Monetary policy shocks and inflation inequality

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September 2022

Abstract

We evaluate household-level inflation rates since 1980, for which we compute various dispersion measures, and we assess their reaction to monetary policy shocks. We find that (i) contractionary monetary policy significantly and persistently decreases inflation dispersion in the economy, and that (ii) different demographic groups are heterogeneously affected by monetary policy. Due to different consumption bundles, middle-income households experience higher median inflation rates, which at the same time are more reactive to a contractionary monetary policy shock, leading to an overall convergence of inflation rates between income groups. These results imply that (iii) 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.

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

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We would like to thank Florin Bilbiie, Jean-Paul Renne, and Andreas Tischbirek for their valuable comments and guidance. We are also grateful to Philippe Bacchetta, Kenza Benhima, Yuriy Gorodnichenko, Andrei Levchenko, Christina Patterson, Ricardo Reis 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.

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 decisions made by the monetary authorities in completely different ways. Therefore, both economic researchers and central bankers in the last years 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.

It is of pivotal importance that central banks take these differences into account for the conduct of a more inclusive monetary policy. This has become especially relevant during the current period of extremely high inflation rates worldwide. The monetary and fiscal policies that are going to be implemented to tackle the rise in inflation need to take into account how different households will be heterogeneously affected by them.

In this paper, we argue that studies of household inequality in terms of expenditure, salary and income cannot abstract from also considering how the inflation rates of their consumption bundles adjust in response to shocks. Despite the fact that high-income households experience an inflation rate that is lower, less volatile[1] and less responsive to monetary shocks[2], how this translates into real consumption inequality has not yet been studied.

The first contribution of this paper is to compute a measure of inflation at the household level and to evaluate how monetary policy influences the distribution of individual inflation rates. We exploit the fact that the consumption bundles across consumers differ in the expenditure shares spent on each subcategories of the Consumer Price Index (CPI) [3]. Therefore,

[1]See, among others, Johannsen (2014), Kaplan and Schulhofer-Wohl (2017) and Jaravel (2019).

[2]See Cravino et al. (2020).

[3]The categories are 21 fairly broad baskets of goods and services, for which we can match the expenditure data to the price data (see chapter 2).

we combine item-level price data from the Bureau of Labor Statistics (BLS) with individual expenditure data from the Consumer Expenditure Survey (CEX) to create household-level inflation rates.

We document that differences in individual inflation rates are sizable. Contractionary monetary policy shocks decrease the median inflation rate and significantly reduce the dispersion and skewness of the distribution. This implies that the households which experience higher inflation rates are also those that observe their inflation decrease the most after a monetary shock.

We then evaluate which sectors are mainly responsible for the decrease in inflation dispersion. Even though they account for only a relatively small expenditure share, *Energy*, *Water* and *Gasoline* explain almost entirely the response of inflation dispersion to monetary shocks.

The second contribution is to study whether the inflation rates of different demographic groups are heterogeneously affected by monetary policy. By defining *inflation inequality* as the cross-sectional standard deviation of the median inflation rates across expenditure, salary and income deciles, we demonstrate that contractionary shocks lead to a substantial and persistent decrease in inflation inequality. On the one hand, the inflation of low- and middle-income households tends to be higher. On the other hand, it is more reactive to shocks than that of high-income households and therefore decreases more after a monetary shock. The same result holds for salary and expenditure deciles, confirming the role of endowments on individual inflation rates.

The third 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 on expenditure inequality. Although the nominal expenditure of low- and middle-income households decreases more after a shock with respect 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, overall, still found to increase after a monetary shock corraborating again the sizable redistributional effects that central banks can have on the economy.

Related literature

This paper contributes to two strands of the literature. First, our results complement the large body of empirical evidence on the relationship between monetary policy and inequality. With an approach analogous to the one we adopt, Coibion et al. (2017) demonstrate how consumption and income inequality increase in the U.S. following a contractionary shock. Similar findings have also been confirmed in other countries, and in different time periods (e.g., Mumtaz and Theophilopoulou, 2017, for the United Kingdom and Samarina and Nguyen, 2019 for the Euro Area).

The second strand is the growing literature on the heterogeneous responses of households to monetary policy shocks across demographic characteristics. An active part of the research community has focused its attention on expenditure inequality. Using the CEX data, **?** documents that young people adjust their consumption more than middle-aged and older households. Exploiting differences in the housing tenure of the survey respondents, Cloyne et al. (2019) show that households with mortgage debt are the most sensitive group to shocks whereas the consumption of homeowners without debt is basically unaffected by the change in interest rates.

Less attention has been paid to heterogeneity in terms of inflation rates across demographic groups. Previous studies include, among others, Johannsen (2014) and Orchard (2022) (using CEX data) and Kaplan and Schulhofer-Wohl (2017) (using Nielsen scanner data) who document substantial cross-sectional dispersion in household inflation rates as well as Jaravel (2019) who find, for the period 2004-2014, that high-income households are exposed to much lower inflation rates than low- and middle-income households.

Particularly related to our results, Cravino et al. (2020) show that the high-income households median inflation rate reacts significantly less than that of middle-income households following a contractionary shock. We see our paper as both complementing and extending their research. We complement their findings on the different inflation rate responses along the income distribution by also looking at the effects on the inflation dispersion across income, salary and expenditure deciles. We extend their research not only by identifying the most important categories for the response of inflation dispersion, but especially by linking inflation heterogeneity and expenditure inequality.

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. We exploit the differences in consumption patterns between different households and apply good-level price indices to expenditure categories in order to retrieve individual, household-level inflation rates.

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 to compute the share of different goods in an aggregate index and therefore provides weights[4]. 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 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 to 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 will call these inflation rates for subgroups of the consumer basket *inflation subindices*[5]. The construction of these inflation rates is subject to a tradeoff between consistent and sufficiently long time series on one hand, and finely disaggregated time series that catch as much of the difference in inflation as possible.

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. 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

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

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

price level, this will lead to differences in terms of experienced inflation[6]. 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[7]. 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 month).

[6]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.

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

Like the inflation subindices, we aggregate the expenditure data into 21 groups[8], matching the classification of the CEX with the one from the price indices. In the next step, we aggregate the 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[9].

Luckily, expenditure shares show large variation that can be explained to a large part by differences in total expenditure, income, or salaries. To show the variance in expenditure shares, we group the households in deciles of total expenditure and employ a correspondence analysis to display the differences in expenditure shares for all categories[10].

2.3 Computation of individual inflation rates

In a 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. Then, we compute the individual inflation rate for household i as:

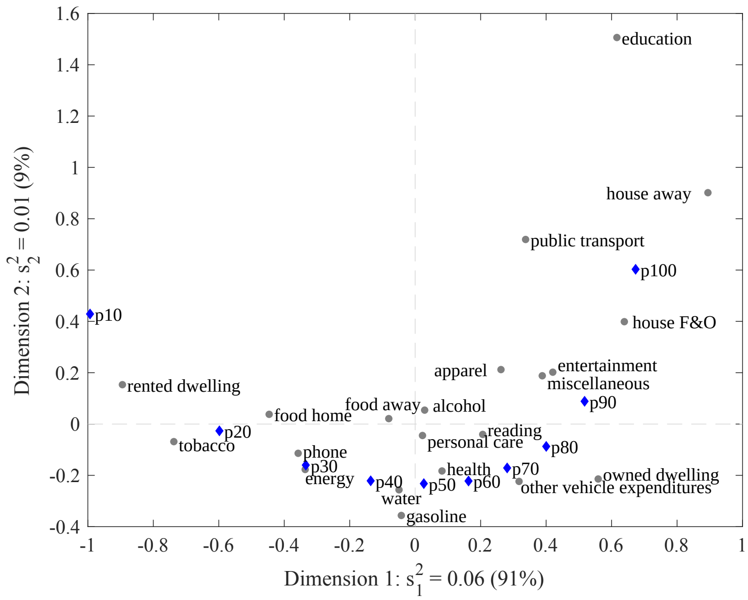
$$\pi^i_{t-k,t} = \sum_{j \in J} w^i_j \pi_{j,t-k,t} \tag{1}$$

[8] 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 inflation rate across deciles, vehicle purchases are included since it is less likely this category can bias the decile-level inflation rates. See Appendix B for more details.

[9] The relevance of the substitution effects is studied in subsection 6.1 where we compute the expenditure shares at higher frequencies.

[10] In the Appendix, Table 2 displays the actual weights for individual sectors along expenditure, income and salary deciles.

Figure 1: Correspondence analysis of the variation in weights for different expenditure deciles



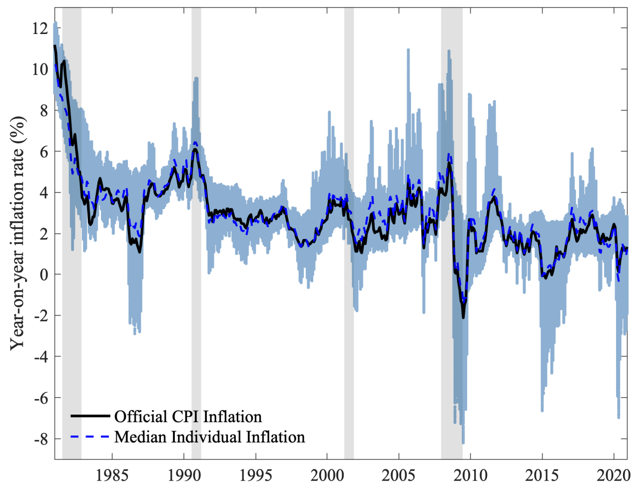
Notes: The correspondence analysis displays the scores for the two largest principal components of the weights for all 21 sectors used in our analysis. The first principal component, on the horizontal axis, accounts for 91% of the variation. It can be interpreted as showing linear differences between expenditure deciles. That is, goods on the left-hand side of the origin are purchased more by low-expenditure households, and vice versa. The vertical axis explains 9% of the variance. Sectors at the top of the figure (with a high y-value) are purchased relatively more by the poles of the distribution, whereas goods at the bottom (negative y-value) of the figure are purchased more by the middle of the distribution (e.g., gasoline). The distribution of weights is very similar across income deciles.

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. The scatter plot of the calculated household-specific rates of inflation depicts the dispersion of individual inflation rates (Figure 2).[11]

Figure 2: Official CPI inflation, dispersion, and median of individual inflation rates



Notes: The scatter plot and median individual inflation rate are computed using winsorized data, meaning that the top and bottom 1% of household-level inflation rates at every point in time are excluded. The gray shaded areas depict U.S. recessions.

On the one hand, 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.

On the other hand, the scatter plot in the same figure reveals 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

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

and implicitly assume that households are exposed to the same inflation rate. Figure 2 seems to strongly reject this assumption.

2.5 Measures of dispersion

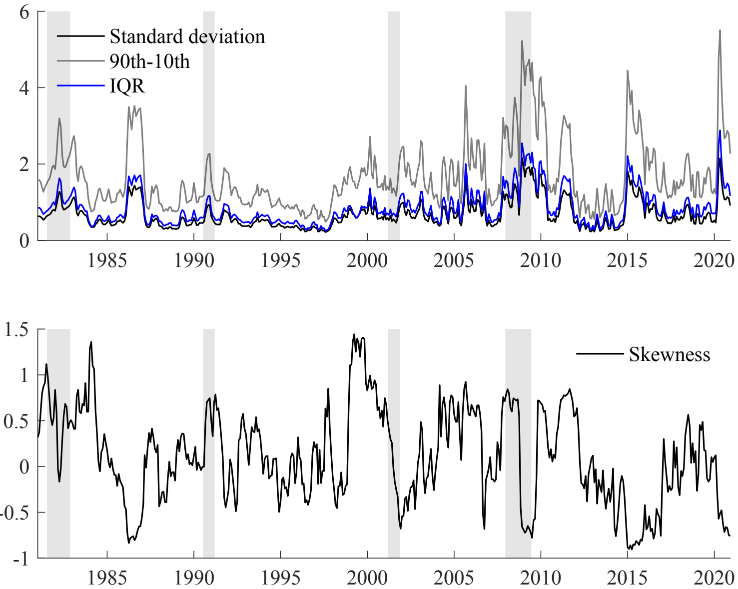
To evaluate how monetary policy shocks affect inflation dispersion in the U.S., we construct three different measures of dispersion: the cross-sectional standard deviation, the difference between the 90th percentile and the 10th percentile (depicted as 90th-10th, henceforth), and the cross-sectional interquartile range (IQR). For our main analysis we deliberately stop before the recent financial crisis to exclude the zero lower bound period.

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.

The top plot in Figure 3 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 Johannsen (2014) found. 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.

The bottom plot displays the time series for the overall skewness of the cross-sectional inflation distribution. The skewness and the dispersion measures are not strongly correlated. Therefore, the study of both the second and third moments will convey complementary information regarding the impact of contractionary monetary policy shocks on the shape of the distribution.

Figure 3: Historical series of inflation dispersion measures and overall skewness



Notes: In the top 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. The bottom plot reports the time series for the overall skewness of the inflation distribution. All the series refer to the period 1981M1:2020M12. The gray shaded areas depict U.S. recessions.

3 The impact of monetary policy shocks on 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 more in-depth how the inflation distribution reacts to contractionary shocks by focusing on the response of the overall skewness. Finally, we evaluate 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). In particular, 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 as in Coibion et al. (2017) and Cravino et al.

(2020):

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

where x is the variable of interest. The monetary policy shocks are denoted by e_t^{RR} and c_h is a vector of horizon dummies. 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* and is used to generate the accumulated impulse response to a 1 percentage point contractionary monetary policy shock[12].

To identify unanticipated changes in the short-term interest rate we use the monetary policy shock series devised by Romer and Romer (2004, henceforth called R&R shocks), and extended by Coibion et al. (2017). The shock series covers the survey sample periods from 1980 to 2007 [13].

3.2 Analysis

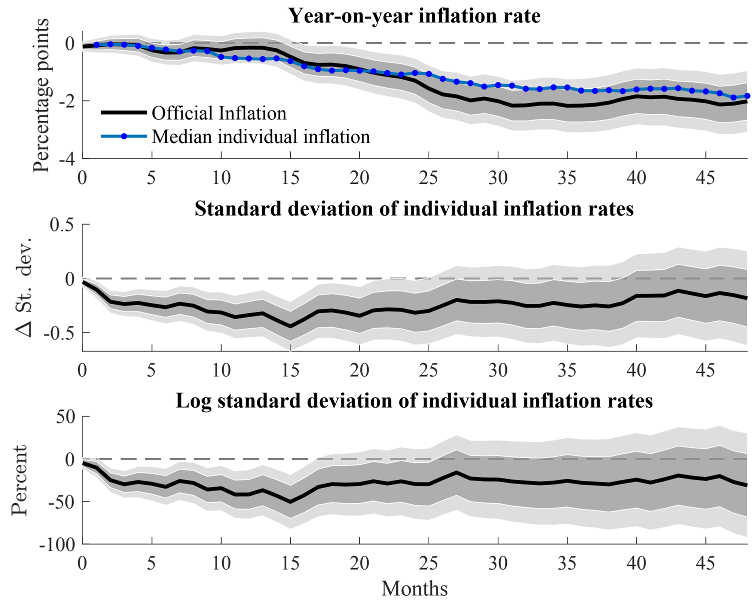
To evaluate the overall effects of a contractionary monetary policy shock on inflation dispersion, we estimate equation (2) using the cross-sectional standard deviation as the baseline measure of inflation dispersion[14]. The impulse responses are computed over a horizon of 48 months using data from 1980M1 to 2007M12 and standard errors are corrected as in Driscoll and Kraay (1998) to allow for arbitrary serial and cross-sectional correlation across horizons and time. For each impulse response, we present one and 1.65 standard deviation confidence intervals.

[12] 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.

[13] 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.

[14] The responses for the difference between the 90th and the 10th percentile of the cross-sectional distribution and the IQR are reported in Figure 20. Given the very high correlation among dispersion measures, the IRFs display similar patterns differing mainly in the magnitude of the response.

Figure 4: 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 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 1980M1:2007M12.

The results are reported in Figure 4. The top panel shows the responses of the annual inflation rate computed by the BLS (black line) as well as of the median inflation rate across households: 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 2, the response of the median inflation rate closely matched the response of aggregate inflation.

In the middle panel, we show the impulse response of our dispersion measure: the 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 3 years and approximately 30% at the end of the horizon considered. The average inflation rate over the time period considered is about 3.75% so a decrease in 1.5 percentage points corresponds to a decrease in 60% of the average value.

3.3 Importance of monetary policy shocks

We assess the importance of monetary policy shocks for inflation dispersion. For this purpose, we compute the share of the variance in inequality explained by the shock over the time period.

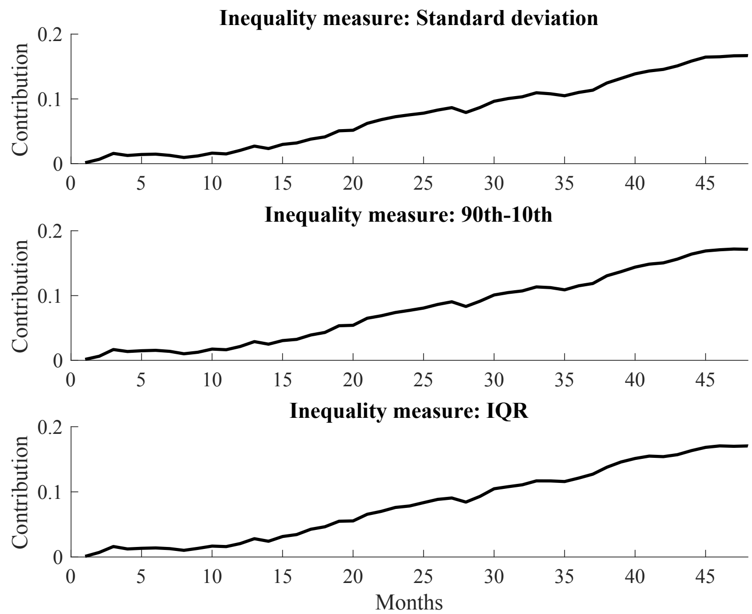
We measure the forecast error variance decomposition adopting the recently proposed estimator by Gorodnichenko and Lee (2019). Using the residuals of the regression in equation (2) as the estimated forecast error $\hat{f}_{t+h,t-1}$, we then estimate the following equation:

$$\hat{f}_{t+h,t-1} = \alpha_0 e^{RR}_{t+h} + ... + \alpha_h e^{RR}_t + \tilde{v}_{t+h,t-1} \tag{3}$$

where e^{RR}_t is the shock at time *t* and $\tilde{v}_{t+h,t-1}$ is the error term due to innovations orthogonal to the shock series.

Our estimate of the share of the variance in dispersion explained by the shock is given by the R^2 of (3) which, by construction, is between 0 and 1. This measure provides an estimate of the extent to which monetary policy shocks are quantitatively important in driving dispersion dynamics.

Figure 5: Forecast error variance decomposition for dispersion measures



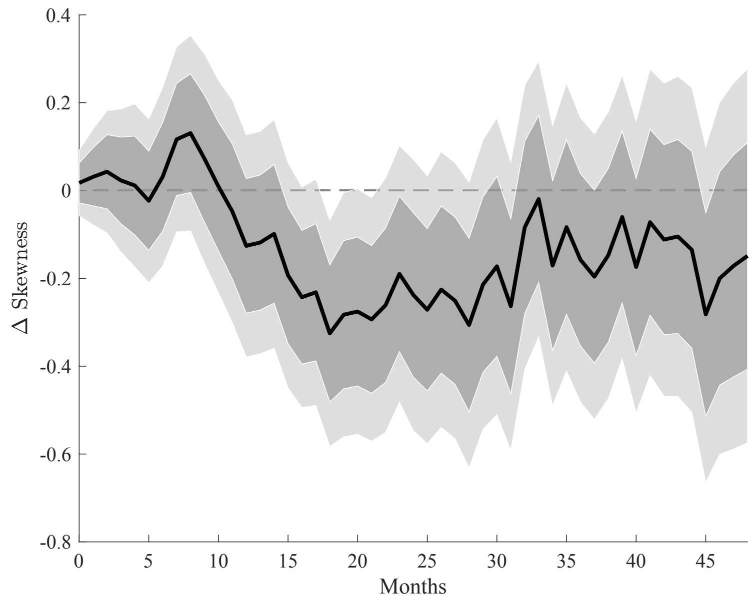
Notes: The figure plots the contribution of monetary policy shocks to the forecast error variance for the respective measure of inflation dispersion at different time horizons (in months).

The results from the variance decompositions are presented in Figure 5. Consistently with the impulse responses of the previous section, monetary policy shocks account for around 20% of the forecast error variance in the long run across the three measures of dispersion considered. These results are quantitatively in line with the contribution of monetary policy shocks to other inequality measures (Coibion et al., 2017, document that monetary policy shocks account for 10-20% of forecast error variance for expenditure and consumption inequality) as well as macroeconomic variables (Christiano et al., 1999).

3.4 Distributional consequences of monetary policy

In the previous section, we show that the dispersion of inflation decreases after a contractionary monetary policy shock. We now study more in-depth how the overall distribution of individual inflation rates adjusts after a monetary shock. We do so by focusing on the response of the cross-sectional skewness.

Figure 6: Impulse responses of inflation skewness

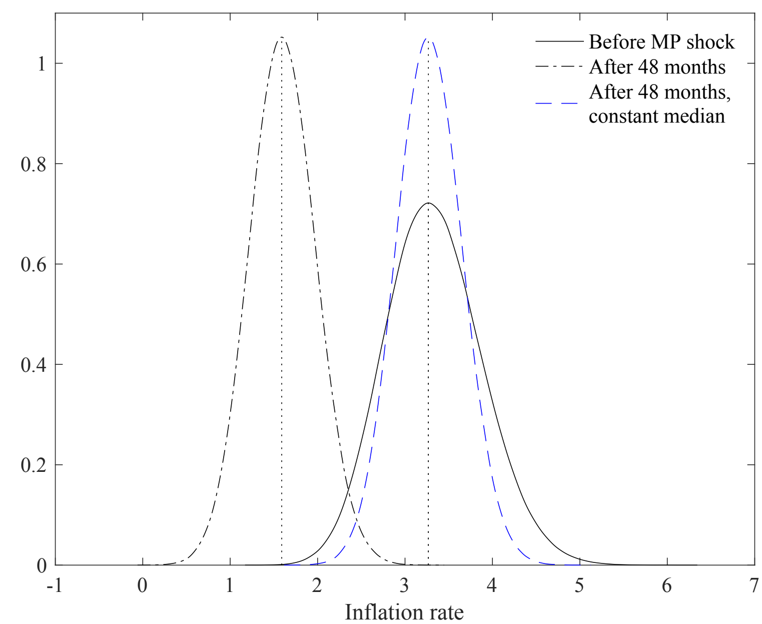


Notes: The figure plots impulse response to a percentage point contractionary monetary policy shock, as well as one and 1.65 standard deviation confidence intervals for the skewness of the inflation distribution. The horizontal axis is in months. Impulse responses are computed at a monthly frequency using data for the period 1980M1:2007M12.

In Figure 6 we estimate equation (2) using the skewness of individual inflation as the dependent variable. A contractionary monetary policy shock results in a decrease in the skewness of the distribution suggesting that the overall effect is asymmetrical. In particular, a lower skewness implies that the resulting distribution will be more left-skewed, i.e., more mass of the distribution is concentrated on the right tail. It follows that after a contractionary shocks, the right tail of the individual inflation distribution reacts more strongly relative to the left tail.

To ease the understanding of the previous results, Figure 7 illustrates the changes in the cross-sectional inflation distribution caused by a monetary policy shock. We start by plotting a Pearson distribution where the first three moments are equal to the unconditional median, standard deviation, and skewness of the individual inflation rates distribution (black solid line). It approximates the empirical distribution. We then derive the resulting median,

Figure 7: Graphical representation of the cumulative change in individual inflation after a monetary policy shock



Notes: The figure shows a Pearson distribution of individual inflation rates before (black solid line) a contractionary monetary policy shock using as median, standard deviation, and skewness the unconditional moments across time. The black dashed line reports the distribution of individual inflation rate 48 months after a contractionary monetary policy shock, matching the first three moments as calculated in the previous section. The blue dashed line displays the same distribution, keeping the median constant to better underline the changes in the second and third moments.

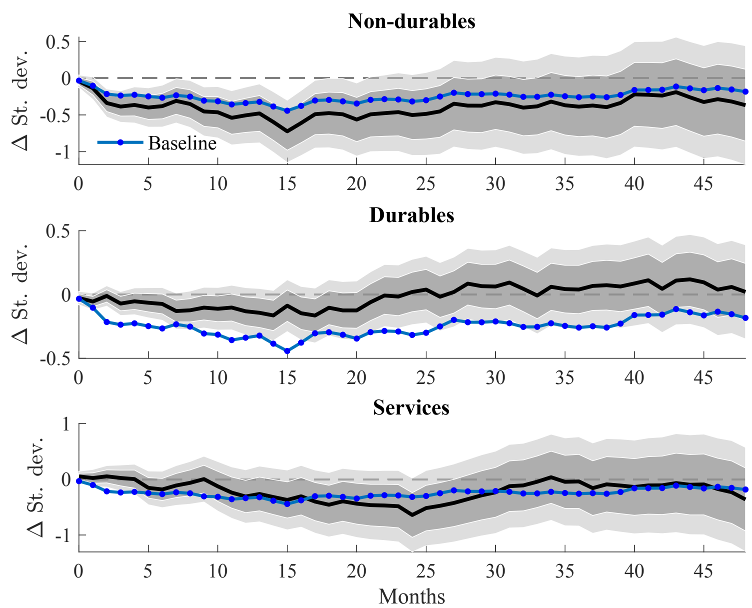
standard deviation, and skewness 48 months after the shock to compute the final distribution (black dashed line) by applying the estimates found in Figure 4 and Figure 6. The blue dashed line is obtained by simply shifting the black dashed line such that the median is kept constant to better visualize the changes in the second and third moments.

A contractionary shock shifts the entire distribution to the left since it reduces aggregate and individual inflation rates. The inflation rates at the right tail of the distribution are more affected relative to those on the left tail. This has two consequences: first, the overall dispersion decreases. Secondly, the asymmetric response of the inflation rates at the two tails makes the distribution more right-skewed (i.e., the skewness of the distribution decreases).

3.5 Sectoral contribution

We now assess which sectors are mainly responsible for the results documented in the previous sections. We start by computing inflation rates at the household-level considering only a subset of the overall consumption bundles. 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.

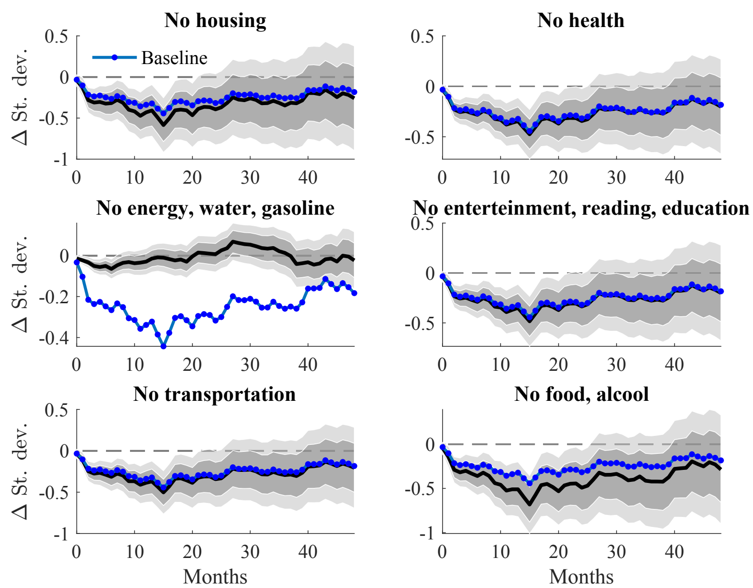
Figure 8: Impulse responses of inflation dispersion for different sub-categories of expenditure



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 1980M1:2007M12.

The results are reported in Figure 8. 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.

Figure 9: 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 1980M1:2007M12.

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 9. 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*. This new specification is close to the definition of

[15] *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*.

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

Core CPI that the Federal Reserve Bank uses to decide which monetary policy to adopt. Not surprisingly, removing three of the most volatile categories cancels out the response of inflation dispersion almost entirely.

To summarize, there is large heterogeneity in the contribution that each sector has on inflation dispersion. Many categories, even though having a large expenditure share, have only a negligible impact. Most of the observed effects is 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: expenditure, salary, and income deciles.

4.1 Expenditure weights

Heterogeneity in inflation rates comes from the fact that households consume different consumption bundles. We report the average expenditure weights for the first, fifth, and tenth decile of income, salary, and expenditure deciles for each of the 21 categories in Table 2.

Several interesting facts can be noticed: first of all, 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*, *Medical 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 on these categories with respect to high-income households.

4.2 Impulse responses by demographic groups

To evaluate how the inflation rate 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 median inflation rates across expenditure, salary, and income deciles which we define as *inflation inequality*[17].

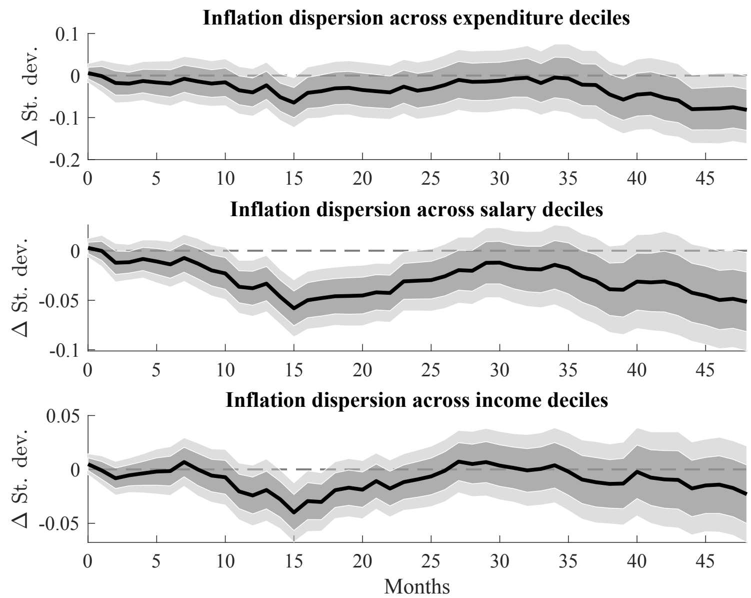
As one can see from Figure 10, following a contractionary monetary policy shock inflation inequality for the three groups significantly and persistently decreases. To better understand the main drivers of this result, we focus first on the median inflation rates of the different expenditure deciles, whose relative impulse responses are reported in the left panel of Figure 11.

Similar to what Cravino et al. (2020) found for income, the annual inflation rate of the households at the top of the expenditure distribution reacts substantially less to monetary policy shocks than the one of those in the middle. This relationship can be better visualized by looking at the right panel of Figure 11 which shows the responses across deciles after 24 and 48 months (dashed and dotted red lines, right axis). The difference between middle- and high-expenditure households is economically sizable. After 24 months, the annual inflation rate of the households in the top decile responds 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 panel the median inflation rates across expenditure deciles relative to the time period considered (black line,

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

Figure 10: Impulse responses of inflation dispersion across expenditure, salary, and income 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 expenditure (top), salary (middle), and income deciles (bottom). Inflation inequality is measured using the cross-sectional standard deviation of the decile median inflation rate. The horizontal axis is in months. Impulse responses are computed at a monthly frequency using data for the period 1980M1:2007M12.

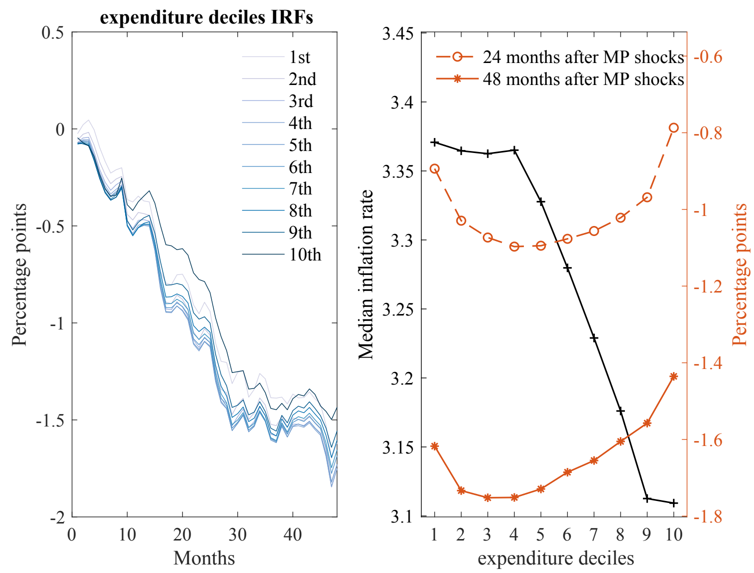
left axis)[18]. One can notice how the higher the decile the lower the median inflation rate. While this result is not new per se[19], most of the literature that focused on inflation inequality used the Nielsen scanner data available only from 2004. Here we show that the heterogeneity in inflation rates across income deciles holds considering the period 1980-2007 as well.

On the one hand, given their consumption bundle, high-expenditure 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

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

[19]See, among others, Jaravel (2019) and Kaplan and Schulhofer-Wohl (2017).

Figure 11: Impulse responses across expenditure deciles



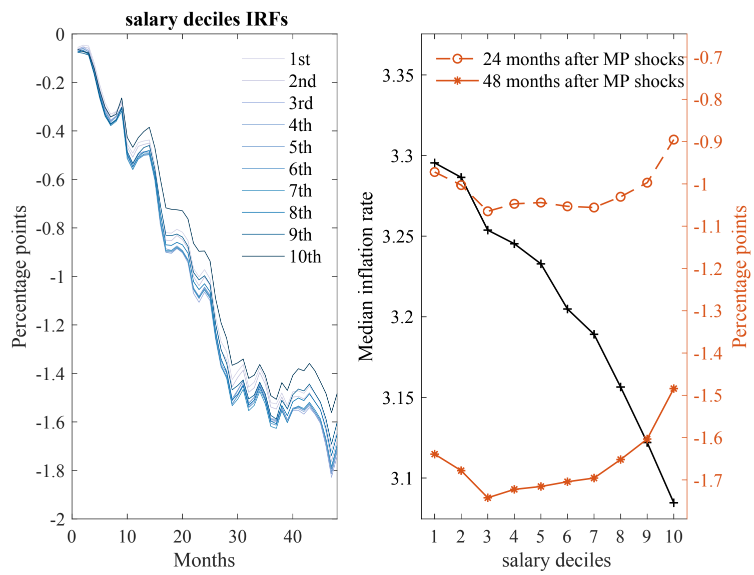
Notes: The left figure plots the impulse responses of the different expenditure deciles following a one percentage-point increase in the monetary policy shock, with monthly data for the period 1980M1:2007M12. The right plot reports the median inflation rate across deciles (left axis) as well as the cross-sectional distribution of the responses after 24 and 48 months after the shock (right axis).

as documented in Figure 10. Similar results can be found focusing on salary and income deciles as shown in Figure 12 and Figure 13 respectively.

Our focus is not on the absolute response of group-based inflation rates to a monetary policy shock, but rather the response relative to a baseline group. Therefore, we estimate again 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 14 reports the responses of the difference in median inflation rate for the 10th and the 5th decile, 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 from Figure 10, Figure 12 and Figure 13, 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

Figure 12: Impulse responses across salary deciles

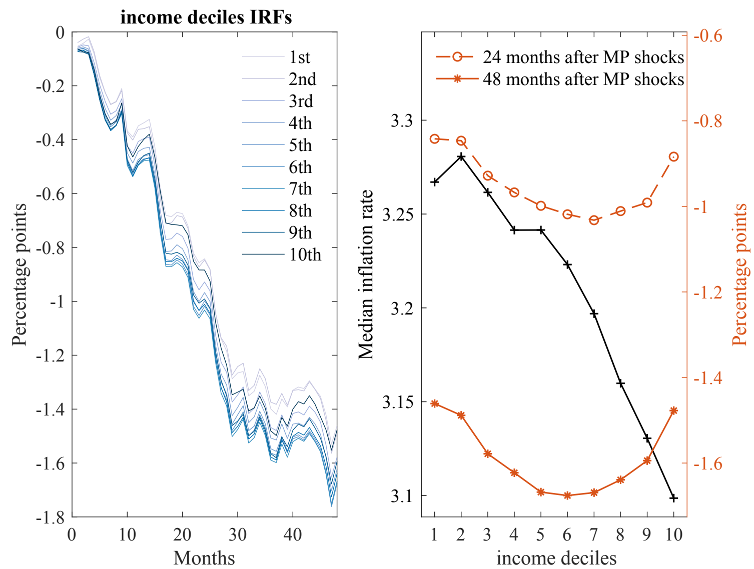


Notes: The left figure plots the impulse responses of the different salary deciles following a one percentage point increase in the monetary policy shock, with monthly data for the period 1980M1:2007M12. The right plot reports the median inflation rate across deciles (left axis) as well as the cross-sectional distribution of the responses after 24 and 48 months after the shock (right axis).

response of their differences. The U-shaped response across deciles is in line with what 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.

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

Figure 13: Impulse responses across income deciles



Notes: The left figure plots the impulse responses of the different income deciles following a one percentage point increase in the monetary policy shock, with monthly data for the period 1980M1:2007M12. The right plot reports the median inflation rate across deciles (left axis) as well as the cross-sectional distribution of the responses after 24 and 48 months after the shock (right axis).

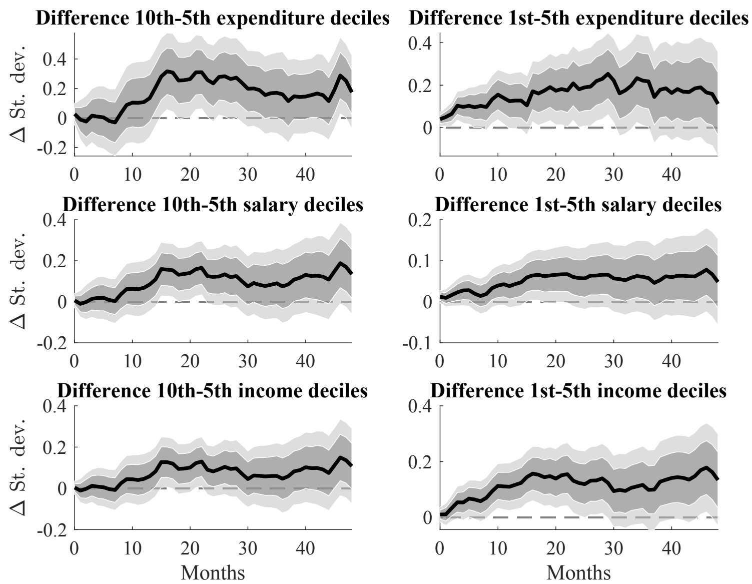
5 Real expenditure inequality

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[20]. 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. On the one hand, in line with the literature, we deflate each category by

[20] 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.

Figure 14: Differences in impulse responses across deciles

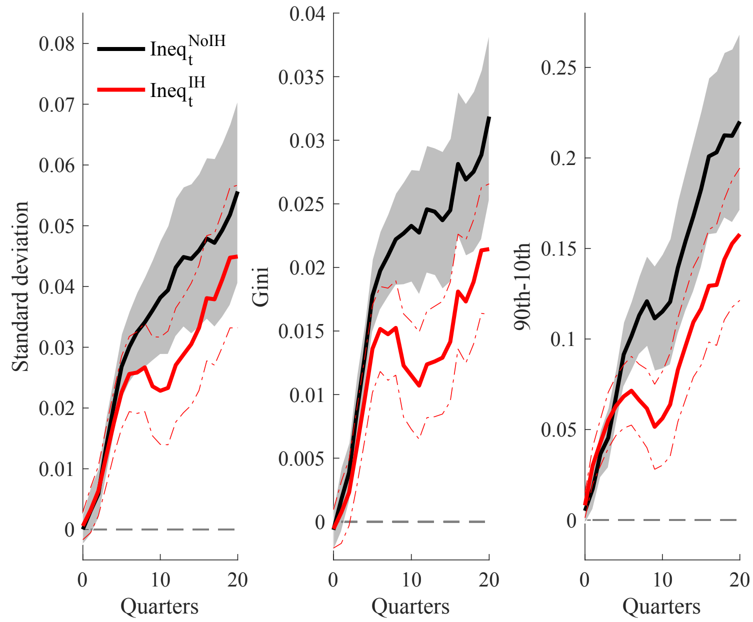


Notes: The figure plots impulse responses to a percentage point contractionary monetary policy shock, as well as one and 1.65 standard deviation confidence intervals for the difference in median inflation rate across deciles of different demographic groups. The first column reports the responses of the difference in median inflation rate for the 10th and the 5th decile, 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 1980M1:2007M12.

the aggregate CPI-U. On the other hand, we deflate 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. 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.

Expenditure 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

Figure 15: 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 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.

households i are equal to $Std(logC_{i,t}^{IH})$ and $Std(logC_{i,t}^{NoIH})$ with:

$$C_{i,t}^{IH} = \sum_{j \in J} \frac{C_{i,j,t}}{P_{j,t}}, \qquad C_{i,t}^{NoIH} = \sum_{j \in J} \frac{C_{i,j,t}}{P_t} \tag{4}$$

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.

In order 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 quarterly frequency) over the same time period, 1980Q1:2008Q4[21]. Since

[21] Similar results are obtained restricting the analysis to our baseline period.

the series are 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.

The results are reported in Figure 15. The black solid lines report the impulse responses of the three measures of expenditure inequality obtained 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 bundles 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, such that monetary policy still has redistributive effects on the economy.

This result can be explained by combining the new empirical evidence of 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 more likely to lose their job in an economic downturn). However, at the same time, the cost of their consumption basket decreases more strongly as well. Hence, the effect is partially offset in real terms. Real consumption heterogeneity, therefore, increases less than when a common inflation rate is assumed, resulting in a more muted, but still significant, response of expenditure inequality.

6 Robustness

In order 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. Firstly, we evaluate the importance of substitution effects. Secondly, we assess the sensitivity of our results to different lag specifications. Thirdly, 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 C. The figures are reported in Appendix D.

6.1 Substitution effects

Throughout the paper, we conduct our analysis under the assumption that changes in inflation dispersion are mainly driven by changes in prices and that changes in expenditure shares play only a marginal role. Both the inflation rate at household-level as well as at 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. In particular, the weights for the household-level inflation rate rely on the entire time series of expenditure (maximum 12 months) whereas the weights at 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 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 whether the granularity of the expenditure categories we choose plays any role. Second, we again compute our measures of inflation inequality across deciles by using annual, quarterly and monthly expenditure shares.

Following the literature, in computing the individual inflation rates we adopt a rather conservative aggregation in the number of categories considered. Not only 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 now show that the main results are basically unaffected by increasing or decreasing the number of categories considered. We report in Figure 21 the response from our baseline specification with 21 categories (blue line) against two alternative aggregations: using price indices at a much more granular level[22] (left panel) and an even more conservative number of categories [23] (right panel). As one can notice, the magnitude and the shape of the responses is basically the same to that obtained in our baseline specification.

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 frequency. It is important to notice that allowing the weights to vary at a much higher frequency than the biannual fre-

[22] 31 categories: 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.

[23] 14 categories: Food, Alcohol, Housing, Apparel, Gasoline, Other Vehicle Expenses, Public Transportation, Medical, Entertainment, Personal Care, Reading, Education, Tobacco and Other Expenses.

quency 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 puchases will account for a larger share.

We report in Figure 22 the response of the cross-sectional standard deviation of the median inflation rates across expenditure 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 the top panel of Figure 10.

Not surprisingly, moving from annual to quarterly and especially to monthly weights makes the response 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 income deciles whose responses are reported in Figure 23 and Figure 24 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 still an important driver of our results.

6.2 Different lag specification

We re-estimate equation (2) with alternative lag specification. In Figure 25 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 26 reports the IRFs obtained using the baseline specification, but starting the sample in 1985M1. In this case, the results are also robust.

As one can see in Figure 27, the results for the differences in inflation rates across deciles are largely unaffected even excluding the Volcker disinflation period by starting the sample in 1985M1.

7 Conclusion

Central bankers and policymakers are more and more strongly advocating the importance of the conduct of a more inclusive monetary policy. Similarly, macroeconomic research has shifted focus from the aggregate effects of monetary shocks towards the different channels through which households and firms might be heterogeneously affected by it.

In this paper, we show that research on household' inequality cannot abstract from also considering how the individual inflation rates react to monetary shocks. Given the different consumption bundles the agents purchase, they experience significantly different inflation both in the long-run as well as in response to shocks.

We rely on individual expenditure data from the CEX and combine it with category-level inflation rates from the BLS to obtain individual inflation rates and dispersion measures. We then evaluate monetary policy transmission by studying the response of these measures to Romer and Romer (2004) shocks. We show that contractionary monetary policy significantly and persistently leads to lower levels of inflation dispersion across households. On a five-year horizon, monetary policy accounts for approximately 20% of the variation in dispersion.

The effect is not symmetric. The right tail of the distribution converges more strongly to the median than the left tail, leading to a slightly left-skewed distribution. *Energy*, *Water* and *Gasoline* are found to explain most of the observed effects despite accounting for a relatively small expenditure share.

Moreover, we evaluate how the inflation rate of different demographic groups is heterogeneously affected by monetary policy. We find that the median inflation rate of the low- and middle-income households is significantly more reactive to monetary shocks than that of high-income households. Since at the same time they experience an higher median inflation rate, contractionary shocks lead to an overall convergence of inflation rates 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. We compute two measures of real consumption inequality: one deflating each expenditure category by the aggregate price index and one in which the categories are deflated by the proper sectoral price index. Accounting for inflation heterogeneity reduces the estimated response of monetary shocks on expenditure inequality by around 20-30% depending on the measure of inequality considered.

In conclusion, our research contributes to a refined, more accurate view of the different effects that monetary policy can have on households. Inflation heterogeneity is sizable, related to demographic characteristics and particularly relevant when it comes to measure expenditure inequality.

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For Online Publication

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)[24]	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[26] (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 (SETB-SETD-SETE-SETF)	3.02	2.34	2.10	0.79	6.75

[25] 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.

[26] Household Furnishings and Operations

Table 1: Item-level CPI statistics (continued)

CPI series (Item Code)[25]	Mean	Median	Standard Deviation	p10	p90
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
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 expenditure 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. In order 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 bracket 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[27]	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

[27] Household Furnishings and Operations

match with the available CPI sub-categories, we create the CPI index by combining the series that match this category (that is, SETB, SETD, SETE, and SETF). For each period we use the official weights provided by the BLS, as displayed in the table "Relative Importance in the CPI". Finally, since *Other Lodging* changed 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	SETB-SETD-SETE-SETF
Public Transportation	SETG
Medical	SAM
Entertainment	SAR
Personal Care	SAG1

Table 3: Matching between CEX expenditure category and CPI (continued)

BLS Expenditure Category	CPI Series (Item Code)
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:

$$X_j^d = \frac{\sum_i fwt_i^d \sum_t c_{i,j,t}^d}{\sum_i fwt_i^d \, MO\_SCOPE_i^d} \times 12 \tag{5}$$

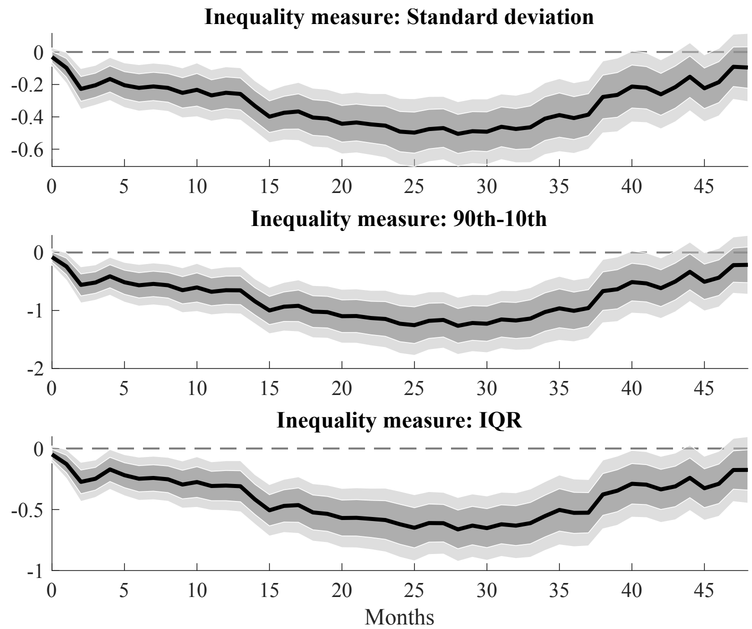
where fwt_i^d is the frequency weight for household i at decile d, $c_{i,j,t}^d$ refers to the annual consumption on category j by household i at decile d and $MO\_SCOPE_i^d$ identify the number of months per year household i reported its expenditure. The decile-level expenditure weight for category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

$$w_j^d = \frac{X_j^d}{\sum_j X_j^d} \tag{6}$$

C Further robustness checks

As a further robustness check, Figure 16 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.

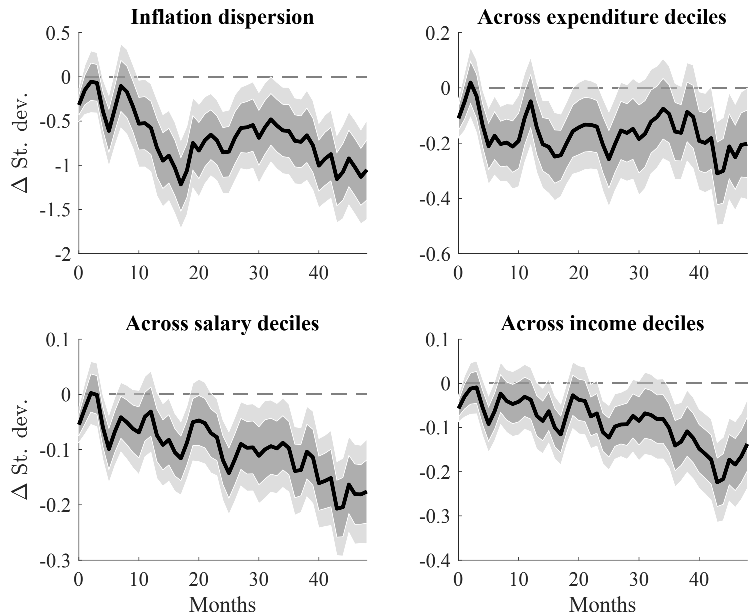
Figure 16: Impulse responses of inflation dispersion (without recession periods)



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 1980M1:2007M12

As a second set of check, we assess whether our results are specific to the shock series we chose (i.e., Romer and Romer, 2004). As an additional estimation technique, we present the results from local projections instrumental variables, LP-IV as in Stock and Watson (2018), using a high frequency identification for monetary shocks. The key idea of this approach is to use changes in future prices around policy announcements. Since the time window around the announcements is relatively small, one can consider these changes entirely due to the announcement itself and orthogonal to the information set of the financial market.

Figure 17: Impulse responses of inflation dispersion using alternative 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 for the inflation dispersion measured as the cross-sectional standard deviation. The horizontal axis is in months. Impulse responses are computed at a monthly frequency using data for the period 1990M1:2007M12.

These high frequency shocks have been extensively used in the literature (e.g., Stock and Watson, 2018, Jarociński and Karadi, 2020) although they are available only from January 1991. We try to overcome this limitation by extracting the estimated structural shocks directly from the proxy-VAR run by Gertler and Karadi (2015) from July 1980 to June 2012. Since the structural shocks extracted from the VAR are identified up to a scaling, we combine them with the LP-IV specification similarly to Cloyne et al. (2018).

The results are presented in Figure 17. The top right panel reports the response of the cross-sectional standard deviation to a contractionary shock, the other three panels show the response of inflation inequality across expenditure, salary and income deciles. All the regressions include the same controls as in the baseline specification. The instrumented variable is the change in federal funds rate and the instruments are the structural shocks discussed above.

The shape and the magnitude of the response computed with Gertler and Karadi (2015) shocks are in line with our baseline results. The standard errors are even smaller than using the Romer and Romer (2004) shocks making the responses more significant. Overall, the results from alternative monetary policy shocks confirm our main findings and point towards a redistributional role played by monetary policy in terms of inflation dispersion.

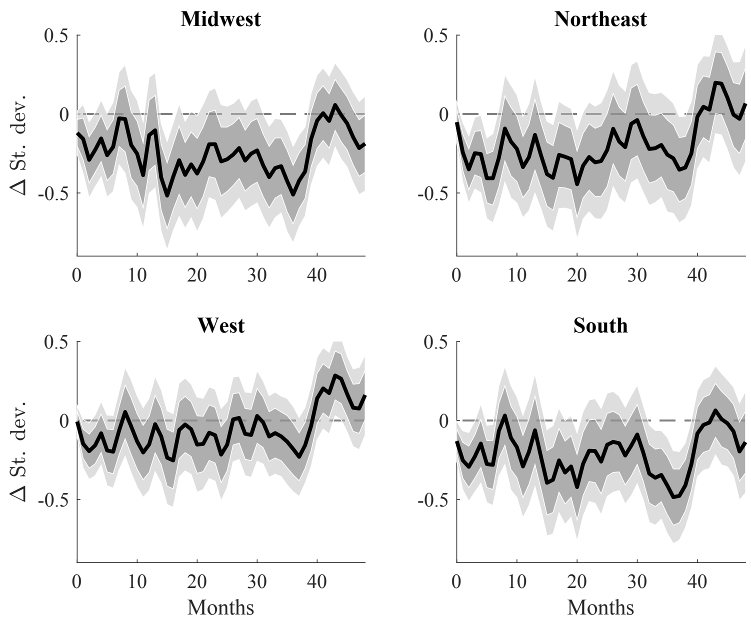
In addition, one might be concerned that part of the inflation heterogeneity we measured is driven by differences in consumption patterns across U.S. states rather than along the income distribution. Since the BLS does not provide price indices at the state level, but only at the division level (Northeast, 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[28].

The responses across U.S. divisions are reported in Figure 18. There are some regional differences in the shape of the responses of inflation dispersion to contractionary shocks. However, the magnitude and the significance of the results are comparable to the baseline specification. The decrease is more muted only for the West division.

Finally, we follow Ramey (2016) and use as controls the lags of the dependent variable, the shock, industrial production, consumer price index, commodity prices, the policy rate, and unemployment rate in the U.S. Figure 19 reports the result for the cross-sectional standard deviation, which significantly decreases after a monetary policy shock.

[28] A more limited number of price indices are available at 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 18: Impulse responses of inflation dispersion across US divisions



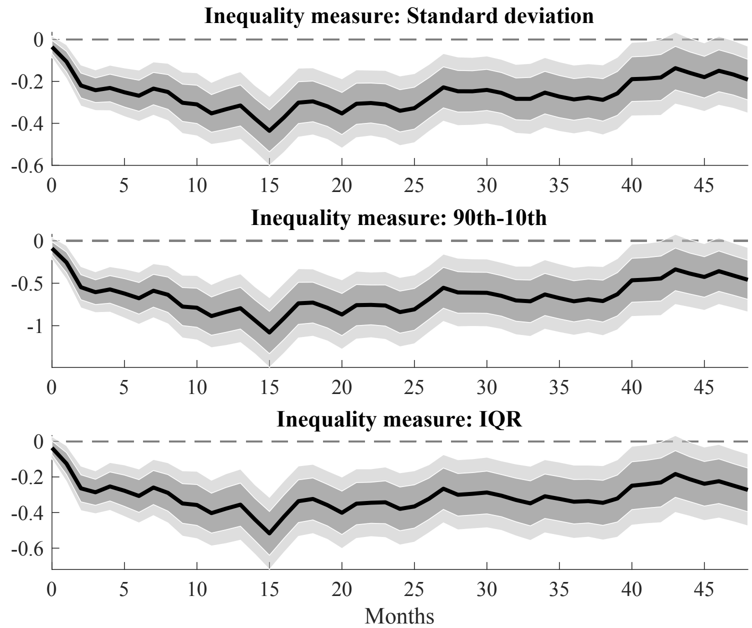
Notes: The figure plots impulse responses to a one percentage point contractionary monetary policy shock, as well as one and 1.65 standard deviation confidence intervals for the inflation dispersion measured as the cross-sectional standard deviation for the four US regions. Impulse responses are computed at a monthly frequency using data relative to the period 1980M1:2007M12

Figure 19: Impulse responses of inflation dispersion using Ramey (2016) controls

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. The controls include the lags of the dependent variable, the shock, industrial production, consumer price index, commodity prices, the policy rate and the unemployment rate. Impulse responses are computed at a monthly frequency using data relative to the period 1980M1:2007M12

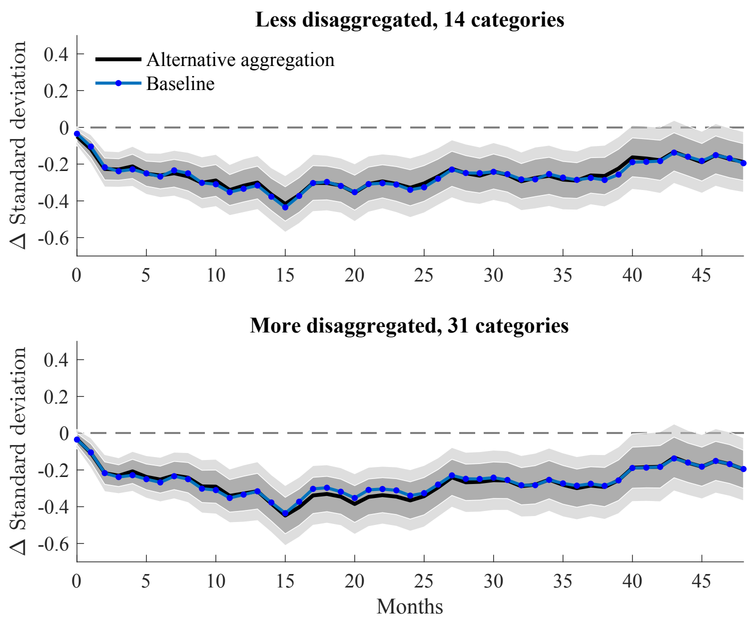
D Robustness plots

Figure 20: Impulse responses of inflation dispersion



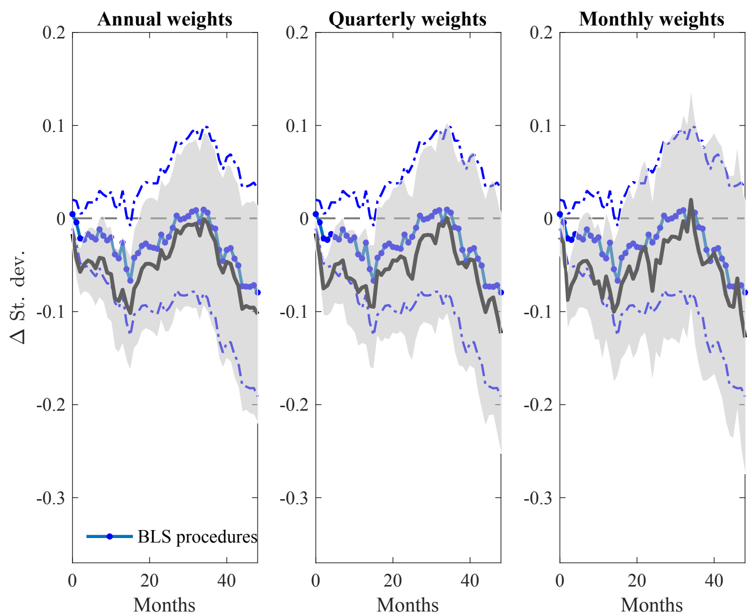
Notes: The figure plots impulse responses to a percentage point contractionary monetary policy shock, as well as one and 1.65 standard deviation confidence intervals for the respective inflation dispersion measures. The horizontal axis is in months. Dispersion is measured using the cross-sectional standard 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 1980M1:2007M12.

Figure 21: Impulse responses of the cross-sectional standard deviation of inflation (alternative aggregations)



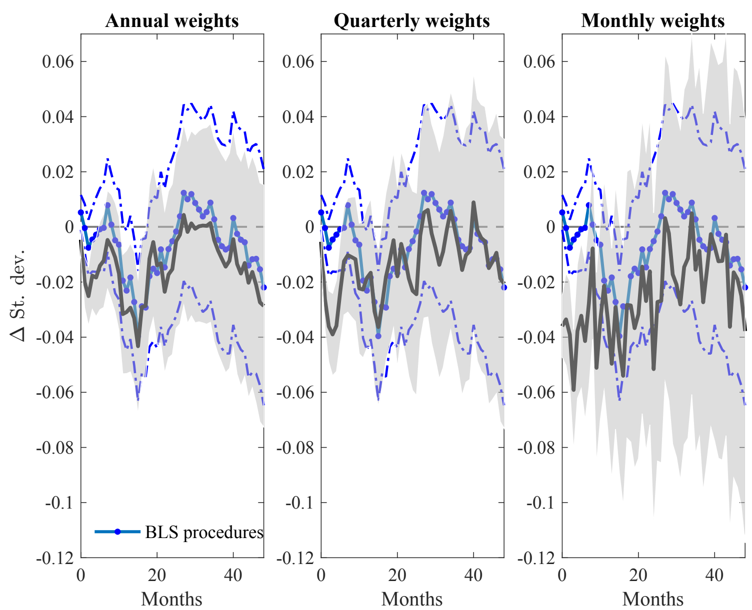
Notes: The figure plots impulse responses of alternatively aggregated inflation rates to a one percentage point contractionary monetary policy shock, as well as one and 1.65 standard deviation confidence intervals for the respective inflation dispersion measures. The solid blue line refers to the impulse response obtained using the baseline categories. Impulse responses are computed at a monthly frequency using data relative to the period 1980M1:2007M12

Figure 22: Impulse responses of inflation inequality across expenditure deciles with time-varying weights



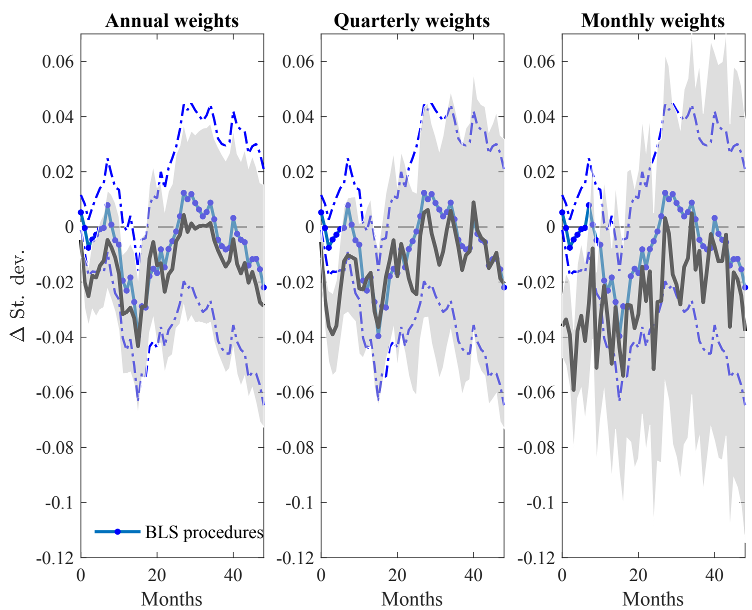
Notes: The figure plots impulse responses to a percentage point contractionary monetary policy shock (black line) as well as one standard deviation confidence interval (gray area) for inflation inequality across expenditure deciles. Inflation inequality is measured using the cross-sectional standard deviation of the decile median inflation rate. 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 1980M1:2007M12.

Figure 23: Impulse responses of inflation inequality across salary deciles with time-varying weights



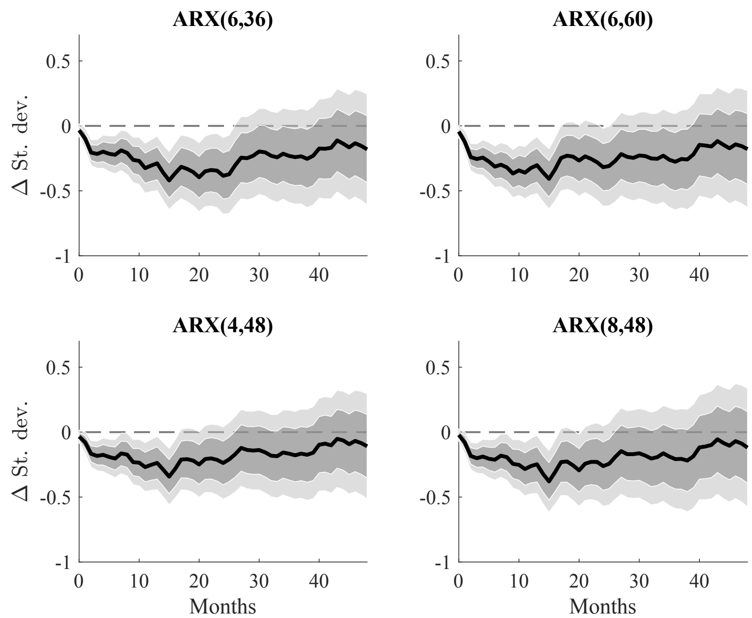
Notes: The figure plots impulse responses to a percentage point contractionary monetary policy shock (black line) as well as one standard deviation confidence interval (gray area) for inflation inequality across salary deciles. Inflation inequality is measured using the cross-sectional standard deviation of the decile median inflation rate. 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 1980M1:2007M12.

Figure 24: Impulse responses of inflation inequality across income deciles with time-varying weights



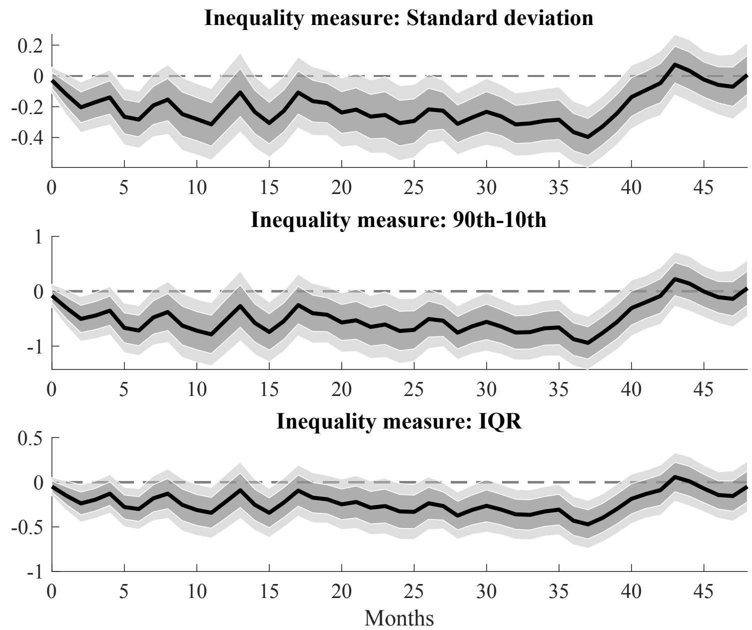
Notes: The figure plots impulse responses to a percentage point contractionary monetary policy shock (black line) as well as one standard deviation confidence interval (gray area) for inflation inequality across income deciles. Inflation inequality is measured using the cross-sectional standard deviation of the decile median inflation rate. 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 1980M1:2007M12.

Figure 25: Impulse responses of inflation dispersion for different lag specifications



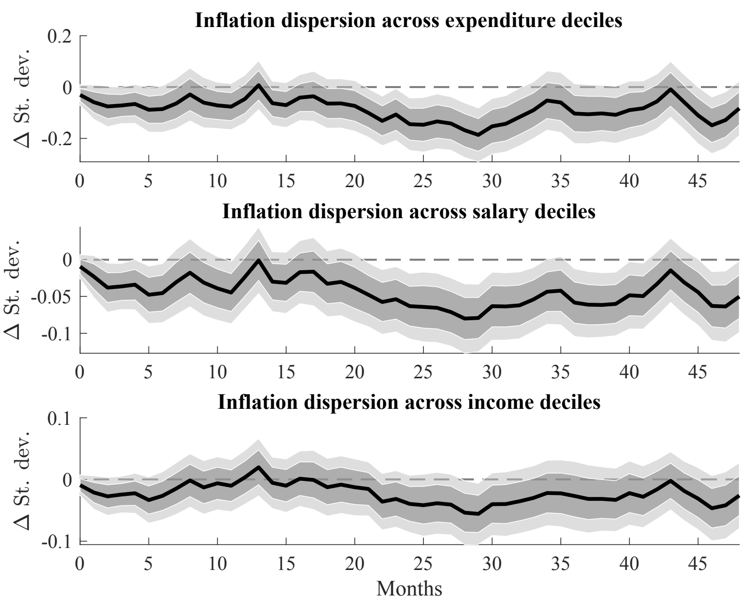
Notes: The figure plots the impulse responses to a one percentage point contractionary monetary policy shock, as well as one and 1.65 standard deviation confidence intervals of the cross-sectional standard deviation. The horizontal axis is in months. In an $ARX(p, r)$-model, we control for p lags of 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 1980M1:2007M12.

Figure 26: 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 1985M1:2007M12 in order to exclude the Volcker disinflation period.

Figure 27: Impulse responses of inflation dispersion across expenditure, salary, and income deciles (without Volcker period)



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 dispersion across expenditure (top), salary (middle), and income deciles (bottom). The horizontal axis is in months. Dispersion is measured using the cross-sectional standard deviation. Impulse responses are computed at a monthly frequency using data for the period 1985M1:2007M12.