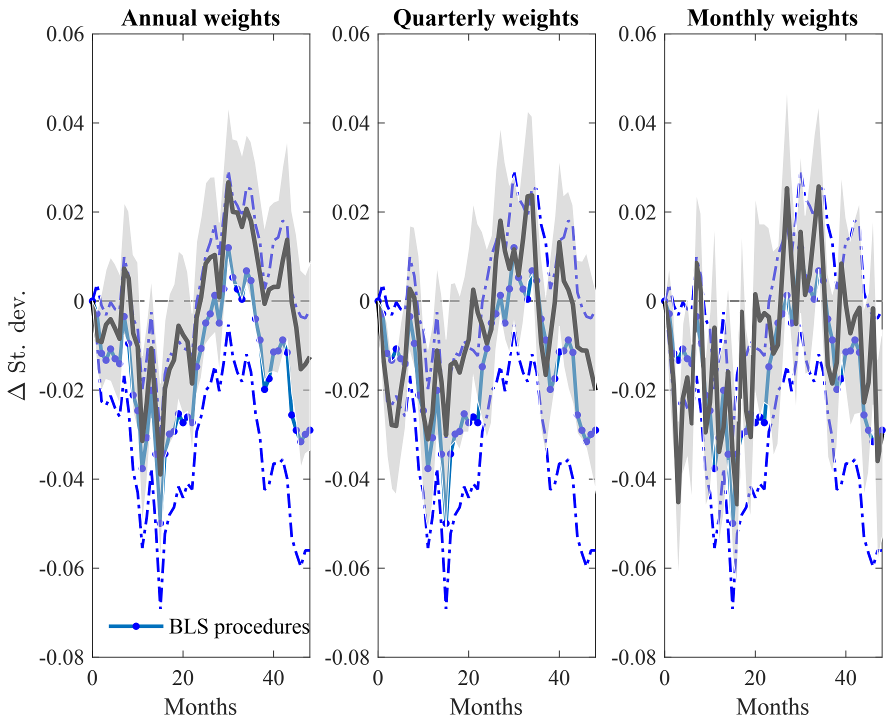
Notes: The figure plots impulse responses of alternatively aggregated inflation rates to a one percentage point contractionary monetary policy shock, as well as one and 1.65 standard deviation confidence intervals for the respective inflation dispersion measures. The solid blue line refers to the impulse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

Figure 18: Impulse responses of inflation inequality across income deciles with time-varying weights



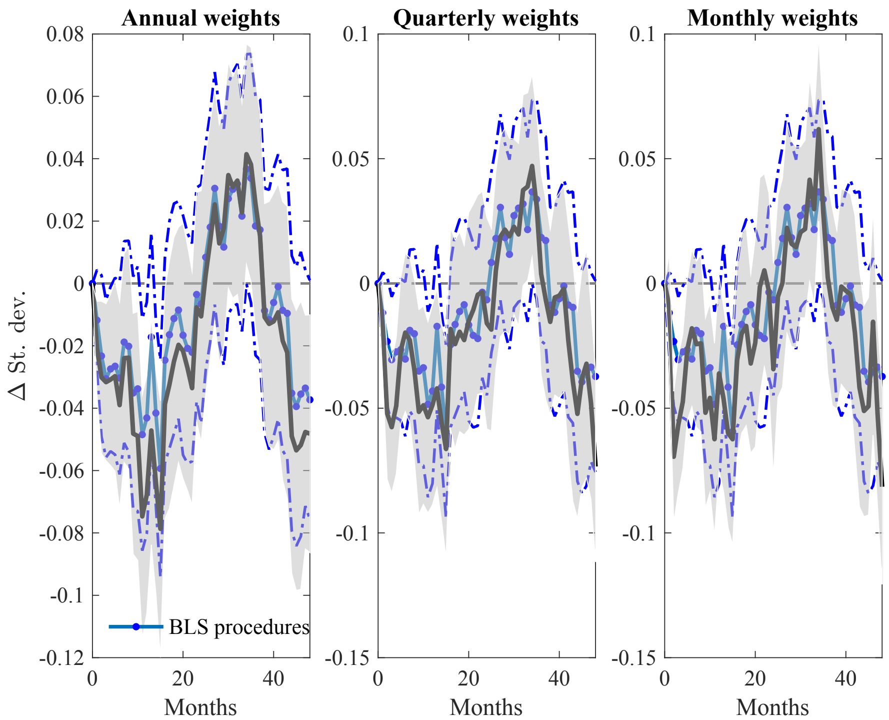
Notes: The figure plots impulse responses to a percentage point contractionary monetary policy shock (black line) as well as one standard deviation confidence interval (gray area) for inflation inequality across income deciles. Inflation inequality is measured using the cross-sectional standard deviation 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 19: Impulse responses of inflation inequality across salary deciles with time-varying weights



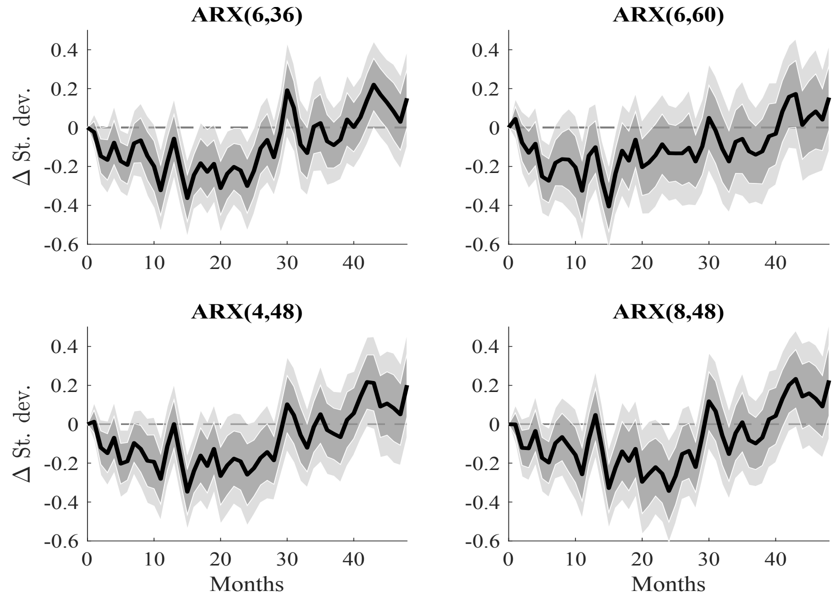
Notes: The figure plots impulse responses to a percentage point contractionary monetary policy shock (black line) as well as one standard deviation confidence interval (gray area) for inflation inequality across salary deciles. Inflation inequality is measured using the cross-sectional standard deviation 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 20: Impulse responses of inflation inequality across expenditure deciles with time-varying weights



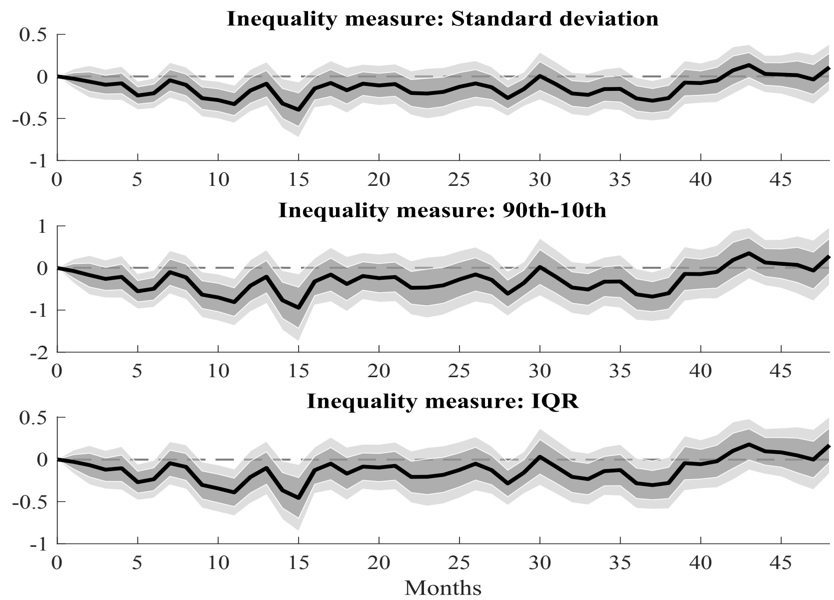
Notes: The figure plots impulse responses to a percentage point contractionary monetary policy shock (black line) as well as one standard deviation confidence interval (gray area) for inflation inequality across expenditure deciles. Inflation inequality is measured using the cross-sectional standard 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 21: Impulse responses of inflation dispersion for different lag specifications



Notes: The figure plots 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 22: Impulse responses of inflation dispersion (without Volcker period)



Notes: The figure plots 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.