Monetary policy shocks and inflation inequality

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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, lower-income households experience higher average inflation, which at the same time is decreasing more after a contractionary monetary policy shock, leading to an overall convergence of inflation rates between income groups. Finally, these results imply that (iii) consumption and income inequality are significantly different when controlling for different inflation rates.

Keywords: monetary policy, inflation inequality, redistributial effects

JEL classification: E31, E52

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1 Introduction

Consumer heterogeneity has become increasingly important in macroeconomic research, both from a theoretical and empirical point of view. This can be seen in the rise of Heterogeneous Agent New Keynesian models (HANK, see Kaplan et al., 2018) which show that differences among households have important repercussions on the transmission of monetary policy. At the same time, Coibion et al. (2017) document that income and expenditure inequality increase after a contractionary monetary policy shock. These results show, on a more general level, that the focus in monetary economics has shifted considerably from aggregate to individual effects.

However, any individual variable needs to be deflated by inflation to get meaningful real variables. This implies that the shift to a more granular level renders inflation rates computed at household level more important as well. Therefore, analyzing the differences and dynamics of inflation heterogeneity is essential for a thorough and unbiased view on disaggregated variables.

In this paper, we demonstrate that differences in individual inflation rates are sizable and that they are systematically different for different demographic groups. We show that monetary policy played a significant role in the evolution of the individual inflation distribution: following a contractionary monetary shocks, the dispersion and skewness of the distribution decrease. Moreover, we find that the level and volatility of the individual inflation rates strongly depend on household income. This non-random behavior of inflation rates has direct effects on monetary policy. By defining inflation inequality as the cross-sectional dispersion of individual inflation rates along the income or expenditure dimension, we demonstrate that contractionary monetary policy shocks lead to a substantial and persistent decrease of inflation inequality in the medium term.

In order to obtain individual inflation rates, we exploit the fact that consumers purchase different consumption bundles, with different shares spent on different goods categories. Assuming all households face the same prices for the same categories of goods and services, we use item-level price data from the Bureau of Labor Statistics (BLS). We combine it with individual expenditure data from the Consumer Expenditure

1 The categories used are 21 fairly broad baskets of goods and services, for which we can match the expenditure data to the price data (see chapter 2).
Survey (CEX) to create inflation rates at the household level. This allows us to study
the distribution of individual inflation rates across a representative sample of households
that includes the same range of goods and services that is used in computing the
Consumer Price Index for the U.S. We analyze the dynamic responses of different
inflation dispersion measures to the exogenous monetary policy shocks derived by
Romer and Romer (2004) and extended by Coibion et al. (2017).

We find that a contractionary shock to monetary policy significantly and persistently
decreases inflation dispersion. This finding is robust across a number of different
reference periods and empirical specifications. In order to assess the asymmetry of the
response, we repeat the analysis on different skewness measures. We find that the right
tail of the distribution converges more strongly than the left tail toward the median
inflation rate. Moreover, household income and expenditure are strongly correlated
with the response of individual inflation. Inflation of low and middle-income households
is more reactive to shocks than that of high-income households and therefore decreases
more strongly after a contractionary monetary policy shock. At the same, the latter
group’s inflation rate tends to be lower over time. This results in a decline in inflation
inequality across income groups. The same results hold for salary and expenditure
deciles, confirming the role of endowments on individual inflation rates. Finally, we
show that neglecting inflation heterogeneity leads to biased estimates of the impact of
monetary policy on expenditure inequality.

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 for the U.S. how consumption and income inequality increase following a
contractionary shock. Similar findings have been confirmed in other countries as well,
and in different time periods (e.g. Mumtaza 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 CEX data as well, Wong (2019) 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 the interest rate.

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

Finally, Cravino et al. (2020) show how following a contractionary shock high-income households’ inflation rate reacts significantly less than the one of middle-income households. Our paper differs over different dimensions: first of all, we compute the inflation rates at the household level instead of at the percentile level. This allows us to provide new evidence on the role played by monetary policy on the individual inflation distribution. Furthermore, when studying the monetary policy transmission across demographic groups, our focus is not on the absolute value of the impulse responses but rather on the relative response among groups. Conditioning on the group median inflation rate over time, we are then able to document whether inflation dispersion increases or decreases in response to a monetary shock.

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 individual inflation distribution. Section 4 studies the heterogeneous responses across different demographic groups. In section 5, we perform a battery of different robustness checks to evaluate the reliability of our findings. Section 6 concludes.
2 Individual inflation rates

In this section, we compute individual inflation rates at the household level. While Cravino et al. (2020) and others have calculated inflation rates at the percentile level, focusing on the differences between different demographic groups, and therefore abstracting from within-group dispersion, we want in a first step to focus on the heterogeneity across all households.

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 key steps needed for the computation of any inflation rate. First, we need information on prices for different goods. In a second step, we need detailed information on (individual) consumer expenditures, which allow assessing the relevance of different goods in an aggregated index and therefore providing weights. The CEX proves rich enough to provide data on expenditures, going back to 1980. Third, statistical agencies have to decide on a methodology to deduce weights and combine price data in order to get a meaningful measure of inflation. In the following, we discuss each step separately.

2.1 Inflation data

We use data from the Consumer Price Index (CPI) as computed by the BLS at a monthly frequency. In particular, we use the not-seasonally-adjusted indices named *US City Average for all urban consumers*. 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 since new goods get introduced and old ones disappear. 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) in creating 21 indices, for which we get consistent inflation rates during our time sample. We will call these inflation rates of subgroups of the consumer basket inflation.
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 price level, this will lead to differences in terms of experienced inflation.

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, that high-end restaurants have different price developments than 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 not a 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 the total household expenditures. Moreover, the dataset is available only from 2004 onward.

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

2.2 Expenditure data

For the computation of expenditure weights, we use the CEX provided by the BLS. This is the same dataset that is used to compute the official CPI of the U.S. The CEX is a quarterly survey of household expenditures and is divided into a diary and an interview survey. The diary survey covers small expenditures on daily items over a period of two

\[2\text{The list and definitions of these subindices can be found in Appendix A.1.}\]
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 will 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), in order to ensure anonymity. Also, since we deal with survey data, there are likely more measurement errors in the CEX compared to other data sources.\(^3\) However, the CEX allows us to get a comprehensive picture of virtually all consumer expenditures and is also sufficiently large in the time dimension (starts in 1980) and along the cross-section (roughly 5000-7000 households each month).

Like the inflation subindices, we aggregate the expenditure data into 21 groups,\(^4\) matching the classification of the CEX with the one from the price indices. In the next step, we aggregate the monthly expenses to yearly expenses. 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, most 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.\(^5\) Since we use inflation data that is the same for all households, it is important to stress the central importance of the variation in individual expenditure shares. All the dispersion in individual inflation rates is due to the variation in expenditure shares. Luckily, expenditure shares show large variation that can be explained to a large part by differences in total expenditure, income or salaries. In order to show the variance in expenditure shares, we order the households in deciles of total expenditures, and employ a correspondence analysis to display the differences in expenditure shares for all categories.\(^6\)

\(^3\)cf: Bee et al. (2013) for an assessment of the quality of our consumer dataset.
\(^4\)We have to alter the Housing group and omit the Vehicle group altogether for reasons specific to the group. See the Appendix for details.
\(^5\)The dataset allows us to exploit differences in inflation due to different consumption bundles. However, we avoid to exploit the short-term dynamics in expenditure shares, since we expect the quality of the month-to-month data to not be sufficiently good. Households are only interviewed for a maximum of 12 months, which does not allow us to capture substitution effects.
\(^6\)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 to a higher share 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.

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 $w_i^j$ for household $i$ and item subgroup $j$, that 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. In order to assess the robustness of our results, we have various scenarios that exclude parts of the consumption basket (see Section 5). Then, we compute the individual inflation rate for household $i$ as:
\[ \pi_{t-k,t} = \sum_{j \in J} w_j \pi_{j,t,t-k} \]

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

In order to assess the validity of the measures of individual inflation computed above, we compare 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).

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.

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 lately been expanded in order to include heterogeneity over different dimensions like consumption, wages, asset portfolio composition, etc. and particular attention has been given to the way monetary policy might indirectly impact the economy. However, most models assume that households are exposed to the same inflation rate and therefore that monetary policy shocks affect them homogeneously. Given that Figure 2 seems to strongly reject this assumption, we will focus on the contributions of monetary policy shocks to the evolution of inflation dispersion over time, and assess whether households are heterogeneously influenced by them.

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7Similar results are obtained for the mean of the distribution.
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.

2.5 Measures of dispersion

To evaluate how monetary policy shocks affect inflation dispersion in the United States, 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 the period 1981M1-2007M12. Our series deliberately stops before the recent financial crisis in order to exclude the zero lower bound period.

To avoid that the change in the survey composition might affect 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 cross-sectional standard deviation from $t$ to $t + 1$, we do it only for the households who are present during both periods. Sampling weights are applied throughout the analysis.
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 overall skewness of the individual inflation distribution. All the series refer to the period 1981M1:2007M12. The gray shaded areas depict U.S. recessions.

The top plot in Figure 3 shows the historical evolution of the three measures of dispersion, together with U.S. recessions. Clearly, the three variables are almost perfectly correlated, suggesting a normal distribution of the computed individual inflation rates. Despite using a different time period and alternative CPI categories, the time series are comparable in magnitude to what Johannsen (2014) found. As one can notice, inflation dispersion increases during U.S. recessions of the early 80s and 90s suggesting some sort of correlation with the business cycle in the economy.

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

Particularly interesting are the sharp increases in dispersion in 1986 and the high volatility from 2000 onward. One possible explanation regarding these two episodes can be found in Figure 4. The official CPI and the inflation rate for the sub-category *Household Energy*, which includes expenditures like natural gas, electricity, and fuel, are depicted on the left axis. On the right axis, we report the inflation dispersion measured as the cross-sectional standard deviation.

**Figure 4:** Historical series of CPI, *Household Energy* inflation and the standard deviation of inflation dispersion

![Graph showing inflation rates and dispersion](image)

*Notes:* The official CPI (blue line) and the sub-category *Household Energy* (dashed black) are depicted on the left axis, whereas the evolution of inflation dispersion (dotted red), as measured with the cross-sectional standard deviation, is on the right axis. The gray shaded areas depict U.S. recessions.

The sub-category *Household Energy* has a weight of approximately 6% in the computation of the CPI, so its influence on aggregate rates is moderate. However, at the individual household level the expenditure share is highly heterogeneous, especially along the income distribution (more on that in Subsection 4). As one can notice, the
sharp drop in energy prices in 1986 and the higher volatility from 2000 onward partially explain the observed behavior in inflation dispersion.

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 absolute distance between the two tails and the median as well as on the overall skewness.

3.1 Methodology

In the baseline specification, we adopt the Local Projection (LP) method developed by Jordà (2005). In particular, we estimate the impulse response of the dependent variable to monetary policy shocks at different horizons by regressing the variable of interest on a distributed lag of the monetary policy shocks as well as the lagged endogenous variable:

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

(2)

where \( x \) is the variable of interest. The monetary policy shocks are denoted by \( e \) and \( c_h \) is a vector of horizon dummies. In line with the literature, we include as control 48 lags of the shocks and 6 lags of the dependent variable. The coefficient \( \beta_h \) 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 compute the impulse response to a 1 percentage point contractionary monetary policy shock.

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),

The LP approach assumes that the shock series is a perfect measurement of the true monetary shock. However, a more reasonable assumption may be to assume that the R&R shocks can only proxy the true monetary shocks, i.e. they are correlated with the true monetary shocks and uncorrelated with other structural shocks. We can then recover the impulse response to a monetary shock from LP and two-stages least squares where the US federal fund rate is instrumented with the R&R shocks series (IV-LP). Specifically, in the first stage, we regress the R&R shocks on the interest rate and in the second stage, we estimate the LP using, instead of the shock series itself, the fitted value of the first stage regression. In Subsection 5.2 we show that LP and IV-LP deliver qualitatively the same results in terms of inflation dispersion and second-moment responses across groups. However, the former approach leads to strong positive comovements between the shocks and inflation. We attribute this to the shocks not being truly exogenous. Therefore, we use the instrumental variable approach as baseline specification.

3.2 Analysis

In order to evaluate the overall effects of a contractionary monetary policy shock on inflation dispersion, we estimate (2) using the three dispersion measures previously defined as dependent variables. The impulse responses are computed over a horizon of 48 months using data from 1981M1 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.

The results are reported in Figure 5. Given the extremely high correlation among dispersion measures, the IRFs display similar patterns differing mainly in the magnitude of the response. Indeed, in a similar way, the three impulse responses decrease after a

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8Coibion (2012) show 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 5 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.
Figure 5: 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 the monthly frequency using data for the period 1981M1:2007M12.

contractionary monetary policy shock and persistently remain below zero\(^9\). 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 responses strongly suggest that monetary policy shocks lead to a decrease in the inflation dispersion in the economy, although not much can be said regarding the magnitude of the effect.

\(^9\)As one can notice, the impulse responses react already in the first months after the shocks although the literature on monetary policy suggests that inflation should not move immediately. We refer to the Appendix B for the explanation of this result.
3.3 Importance of monetary policy shocks

We now focus on quantitatively assess how important are the monetary policy shocks to explain the evolution of inflation dispersion in the U.S. The forecast error variance decomposition, i.e. the share of the variance in dispersion explained by a shock, is commonly used to answer this question.

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

$$\hat{f}_{t+h,t-1} = \alpha_0 e_t + \ldots + \alpha_h e_t + \tilde{v}_{t+h,t-1}$$

where $e_t$ 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.

The results from the variance decompositions are presented in Figure 6. 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 all the three measures of dispersion considered. Moreover, these results are quantitatively in line with the contribution of monetary policy shocks to other inequality measures (Coibion et al., 2017, documented 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 how the dispersion of inflation increases after a contractionary monetary policy shock. We now study more in-depth the main potential drivers of this result. Indeed, monetary policy can lead to a decrease in standard deviation through multiple channels.
Figure 6: 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).

We first evaluate how the two tails of the distribution react to monetary policy. Therefore, for every period we compute the change in inflation for the households at the 90th, 50th and 10th percentile in terms of individual inflation. We then investigate how the absolute difference between the inflation at the 90th and the 50th as well as the 50th and the 10th percentiles respond to monetary policy shocks.

Results are reported in Figure 7. As one can notice, after a contractionary shock the absolute distance between both tails and the median decreases significantly. However, the responses are asymmetrical: at the horizon, the magnitude for the distance between the 90th and the 50th percentiles is more than twice the magnitude for the difference between the 50th and the 10th percentiles. This implies that part of the decrease in inflation dispersion previously observed is driven by a stronger reduction in inflation rates for the households at the top of the distribution.
Figure 7: Distributional effects of monetary policy shock

Notes: The figure plots impulse responses to a one percentage point contractionary monetary policy shock with the one standard deviation confidence intervals for the absolute distance between the inflation at the 90th and 50th percentile (blue line) as well as between the 50th and the 10th percentile (red line). The horizontal axis is in months. Impulse responses are computed at the monthly frequency using data for the period 1981M1:2007M12.

Combining the results obtained, we can understand how monetary policy shocks shape the individual inflation distribution. Following a contractionary shock, the right tail of the distribution decreases much more relative to the median with respect to the left tail. Nor surprisingly, since both distances decrease, we observe a reduction in the overall standard deviation. Finally, the tails behavior suggests as well that the mass of households on the right side of the median will squeeze much more than on the left side predicting that the distribution will be more negatively skewed.

In Figure 8 we test this hypothesis by estimating (2) using the overall skewness of individual inflation as dependent variable. As expected, a contractionary monetary policy shock results in a significant and persistent decrease in the overall skewness of the distribution.
Figure 8: 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 individual inflation distribution. The horizontal axis is in months. Impulse responses are computed at the monthly frequency using data for the period 1981M1:2007M12.

To ease the understanding of the previous results, Figure 9 shows a graphical representation of the changes in individual inflation distribution caused by a monetary policy shock. Starting from a standard normal distribution, a contractionary shock shifts the entire distribution to the left since it reduces aggregate and individual inflation rates. However, since we are more interested in showing how the higher moments evolve, in the plot we neglect this effect. As suggested in Figure 7, the distance between the right tail and the median reduces more than the distance between the left tail and the median. This has two consequences: first of all, the overall dispersion clearly 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).
Figure 9: Graphical representation of the change in individual inflation after a monetary policy shock

Notes: The figure shows the distribution of individual inflation before (thick line) and after (dashed line) a contractionary monetary policy shock based on the changes in the distributional moments found in the previous sections.

4 Heterogeneity across demographic categories

Having shown that monetary policy shocks decrease inflation dispersion in the economy, we now evaluate which observable household characteristics are more sensitive to monetary policy shocks in terms of individual inflation and how this affects the cross-sectional inflation dispersion. We focus in particular on six demographic categories: income, salary, and expenditure deciles, gender (male, female), age (younger than 35 years old, between 35 and 55, older than 55), and education level (high school, some college, college).
4.1 Expenditure weights

Heterogeneity in inflation rates comes from the fact that households consume different consumption bundles, i.e. the weight given to each expenditure category varies across individuals. To study over which category demographic groups differ, we report in Table 2 the average expenditure weights for the first, fifth and tenth decile of income, salary and expenditure deciles for each of the 21 categories.

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 actually experienced by middle-income households. Finally, from the weights differences across deciles we can understand which categories are mainly responsible for the inflation inequality. In particular, as we will show, a major role is played by Food at home and Energy. Indeed, not only low-income households consume a significantly higher share of their income on these categories with respect to high-income households but their price level is also extremely volatile.

4.2 Impulse responses by demographic groups

To evaluate how the different demographic categories react to monetary policy shocks, we estimate the IV-LP with R&R shocks using as dependent variable the median inflation rate of each group within a category.

Figure 10 reports the impulse responses for gender, age, and education level and Figure 11 for income, salary and expenditure deciles. In order to study how the across-groups inflation inequality reacts after a monetary policy shock, the impulse responses of each group are rescaled such that at time zero they are equal to their respective conditional median inflation over time. Note that at this stage we do not claim that
the responses across groups are statistically significant since we will only report the IRF coefficients and not the relative standard errors.

Starting with the impulse responses across the two genders, it seems that after an initial increase in inequality between male and female, the inequality level returns to the initial value at the horizon. As we will see below, this change is not significant; males and females have similar consumption bundles, which results in similar responses. Focusing on the different age groups, the results suggest that the inflation rate for young people reacts more strongly to monetary policy shocks when compared to older households. Since the former group has lower median inflation as well, we can see an increase in the cross-sectional standard deviation across age groups following a contractionary shock. The higher inflation rates for older households was previously
Figure 11: Impulse responses of different demographic groups’ inflation rates (2)

IRF for category: Income deciles

IRF for category: Salary deciles

IRF for category: Expenditure deciles

Notes: The figure plots the impulse responses of inflation rates to a one percentage point contractionary monetary policy shock. The responses are shifted such that at time zero they are equal to the group median inflation rate for the sample period. Impulse responses are computed at the monthly frequency using data for the period 1981M1:2007M12.

documented by Stewart (2008) and explained by the persistently high health care cost inflation.

The opposite happens across education levels, higher educated households experience a much lower median inflation but at the same time the goods and services they regularly buy come from sectors that are less sensitive to changes in the interest rate. As a result, the across group inequality decreases over time.

The differences in consumption bundles composition that drive the latest result can be explained by looking at the plots for wealth deciles. Two findings are worth mentioning: first of all, one can notice how the higher the decile the lower the median inflation rate. While this result is not new per se, 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 groups holds considering
the period 1981-2007 as well.

Second, in line with Cravino et al. (2020), households at the top of the income, salary,
and expenditure distribution experience substantially smaller changes in inflation rates
after a contractionary monetary policy shock with respect to low and middle-income
deciles. The two previous results combined lead to a persistent decrease in inflation
inequality across groups consistent with our findings in Subsection 3.2.

However, 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 (2) using as dependent variable the difference between the inflation
rate of each group within a category and the inflation rate of the median group. To
make the results easier to read, Figure 12 reports the impulse response coefficient as
well as the 1.65 standard deviation confidence interval at the last horizon considered
($h = 48$). As we will show in Section 5, the size of the estimated coefficients is rather
sensitive to the empirical approach adopted and to the period considered while the
relative distribution of the coefficients across groups is not. Therefore, although we
cannot say much about the overall magnitude of the effect, we can confidently argue
about the consistency and statistical significance of the findings.

As previously anticipated, the difference in inflation rates between men and women is
not significant. This is not an unexpected result considering their consumption bundles
are quite similar. Considering the differences across age groups, since the median
inflation rate of the older households is higher and it decreases less than the baseline
age group (between 35 and 55 years old), their difference is positive and statistically
significant.

On the contrary, for education status, the high school group inflation rate decreases
more than the inflation rate for the base group (respondents with some degree) therefore
their difference is negative. For households with a college degree, it is the opposite. As
previously underlined, the statistically significant difference in impulse responses can
be explained by looking at the heterogeneity in household wealth.
Figure 12: Differences in impulse responses between demographic groups after 48 months

Notes: The figure plots the difference between impulse responses of different demographic groups at a horizon of 48 months. Impulse responses are computed for a one-percentage point increase in the monetary policy shock, with monthly data for the period 1981M1:2007M12. The error bars depict 95% confidence intervals, computed by a standard bootstrapping algorithm.

The top income, salary, and expenditures deciles react much less to a monetary policy shock than the baseline group (6th decile) resulting in a positive and significant difference. On the other hand, the inflation rates of smaller deciles reacts as much as or slightly more strongly than the baseline resulting in a rather flat U-shaped response across groups. Indeed, as found by Cravino et al. (2020), 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 the middle-income households being exposed to slightly more price volatility than the lower-income ones.

Therefore, our empirical analysis strongly suggests that monetary policy shocks can have a significant and not negligible distributional effects in the economy. In particular, since the inflation rate of the higher-income households is lower in median over time
relative to low and middle-income households and at the same time it reacts less to unexpected changes in the interest rate, this results in a decrease in inflation inequality following a contractionary shock.

4.3 Expenditure inequality

Does the identified inflation inequality have any effect on the estimates of other forms of 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\textsuperscript{11}. 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 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 level to reduce sampling error and to avoid that unusual purchases might bias the analysis. The measure of expenditure is winsorized at the bottom and top 1 percent and inequality across households is computed as the cross-sectional standard deviations of log levels, the Gini coefficients of levels and the difference between the 90th percentile and the 10th percentile of log levels. Finally, we use X-12 to seasonally adjust the series.

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) over the same time period, 1980Q1:2008Q4\textsuperscript{12}. Since 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 a period of 20 quarters.

\textsuperscript{11}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.

\textsuperscript{12}Similar results are obtained using the IV-LP approach and restricting the analysis to our baseline period.
Figure 13: 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 quarter 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 categories by their respective price index. Impulse responses are computed at the quarterly frequency using data for the period 1980Q1:2008Q4.

The results are reported in Figure 13. The shape and the magnitude of the responses are very close to the ones obtained by Coibion et al. (2017) for all three measures of inequality. After a contractionary monetary policy shock, expenditure inequality persistently and significantly increases. However, neglecting inflation heterogeneity across consumption bundles leads to an overestimate of the overall effect. 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.
5 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 assess the sensitivity of our results to different lag specifications. Secondly, we compare the results using the original LP approach (Jordà, 2005) instead of the instrumental variable approach applied in the baseline specification. Thirdly, we perform the same analysis starting our sample in 1985M1 to control for the Volcker disinflation period. Finally, since households respond to a different number of interviews, we create a new decile classification in which the respondents’ contribution to the decile inflation rate is weighted by the number of months over which they provide expenditure data\textsuperscript{13}. The figures are reported in Appendix E.

5.1 Different lag specification

We re-estimate (2) again but trying alternative lags specification. In Figure 20 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 obtained for the other measures of dispersion as well. As one can notice, 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.

5.2 Local projection with and without instrumental variables

As a further robustness check, we replicate the main results of our empirical analysis using the LP approach with R&R shocks. The underlying assumption, in this case, is that the shock series perfectly identify the exogenous and unexpected component of the true monetary shock therefore they are plugged directly into (2):

\[ x_{t+h} - x_{t+h-1} = c_h + \beta_h e_{t}^{RR} + \sum_{j=1}^{J} \theta_{h,j}(x_{t-j} - x_{t-j-1}) + \sum_{i=1}^{I} \gamma_{h,i} e_{t-i}^{RR} + \epsilon_{t+h} \] (4)

\textsuperscript{13}Further details are provided in Appendix C.
The results are reported in Figure 21. The magnitude of the impulse responses is lower with respect to the IV-LP approach but the shape is basically unaffected. With this specification as well, we can statistically claim that contractionary monetary policy shocks have redistributive effects in terms of inflation dispersion.

The results from the variance decompositions using LP (Figure 22) confirm as well that monetary policy shocks account for around 20% of the forecast error variance in the long run across all the three measures of dispersion considered.

Figure 23 shows how the different deciles for income, salary, and expenditure are affected by monetary policy shocks. As one can notice, the simple LP approach is not able to correct for the price puzzle in the considered period (1981-2007). However, as already stated, we are not interested in the absolute impulse responses but rather on their relative evolution. Even in this case, similarly to what we found with the IV-LP approach, households in higher deciles experienced a lower inflation rate across time. Moreover, their median inflation is less sensitive to monetary policy shocks therefore it decreases less than the one of lower deciles. As a consequence, inflation dispersion persistently decreases after a contractionary monetary policy shock.

Finally, Figure 24 reports the estimated coefficient at the end of the horizon considered as well as the 1.65 the standard deviation confidence interval of (4) using as dependent variable the difference between the inflation rate of each group within a category and the inflation rate of the median group to test whether the groups’ responses are statistically different. The size of the coefficients is again lower than with respect to the baseline specification, but the main results still hold: higher deciles react significantly more than the baseline while lower deciles react as much as or slightly less.

5.3 Volcker disinflation

Coibion (2012) showed 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 25 reports the IRFs obtained using the baseline specification but starting the sample in 1985M1. Also in this case, the results are robust.
As one can see in Figure 26, the results for the difference in inflation rates across groups for each demographic category is largely unaffected even excluding the Volcker disinflation period by starting the sample in 1985M1.

5.4 Decile-based inflation

Finally, computing the impulse responses over the median individual inflation rates for each decile, as we did in Subsection 4, could lead to biased results since households respond to a different number of interviews. Therefore, following Cravino et al. (2020) and in line with the BLS procedure, we create decile-based inflation rates for income, salary, median and mean expenditure in which the household contribution to the average decile inflation rate is weighted by the number of interviews.

As one can notice in Figure 27, the first and second moments of the impulse responses are consistent with the previous results: the median inflation rate is lower for high income, salary, and expenditure households, consistently with the empirical evidence. Also, the lower the decile, the more responsive is the inflation rate to the shocks leading to an overall reduction of the cross-section inflation inequality.

Similarly to what we found for the baseline specification, after a contractionary monetary policy shock, the inflation rate of the highest deciles decrease less than the inflation rate for low- and middle-income households and the difference is statistically significant as reported in Figure 28.

6 Conclusion

Macroeconomic research has shifted focus towards the heterogeneity of consumers and inequality. We provide a refined view of the relationship between the two by exploiting the differences in individual inflation rates, which households face due to different consumption bundles.

For doing so, we use individual expenditure data from the CEX and combine it with category-level inflation rates from the CPI to get 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. This effect is not symmetric. Indeed, the right tail of the distribution converges more strongly to the median than the left tail, leading to a slightly left-skewed distribution.

We show that the median inflation rate of the high-income households is significantly less reactive to contractionary shocks than the one lower-income households, leading to an overall reduction of inflation inequality across income groups. The same is true for expenditure and salary deciles. Other demographic characteristics such as age, gender, and education show the same behavior, albeit not as significant. This is not surprising, as the different demographic measures are correlated with income groups.

These findings contribute to a refined, more accurate view of consumption and income differences across households because they account for differences in inflation rates faced by consumers. They are relevant because the differences between households are sizable and non-random. They are systematically different across income groups, and they react differently to monetary policy shocks. Hence, assuming that all consumers face the same inflation rate in a heterogeneous agent setting may lead to biased results, as well as exaggerated levels of inequality. With heterogeneous consumers, future researchers are able to have a more accurate measure of the economic conditions faced by individual households, and of the real outcomes on a more disaggregated level.
References


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

15 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.  
16 Household Furnishings and Operations
Table 1: Item-level CPI statistics (continued)

<table>
<thead>
<tr>
<th>CPI series (Item Code)15</th>
<th>Mean</th>
<th>Median</th>
<th>Standard Deviation</th>
<th>p10</th>
<th>p90</th>
</tr>
</thead>
<tbody>
<tr>
<td>Reading (SERG)</td>
<td>3.64</td>
<td>3.36</td>
<td>2.50</td>
<td>0.86</td>
<td>7.01</td>
</tr>
<tr>
<td>Education (SAE)</td>
<td>2.40</td>
<td>2.40</td>
<td>0.96</td>
<td>1.10</td>
<td>3.70</td>
</tr>
<tr>
<td>Tobacco (SEGA)</td>
<td>7.56</td>
<td>7.11</td>
<td>6.08</td>
<td>2.27</td>
<td>12.75</td>
</tr>
<tr>
<td>Other Expenses (SEGD)</td>
<td>5.73</td>
<td>4.93</td>
<td>2.84</td>
<td>3.29</td>
<td>11.48</td>
</tr>
<tr>
<td>CPI-U (SA0)</td>
<td>3.42</td>
<td>3.04</td>
<td>1.72</td>
<td>1.68</td>
<td>5.01</td>
</tr>
</tbody>
</table>

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 gathers is structured as follows: the expenditure data are recovered from the disaggregated MTAB files, income data are derived from the FMLY files and additional information regarding the households can be found in the MEMB files.

In line with the literature, we aggregate together expenditures about the same month which is reported in different interviews. Then, we drop households that report zero expenditure on food as well as those who report negative expenditures for categories that cannot be negative according to the data codebook, such as expenditures for elderly care. Respondents younger than 25 years and older than 75 are excluded as well. 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 from the original series the effect of the dummies. For all these transformations, we rely heavily on Coibion et al. (2017).

Finally, the CEX data started to include the imputed income since 2004. In order 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 at annual level and with sampling weights 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 month, unadjusted family size, the number of children less than 18, the number of persons over 64, the number of earners and 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.

**Expenditure weights**

In a next step, we calculate expenditure shares from the cleaned expenditure data, which constitute the weights used to calculate individual inflation rates. The differences in these weights are highly consequential, as they are responsible for the entire dispersion in our dataset. We find substantial variation in the weights, variation that can be explained to a large part by either, income, salary, or expenditure deciles. For expositional purposes, Table 2 only 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

<table>
<thead>
<tr>
<th></th>
<th>Income deciles</th>
<th>Salary deciles</th>
<th>Expenditure deciles</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1st 5th 10th</td>
<td>1st 5th 10th</td>
<td>1st 5th 10th</td>
</tr>
<tr>
<td>Food at Home</td>
<td>18.7 14.2 11.1</td>
<td>16.5 14.0 11.1</td>
<td>22.0 14.3 9.9</td>
</tr>
<tr>
<td>Food Away</td>
<td>7.2 7.5 7.3</td>
<td>7.7 7.6 7.2</td>
<td>8.0 7.3 6.9</td>
</tr>
<tr>
<td>Alcohol</td>
<td>1.0 1.1 1.2</td>
<td>1.1 1.2 1.2</td>
<td>1.1 1.1 1.1</td>
</tr>
<tr>
<td>Rented Dwellings</td>
<td>15.6 12.4 6.0</td>
<td>13.7 12.4 6.0</td>
<td>21.8 10.6 5.9</td>
</tr>
<tr>
<td>Owned Dwellings</td>
<td>15.4 17.1 22.6</td>
<td>14.5 16.8 22.8</td>
<td>6.5 19.3 22.6</td>
</tr>
<tr>
<td>Other Lodging</td>
<td>0.5 0.6 1.4</td>
<td>0.7 0.6 1.3</td>
<td>0.3 0.6 1.5</td>
</tr>
<tr>
<td>Energy</td>
<td>6.2 5.4 4.3</td>
<td>5.7 5.2 4.3</td>
<td>6.6 5.6 3.7</td>
</tr>
<tr>
<td>Water</td>
<td>0.9 1.0 0.9</td>
<td>0.9 0.9 0.9</td>
<td>0.9 1.0 0.8</td>
</tr>
<tr>
<td>Phone</td>
<td>3.4 3.0 2.3</td>
<td>3.2 3.0 2.3</td>
<td>3.8 3.0 2.1</td>
</tr>
</tbody>
</table>
Table 2: Expenditure weights for the first, fifth and tenth decile of income, salary and expenditure (continued)

<table>
<thead>
<tr>
<th></th>
<th>Income deciles</th>
<th>Salary deciles</th>
<th>Expenditure deciles</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1st</td>
<td>5th</td>
<td>10th</td>
</tr>
<tr>
<td>Household F&amp;O</td>
<td>3.3</td>
<td>4.5</td>
<td>7.0</td>
</tr>
<tr>
<td>Apparel</td>
<td>4.0</td>
<td>4.3</td>
<td>5.6</td>
</tr>
<tr>
<td>Gasoline</td>
<td>4.2</td>
<td>5.3</td>
<td>4.4</td>
</tr>
<tr>
<td>Other Vehicle Expenses</td>
<td>4.3</td>
<td>6.8</td>
<td>7.2</td>
</tr>
<tr>
<td>Public Transportation</td>
<td>1.0</td>
<td>1.0</td>
<td>1.7</td>
</tr>
<tr>
<td>Medical</td>
<td>5.0</td>
<td>6.2</td>
<td>5.0</td>
</tr>
<tr>
<td>Entertainment</td>
<td>3.8</td>
<td>4.9</td>
<td>6.5</td>
</tr>
<tr>
<td>Personal Care</td>
<td>0.9</td>
<td>1.0</td>
<td>1.0</td>
</tr>
<tr>
<td>Reading</td>
<td>0.4</td>
<td>0.5</td>
<td>0.6</td>
</tr>
<tr>
<td>Education</td>
<td>1.6</td>
<td>0.8</td>
<td>2.3</td>
</tr>
<tr>
<td>Tobacco</td>
<td>1.7</td>
<td>1.4</td>
<td>0.6</td>
</tr>
<tr>
<td>Other Expenses</td>
<td>0.8</td>
<td>1.1</td>
<td>1.1</td>
</tr>
</tbody>
</table>

A.3 Matching of expenditure and inflation data

We matched the expenditure categories with the respective price indices. Following Hobijn and Lagakos (2005), for the category Other Vehicle Expenses which did not have a perfect match with the available CPI sub-categories, we create the CPI index by combining the series that match this category (that is, SETB, SETD, SETE, and SETF). For each period we used the official weights provided by the BLS, as displayed in the table “Relative Importance in the CPI”. Finally, since Other Lodging changed name, we used 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>
<thead>
<tr>
<th>CEX Expenditure Category</th>
<th>CPI Series (Item Code)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Food at Home</td>
<td>SAF11</td>
</tr>
<tr>
<td>Food Away from Home</td>
<td>SEFV</td>
</tr>
<tr>
<td>Alcohol</td>
<td>SAF116</td>
</tr>
<tr>
<td>Owned Dwellings</td>
<td>SEHC</td>
</tr>
<tr>
<td>Rented Dwellings</td>
<td>SEHA</td>
</tr>
<tr>
<td>Other Lodging</td>
<td>MUUR0000SE2102-SEHB</td>
</tr>
<tr>
<td>Energy</td>
<td>SAH21</td>
</tr>
<tr>
<td>Water</td>
<td>SEHG01</td>
</tr>
<tr>
<td>Phone</td>
<td>SAE2</td>
</tr>
<tr>
<td>Household Furnishings and Operations</td>
<td>SAH3</td>
</tr>
<tr>
<td>Apparel</td>
<td>SAA</td>
</tr>
<tr>
<td>Gasoline</td>
<td>SETB</td>
</tr>
<tr>
<td>Other Vehicle Expenses</td>
<td>SETB-SETD-SETE-SETF</td>
</tr>
<tr>
<td>Public Transportation</td>
<td>SETG</td>
</tr>
<tr>
<td>Medical</td>
<td>SAM</td>
</tr>
<tr>
<td>Entertainment</td>
<td>SAR</td>
</tr>
<tr>
<td>Personal Care</td>
<td>SAG1</td>
</tr>
<tr>
<td>Reading</td>
<td>SERG</td>
</tr>
<tr>
<td>Education</td>
<td>SAE</td>
</tr>
<tr>
<td>Tobacco</td>
<td>SEGA</td>
</tr>
<tr>
<td>Other Expenses</td>
<td>SEGD</td>
</tr>
</tbody>
</table>
B Sectoral heterogeneity

Our baseline result suggests that inflation dispersion decreases after a contractionary monetary shock and that this happens right on impact. This might seem to be at odds with the extensive literature on monetary policy shocks, which argues that inflation should not react immediately. However, this is no contradiction. While aggregate inflation might not be initially affected by a shock, some sectoral inflation rates react immediately to a monetary policy shock, thereby affecting the dispersion.

**Figure 14: Sectoral price impulse responses**

*Notes:* The figure plots the impulse responses of some of the different sectoral inflation rates that compose the Official CPI inflation (thick black line) to a one percentage point contractionary monetary policy shock. Impulse responses are computed at the monthly frequency using data relative to the period 1981M1:2007M12.

In Figure 14 we report the impulse responses of some of the expenditure categories that compose the Official CPI inflation using the specification (2) and the Romer and Romer (2004) shocks as instruments. As expected, the Official CPI inflation starts to decrease only after the first twelve months. However, the impulse responses across
expenditure sectors display significant heterogeneity both in terms of magnitude and pattern.

Indeed, by estimating a factor-augmented vector autoregression, Boivin et al. (2009) showed how the impact of monetary shocks on prices is extremely heterogeneous across goods categories in line with the findings of Nakamura and Steinsson (2008) who measured different frequencies of price adjustment across the categories.
C Decile-level expenditure weights

Households are 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 with the calendar year. To control for this, we compute decile-based inflation rate similarly to Cravino et al. (2020). First of all, 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 its 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 expenditures 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 expenditures are 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 expenditures for category $j$ by the weighted number of months household at decile $d$ reported expenditures during the calendar year. To annualized the average category expenditure at decile level it is enough to multiply the monthly average expenditure by twelve:

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

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 expenditures. The
decile-level expenditure weight for category $d$ can then computed as:

$$w^d_j = \frac{X^d_j}{\sum_j X^d_j}$$

## D Further robustness checks

As a further robustness check, Figure 15 computes the impulse responses excluding from the analysis all the U.S. recession periods (1981M07:1982M11, 1990M07:1991M03, 2001M03:2001M11). The results remain qualitatively unchanged with respect to the baseline specification.

**Figure 15:** Impulse responses of inflation dispersion (without recession periods)

- **Inequality measure: Standard deviation**
- **Inequality measure: 90th-10th**
- **Inequality measure: IQR**

**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 the monthly frequency using data relative to the period 1981M1:2007M12.
As a second set of checks, we assess whether our results are robust to household characteristics. Therefore, following Coibion et al. (2017), the measures of inflation dispersion are normalized by the number of individuals in the household using the OECD equivalent scale. This variable assigns a value of 1 to the first household member, of 0.7 to each additional adult and of 0.5 to each child. The results are reported in Figure 16.

The magnitude of the impulse responses is comparable to the baseline specification. Moreover, after a monetary policy shocks the decrease in inflation dispersion is more persistent while the confidence intervals are slightly bigger with respect to the baseline case. However, the responses are still statistically significant across the three measures of dispersion.

Moreover, we test whether our results are specific to the shock series we chose (i.e. Romer and Romer, 2004). We confront our estimates with the ones obtained using the shocks proposed by Barakchian and Crowe (2013) and Gertler and Karadi (2015). They identify a monetary policy shock by measuring the change in the expected federal funds target rate in a short time window around the FOMC meetings.

Although the high-frequency approach has been widely used, the two-time series are available only starting from the first month of 1990, making them not a viable option for our analysis. In Figure 17 we compare the impulse responses from the local projection using the alternative shocks against our baseline Romer and Romer (2004) shocks. We use the cross-sectional standard deviation as dispersion measure and the data is restricted from 1990M1 to 2007M12 to make the responses comparable.

Removing almost ten years from our sample reduces the magnitude of our baseline response (blue line). However, the coefficients are still largely significant confirming that inflation dispersion decreases after a contractionary monetary policy shock. The coefficients estimated using the Barakchian and Crowe (2013) shocks are close to the zero line for most of the horizon considered but become negative and significant toward the end of the period.

The shape and the magnitude of the response computed with Gertler and Karadi (2015) shocks are more in line with our baseline result. Although the plot is noisier than the one obtained with Romer and Romer (2004) shocks, one can notice how it becomes
Figure 16: Impulse responses of inflation dispersion (OECD equivalent scale)

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. Dispersion is measured using the cross-sectional standard deviation (top), the difference between the 90th and the 10th percentiles of the cross-sectional distribution (middle) and the IQR (bottom). The dispersion measures are adjusted using the OECD equivalent scale to control for the household size. Impulse responses are computed at the monthly frequency using data relative to the period 1981M1:2007M12.

significant only for negative values. Overall, the results from alternative monetary policy shocks do not contradict our main findings and point towards a redistributitional 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 actually driven by differences in consumption patterns across US states rather than along the income distribution. Since the BLS does not provide price indeces at state level but only at division level (Northeast, Midwest, South and West), we compute the cross-sectional standard deviation of inflation for the four divisions using
**Figure 17:** Impulse responses of inflation dispersion using alternative shocks

![Impulse responses of inflation dispersion using alternative shocks](image)

**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 the monthly frequency using data for the period 1990M1:2007M12.

expenditure weights as well as price indexes at division level\(^\text{18}\). As one can notice in Figure 18, there are not significant differences across divisions in the way our measure of inflation dispersion reacts to a monetary policy shock.

Finally, we test whether the expenditure categories we chose played any role in our results. Indeed, the BLS reports the price index at different granular levels. For instance, not only do we have data for *Food and Beverage*, the most aggregate, but we also for the sub-category *Eggs*, the most disaggregate. In choosing the baseline aggregation, we faced a trade-off between using data as disaggregate as possible to fully capture

\(^{18}\text{A more limited number of price indexes are available at division level therefore we used the following expenditure categories: Food at Home, Food Away from Home, Alcohol, Rented Dwellings, Owned Dwellings, Household Furnishings and Operations, Utility, Apparel, Private Transportation, Public Transportation, Gasoline, Medical, Education and Miscellaneous.}\)
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 the monthly frequency using data relative to the period 1981M1:2007M12

inflation dispersion and the quality of the price index. Not all price series are indeed available since the early 80s and this is true especially for the most disaggregate goods and services.

Following the literature, we adopt a rather conservative aggregation. In this section, we show that using alternative expenditure categories, the main results are basically unaffected.

In Figure 19, we report the response from our baseline specification with 21 categories (blue line) against three alternative aggregations: using price indeces at a much more
Figure 19: 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 the monthly frequency using data relative to the period 1981M1:2007M12
granular level\(^\text{19}\) (top left), an even more conservative number of categories\(^\text{20}\) (top right) and an intermediate aggregation\(^\text{21}\) (bottom left).

\(^{19}\)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, Vehicles Expenditures (durables), Vehicles Expenditures (services), Public Transportation, Medical, Entertainment, Personal Care (durables), Personal Care (services), Reading, Education, Tobacco and Other Expenses.

\(^{20}\)14 categories: Food, Alcohol, Housing, Apparel, Gasoline, Other Vehicle Expenses, Public Transportation, Medical, Entertainment, Personal Care, Reading, Education, Tobacco and Other Expenses.

\(^{21}\)27 categories: Food at Home, Food Away from Home, Alcohol at Home, Alcohol Away from Home, Owned Dwellings, Rented Dwellings, Other Lodging, Energy, Water, Phone, Household Furnishings and Operations, Jewelry, Clothing (durables), Clothing (services), Gasoline, Vehicles Expenditures (durables), Vehicles Expenditures (services), Public Transportation, Medical, Entertainment, Personal Care (durables), Personal Care (services), Reading, Education, Tobacco and Other Expenses.
As one can notice, the magnitude of the responses is rather similar to the one obtained in our baseline specification. Increasing the number of categories slightly increases the size of the response but the change is basically negligible. Reducing the number of categories has no effect on the estimate.

This result is particularly important because it partially allows us to address one of the potential critic of the paper: the substitution bias across expenditure categories. Indeed, throughout the paper we have conducted our analysis under the assumption that changes in inflation dispersion are driven mainly by changes in prices and that changes in expenditure shares play only a marginal role. Cravino et al. (2020) already tested this assumption for CEX by using the differences between the Laspeyres and Paasche price index as a proxy for the substitution bias from 1987 and 2004. The authors showed that the difference between the two indices is basically zero over time demonstrating that the substitution bias is indeed negligible.

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 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 had different expenditure shares. The between component accounts for more than 70% of the inflation difference.

The three plots in Figure 19 seem to confirm these findings. The size of the response for inflation dispersion following a contractionary monetary policy shock is basically unaffected when we increase and decrease the number of expenditure categories. This suggests that inflation dispersion is mainly caused by heterogeneity in prices across rather than within expenditure categories.

Finally, the bottom right plot shows the inflation dispersion response when we exclude the categories Food, Energy and Gasoline. This new specification is close to the definition of Core CPI that the Federal Reserve Bank uses to decide which monetary
policy to adopt. Not surprisingly, removing three of the most volatile categories reduces the magnitude of the impulse response by half. However, also under this specification, inflation dispersion significantly and persistently decreases after a monetary policy shock.
E Robustness plots

The figures displayed in this section relate to different analyses from section 5. Namely, figure 20 refers to subsection 5.1 (different lag lengths), figures 21, 22, 23, and 24 to subsection 5.2 (LP approach vs. IV-LP), whereas Figures 25 and 26 are discussed in subsection 5.3 (without the Volcker period). Finally, subsection 5.4 is illustrated by 27 and 28 (decile-based inflation rates).

**Figure 20: Impulse responses of inflation dispersion for different lag specifications**

![Impulse responses graphs for different ARX models](image)

**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 are controlling for \(p\) lags of the dependent variable, and for \(r\) lags of the shock variable. Impulse responses are computed at the monthly frequency using data relative to the period 1981M1:2007M12.
Figure 21: Impulse responses of inflation dispersion (LP approach)

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 LP approach feeds the R&R shocks directly into the local projections algorithm (as opposed to using them as instruments as in the baseline approach): 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 the monthly frequency using data for the period 1981M1:2007M12.
Figure 22: Forecast error variance decompositions (LP approach)

Notes: The figure plots the contribution of monetary policy shocks to the forecast error variance for different measures of inflation dispersion at different time horizons (in months).
**Figure 23:** Impulse responses of different demographic groups’ inflation rates (LP approach)

*IRF for category: Income deciles*

*IRF for category: Salary deciles*

*IRF for category: Expenditure deciles*

*Notes:* The figure plots the impulse responses of a specific demographic groups’ inflation rate to a one percentage point contractionary monetary policy shock. The responses are shifted such that at time zero they are equal to the group median inflation rate for the sample period. Impulse responses are computed at the monthly frequency using data for the period 1981M1:2007M12.
Figure 24: Differences in impulse responses between demographic groups (LP approach)

Notes: The figure plots the difference between impulse responses of different demographic groups at a horizon of 48 months. Impulse responses are computed for a one-percentage-point increases in the monetary policy shock, with monthly data for the period 1981M1:2007M12. The error bars depict 95% confidence intervals, computed by a standard bootstrapping algorithm. The LP approach feeds the R&R shocks directly into the local projections algorithm (as opposed to using them as instruments as in the baseline approach).
**Figure 25:** Impulse responses of inflation dispersion (without Volcker period)

- **Inequality measure: Standard deviation**
- **Inequality measure: 90th-10th**
- **Inequality measure: IQR**

**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 the monthly frequency using data relative to the period 1985M1:2007M12 in order to exclude the Volcker disinflation period.
Figure 26: Differences in impulse responses (without Volcker period)

Notes: The figure plots the difference between impulse responses of different demographic groups at a horizon of 48 months. Impulse responses are computed for a one-percentage-point increases in the monetary policy shock, with monthly data for the period 1981M1:2007M12. The error bars depict 95% confidence intervals, computed by a standard bootstrapping algorithm. Impulse responses are computed at the monthly frequency using data relative to the period 1985M1:2007M12 in order to exclude the Volcker disinflation.
Figure 27: Impulse responses of decile-based inflation rates

Notes: The figure plots the impulse responses of the median inflation rate computed at decile-level following the BLS procedure. The responses are rescaled such that at time zero they are equal to the median group inflation rate in the sample. Impulse responses are computed at the monthly frequency using data relative to the period 1981M1:2007M12.
Figure 28: Differences in inflation rate between deciles

Notes: The figure plots the difference between impulse responses of the group-based inflation rates at a horizon of 48 months. Impulse responses are computed for a one-percentage-point increase in the monetary policy shock, with monthly data for the period 1981M1:2007M12. The error bars depict 95% confidence intervals, computed by a standard bootstrapping algorithm.